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Intangibles within Firm Boundaries

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Abstract

This paper extends a production function estimator to test whether intangible transfers within firm boundaries lead to overall efficiency gains. Using a panel of European majority owned parent-affiliate relationships, we present novel evidence that parent firms strongly benefit from such transfers alongside productivity enhancements for affiliates. In relative terms, affiliates' long-run efficiency improvements are twice those of the parent. Such gains appear to be induced by synergies for the affiliate but not for the parent, supporting theories on the existence of common ownership. A falsification exercise suggests that only 2/3 of these gains are actually internalised within firm boundaries.

Keywords: Intangibles, Firm Boundaries, Technology Transfers, Productivity, Learning, Spillovers
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1 Introduction

Questions revolving around the existence of firm ownership have generated a considerable amount of research. At one end of the spectrum, the literature suggests that ownership structures accommodate the efficient transfer of tangibles. At the other end, ownership is seen as facilitating the efficient transfer of intangibles.

The flow of physical goods within ownership groups is highly concentrated among a small number of affiliates that are owned by large parent firms, both domestically (Atalay et al. 2014) and internationally (Ramondo et al. 2016; Blanas and Seric 2018). This suggests that ownership structures are primarily used to facilitate the efficient transfer of intangibles. As considered theoretically by Arrow (1975) and Teece (1982), common ownership allows the firm to transfer intangible inputs across its vertically integrated production units, as the alternative of the market is most likely a non-viable substitute.

Since the transfer of tangibles can only explain a small fraction of ownership structures in the economy, the need to examine the existence and prevalence of the alternative explanation, i.e. the transfer of intangibles, in depth, is primary.[1] However, any relevant empirical research to date only provides suggestive evidence of this possibility.[2] Likely, this is due to data restrictions which make it difficult to explicitly measure intangibles (Haskel and Westlake 2018). In most cases, researchers rely on proxies or incomplete measures such as R&D, royalties, corporate transferees, etc.

To the best of our knowledge, there are no micro-level panel datasets that combine information on the full set of intangibles for both the parent and affiliate with standard balance sheet information. Such a dataset would allow researchers to fully specify the production function of each parent and affiliate, and hence quantify any transfers of intangibles. A notable exception is the work of Bilir and Morales (2019). They show, based on a panel of US parents and foreign affiliate(s) with information on output, inputs, and R&D investment that expected affiliate productivity increases with parent innovation.

However, R&D spending only captures a specific subset (i.e. proprietary knowledge) of a broad range of intangibles that are potentially transferred within ownership structures. These include but are not limited to: tacit knowledge; know-how; marketing techniques; and managerial/organisational practices.[3] In addition, there is a set of domestic ownership

[1]The existence of one explanation does not mutually exclude the other. To become productive, transfers of tangibles can also be found vis-a-vis to transfers of intangibles, i.e. parental assistance and coordination (Keller and Yeaple 2013; Blanas and Seric 2018).

[2]Atalay et al. (2014) document that, despite the lack of shipments of physical goods within multi-plant firms in the United States, newly vertically integrated affiliates start resembling their parent along the production and trade activities. Ramondo et al. (2016) confirm this lack of shipments across affiliates of U.S. multinationals. Arnold and Javorcik (2009) and Guadalupe et al. (2012) find that foreign acquisition of domestic firms leads to improvements in: sales; productivity; investment; wages; employment; and innovation. For further documentation on the existence of international technology transfers within the boundaries of the firm see Branstetter et al. (2006); Keller and Yeaple (2013) and Gumpert (2018).

[3]On a similar note, Cho (2018) provides evidence on knowledge transfers based on the positive association

structures—usually glossed over in the literature—which, according to our data, represent a relatively larger share of firms which are of smaller size. Nonetheless, these domestically owned firms might not employ the types of intangibles which are easy to measure in the data. For example, they might be less intensive in R&D spending (OECD 2017). Therefore, restricting the analysis to some very special cases of observed intangibles (R&D, patents, etc.), limits our understanding about the importance of intangibles themselves (Haskel and Westlake 2018). Overall, there is ample space to validate or provide further empirical support to ownership theories which argue that firm boundaries exist to facilitate the transfer of intangibles.

This paper takes a step in that direction by identifying transfers of intangibles and demonstrating how they determine a firm's productivity evolution. We use a carefully constructed European panel of majority owned parent-affiliate groups with full balance sheet information on both sides for the period 2004-2015 and extend a typical production function estimation procedure. In response to data limitations on intangible inputs, we devise a method to characterise the full set of intangibles transferred between parent and affiliate firms.

Specifically, in any production function setup, the productivity term captures both disembodied technological change and any potential intangible inputs used in the production of the final output that are not observed in the data. The former includes innate characteristics of workers, know-how, etc., while the latter includes management practices, acquired characteristics of workers, innovation, among others. As such, the leftover output variation after conditioning on tangible inputs of production (observed in the data) is expected to be informative about the intangible aspects of the firm (unobserved in the data) . With this in mind, we exploit observed ownership links in the data and extend a standard production function system by introducing the productivity of the ownership-linked firm as a potential determinant of its future productivity. The modelling approach we follow is, among others, similar to Bilir and Morales (2019) where firms are affected by their actions or changes in their operating environment. To the extent that ownership-linked productivity contains meaningful variation on intangibles, this empirical model is expected to capture potential productivity effects from intangible transfers between ownership-linked firms.

The following findings emerge. First, we show that the transfer of intangibles within the boundaries of the firm leads to productivity enhancements of the affiliates. This result complements and expands upon others in the literature to this effect by considering a broader set of intangibles. Second, we present a novel finding that the transfer of intangibles from the affiliate also leads to productivity enhancements of the parent. To the best of our knowledge, this is the first study to uncover this fact. Importantly, both of these findings advance existing empirical evidence which supports the importance of intangibles in explaining common ownership. In terms of the relative importance of these two effects, we find that the affiliate benefits twice as much as the parent. Nonetheless, productivity effects for the parent are non-trivial. As such, we argue that these results should be considered in any cost-benefit analysis of policies which target

between the transfer of mangers from the parent to the foreign affiliate and the affiliates' productivity growth.

intangible investment.

Exploring possible mechanisms, we find that affiliate firms benefit from complementarities with their parents' intangibles, in line with their very nature (Haskel and Westlake 2018). On the flip side, such synergies are not present for the parent. Instead, our analysis suggests that parent firms are pure recipients of affiliate-specific intangible technology. This further highlights the true motives of firm ownership (Teece 1982; Atalay et al. 2014). Moreover, these results are supported by cross-country and cross-industry heterogeneity in the data.

As a cross-validation, we rely on a specific type of intangible which is directly observable—patents. While important, patents are only responsible for a small share of the total impact. Lastly, we further validate our results through a falsification exercise whereby we repeat our estimation on a (a) randomly assigned and (b) closely matched sample of firms with no ownership links. In the first case results cease to exist. This further confirms that our findings are specific to ownership-linked firms and do not exhibit spurious effects. In the second case, we find an effect which amounts to one third of the baseline estimates, representing spillovers to the local economy (Javorcik 2010). In contrast, two thirds of the baseline effects appear to be fully internalised within the boundaries of the firm. All results remain robust to a battery of robustness exercises which address potential concerns with the baseline empirical model and underlying economic assumptions.

The remainder of this paper is organised as follows. First, Section 2 discusses the construction and novelty of the dataset used for this analysis. Section 3 explains the empirical model, whose identification is subsequently discussed in Section 4. Section 5 presents the main results which stem from the baseline model, discusses mechanisms, and provides cross-validation exercises related to patents and falsification tests. Next, Section 6 goes through robustness exercises. Finally, Section 7 concludes.

2 Data

In this section we describe the construction of the available panel dataset that delivers two building blocks of firm-level information. The first, more standard in the empirical literature, refers to output and inputs involved in production. The second, less frequently encountered, provides information about ownership links between firms. Combining these two elements results in a unique firm-level dataset with information about the tangible parts of production within firm boundaries.

We construct a panel of firms in 19 EU countries[4] for the period 2004-2015. Data come from the Amadeus database by Bureau van Dijk Electronic Publishing (2018) (BvDEP). BvDEP regularly updates the information set in Amadeus and releases a monthly version which contains

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

the latest information on ownership. Firms that exit the market are thus dropped fairly rapidly. For a complete set of financial and ownership information over time, we use a time series of (annual) releases to construct a consistent database. In particular, following Merlevede et al. (2015), we build a dataset with nearly full financial and administrative information, i.e. balance sheet, profit and loss account activities, location, ownership, entry and exit. Concerning the representativeness of the data, Table C.2 in Appendix C contains the number of firms and employees covered by the dataset both in levels and as a share of inward Foreign Affiliates Statistics (FATS) provided by Eurostat for the year 2012 (Eurostat 2018). For both measures, the dataset covers close to 60% of what is reported in FATS. Merlevede et al. (2015) describe in detail the construction of the data and coverage across EU countries at length.

Table 1: Summary statistics of baseline database

Affiliate	Obs.	Mean	St.Dev.	p25	p50	p75
Output†	71,119	31	211	1.9	6.1	19
Capital†	71,119	7.1	151	.18	1	4.2
Material†	71,119	20	146	.8	3	11
Labour	71,119	111	453	13	36	98
Parent						
Output†	54,098	138	1,141	7.7	24	72
Capital†	54,098	24	140	1	3.9	14
Material†	54,098	88	868	3.5	12	40
Labour	54,098	381	2,103	38	103	281
$N^{\underline{o}}$ Affiliates	54,098	1.3	.85	1	1	1

Notes: † Monetary variables in millions of Euro. Unbalanced panel of 12,665 parent and 17,661 affiliate firms in 22 NACE 2-digit manufacturing industries and across 19 EU countries over the period 2004 to 2015. Underline data sourced from Amadeus database by BvDEP.

We focus on the sample of firms with majority ownership links. This includes affiliate firms where more than 50% of their shares are owned by a domestic or foreign parent firm. Each affiliate can have only one majority controlling parent, while parent firms can control multiple affiliates. This allows us to focus on the interactions within each ownership group where the parent has complete control of its boundaries. Of these firms, we keep the active firms in order to exclude cases which are hard to model empirically since their assets can genuinely go down to (almost) zero.[5] Continuing, we only consider firms that file unconsolidated accounts to control for double counting in accounts integrating the statements of possible controlled subsidiaries or branches of the concerned company.[6] To address potential concerns about misreporting, transfer pricing, and tax evasion, we only include firms whose reported NACE 2-digit industry classification falls within the manufacturing sector. In addition, due to small sample size,

[5]We exclude firms that are dissolved, in liquidation, inactive and in bankruptcy.

[6]Note that this does not control for the case of multi-plant firms since such information is unavailable.

we exclude the following industries: NACE 19 - Manufacture of coke and refined petroleum products; and NACE 21 - Manufacture of rubber and plastic products. To abstain from excluding other small-sized industries, e.g. NACE 12 - Manufacture of tobacco products and NACE 15 - Manufacture of leather and related products, we use the more aggregate classification A*38.[7]

After completing these steps, we retain firms which report strictly positive sales, tangible fixed assets, number of employees and material costs. Finally, we remove outliers using the BACON method proposed by Billor et al. (2000) to ensure that such observations do not drive overall results.[8] Cleaning the data in this way results in an unbalanced panel of 12,665 parent and 17,661 affiliate firms with 54,098 and 71,119 observations, respectively, across 19 EU countries for the period 2004-2015.

The information presented in Table 1 constitutes the baseline dataset used to estimate the empirical model described in section 3. All monetary variables are deflated using the appropriate country-industry output deflator from the EU KLEMS database. (Real) Output (Y) is sales deflated with producer price indices. Capital (K) is the reported book value of tangible fixed assets deflated by the average of the deflators of various industries (Javorcik 2004).[9] (Real) Material (M) is material inputs deflated by an intermediate input deflator constructed as a weighted average of output deflators, where country-industry-time specific weights are based on intermediate input uses retrieved from input-output tables. Labour (L) is the number of employees. Affiliates refers to the number of majority controlled affiliates from each parent. Note that only 20% of observations report multiple affiliates, with a maximum of 22 affiliates.[10] Note that so far the dataset does not include directly observable information on firm level intangibles. This will be identified with the help of the empirical model described in Section 3 below.

[7]Appendix Table C.1 provides an overview of the NACE Rev.2 2-digit industries and their correspondence to the intermediate aggregation A*38 (Eurostat 2020). Also, a direct mapping to the Classification of Products by Activity (CPA) is available since both classifications are completely aligned down to the class level (Eurostat 2019). For robustness, we provide checks under the alternative classifications and when including the omitted industries from the sample.

[8]BACON stands for Block Adaptive Computationally efficient Outlier Nominators. It is a multiple outlier detection method. The variables considered in the method are log of output, labour, capital, material and material's revenue share. We first trim at the industry and then manufacturing level. As in any outlier detection method, the threshold defining the outlying points is chosen by the researcher, therefore, we will provide robustness checks over the choice of more lenient thresholds.

[9]This includes the following NACE Rev.2 2-digit industries: Electrical equipment (27); machinery and equipment n.e.c. (28); motor vehicles, trailers and semi-trailers (29); and other transport equipment (30).

[10]When considering non-European affiliates, 23% of parent-year observations report multiple affiliates, with a maximum of 36 affiliates. However, the Amadeus Orbis Europe dataset does not contain the balance sheet information of non-European affiliates. As such, we solely focus on affiliates located in European countries. When considering all other sectors in the economy the maximum number of affiliates reaches 197 (with 28% of parent-year observations reporting more than one affiliate).

3 Empirical Model

This section describes the empirical model of intangible transfers in majority owned firms, and their effect on productivity within ownership groups. We extend a typical production function setup to capture potential productivity effects from intangible transfers between ownership-linked firms. In the baseline specification, we focus on the classic case of perfect competition in output and input markets where both parent and affiliate firms take output and input prices as given. Robustness Section 6 presents the case of imperfect competition in the output market.

3.1 Definitions and Setup

We observe a panel of ownership groups $g = 1,\dots,G$ over periods $t = 1,\dots,T$.[11] In each ownership group g and period t the set of active firms $\mathscr{F}_{gt}$ are indexed by 0 for the parent firm that has majority control of its affiliate(s) $i = 1,\dots,I_g$. Parent firms can be located in country $c = 1,\dots,C$ and produce in industry $j = 1,\dots,J$ other than those of their affiliate(s)—see Appendix Tables C.3 and C.4 for a tabulation of firm-year observations across country-industry pairs for the parent and affiliate, respectively. Firms are assumed as single-product producers with their production activity defined by their industry classification.[12]

In period t, ownership group-g has access to information denoted by $\mathscr{I}_{gt}$. This information set includes any type of information available to the management board when making its periodic decisions and is the union of the information sub-sets available to the parent and affiliate(s), $\mathscr{I}_{gt} = \mathscr{I}_{g0t} \cup \left(\cup_i \mathscr{I}_{git} \right)$.[13] Overall, without loss of generality, we assume a centralized management system where decisions for both the parent and affiliate(s) are made at the management board level which has access to all available information within the ownership group.[14] At this stage, we impose no restrictions on the interdependence and dynamics of decision making within each ownership group, something that we will revisit when considering the identification strategy in Section 4.

[11]This is a standard short panel framework with fixed T and with the number of ownership groups as the asymptotic dimension of the data, i.e. $G \to \infty$.

[12]Note that we do not observe data on multi-product firms and thus need to assume that each firm produces one unique product. However, in the presence of such data, the empirical model can be directly extended to allow for the case of multi-product firms in line with the applications of De Loecker (2011); De Loecker et al. (2016) and Blum et al. (2018).

[13]Given our focus on majority ownership, the intersection of these sub-sets is expected to be non-empty, i.e. $\mathscr{I}_{g0t} \cap \mathscr{I}_{git} \neq \emptyset$. However, the size of this intersection set directly depends on the degree of autonomy of affiliates. For example, in cases of full centralisation, the information set of affiliates will be a subset of the parent set, assuming that all decisions are made at the parent firm.

[14]The empirical model is consistent with any other alaternative management system. For example, one could allow for a more decentralised management style where affiliates can have their own decision-making body (subordinated to the highest decision making) and access to exclusive information. See Sageder and Feldbauer-Durstmüller (2018) for a literature review on different management control systems in multinational companies.

3.2 Production Technology

For the parent, we consider a gross output production function $Y_{g0t} = H(K_{g0t}, L_{g0t}, M_{g0t})\mathrm{e}^{\omega_{g0t}+\varepsilon_{g0t}}$, with Hicks-neutral total factor productivity (TFP) ω_{g0t}.[15] In logs, the production function takes the following form:

$$y_{g0t} = h(k_{g0t}, l_{g0t}, m_{g0t}) + \omega_{g0t} + \varepsilon_{g0t} \tag{1}$$

where y_{g0t}, k_{g0t} and m_{g0t} are log values of deflated (at the country-industry-year level) sales, tangible fixed assets, and material costs, respectively. l_{g0t} is the log of the total number of employees of parent 0 in ownership group g (in industry j and country c) at time t. TFP is unobserved to the econometrician but known to the firm when decisions are made, i.e. $\omega_{g0t} \in \mathscr{I}_{g0t}$. Ex-post shocks, i.e. shocks which occur after the period t decisions, are picked up by ε_{g0t} and are not part of the firm's information set $\varepsilon_{g0t} \notin \mathscr{I}_{g0t}$.[16]

In the same spirit, we consider the production function of the affiliate(s) in logs:

$$y_{git} = f(k_{git}, l_{git}, m_{git}) + \omega_{git} + \varepsilon_{git} \tag{2}$$

where now the affiliate's joint output of log capital (k_{git}), labour (l_{git}) and material (m_{git}), is delivered from a production function $f_j(\cdot)$. Equations (1) and (2) account for cases where, even within the same country and industry, affiliates can have different production technologies from the parent. Analogous to the parent, $\omega_{git} \in \mathscr{I}_{git}$ is part of the firm's period t information set while $\varepsilon_{git} \notin \mathscr{I}_{git}$ is unanticipated. Overall, equations (1) and (2) represent standard production functions that one could readily identify from the data.

3.3 A Model of Intangible Transfers and Firm Performance

Productivity is empirically well-documented to be highly persistent over time (Syverson 2011). This lends support to standard working assumptions over its law of motion. As such, we assume that parent and affiliate TFP evolve over time according to the following stochastic processes:

$$\omega_{g0t} = E[\omega_{g0t} | \mathscr{I}_{gt-1}] + \xi_{g0t} \tag{3}$$

and

$$\omega_{git} = E[\omega_{git} | \mathscr{I}_{gt-1}] + \xi_{git} \tag{4}$$

where ξ_{gt}'s capture unanticipated exogenous shocks in period $t-1$ that affect each firm's TFP in t, i.e. $E[\xi_{gt} | \mathscr{I}_{gt-1}] = 0$. In the seminal work of Olley and Pakes (1996), an 'exogenous' first order Markov process is assumed, i.e. for a generic firm i $\omega_{it} = E[\omega_{it} | \omega_{it-1}] + \xi_{it}$. However,

[15]This implies that technological change increases the productivity of production factors in equal terms. For a production function framework with multi-dimensional productivity and factor-augmenting technology differences see Doraszelski and Jaumandreu (2018) and Harrigan et al. (2018).

[16]Alternatively, one can also think of ε_{g0t} as a classical measurement error in output. For robustness, we will also consider cases with measurement error in both output and inputs (Section 6).

exogeneity should be relaxed in order to accommodate the fact that TFP evolves endogenously in response to the firm's actions—including importing (Kasahara and Rodrigue 2008); R&D (Aw et al. 2011; Doraszelski and Jaumandreu 2013); exporting (De Loecker 2013)—as well as changes in the firm's operating environment, such as trade liberalisation (De Loecker 2011; De Loecker et al. 2016).

In the context of ownership groups, the set of actions that can influence firm performance includes not only those from the firm itself but also those from other ownership-linked firms. More concretely, if transfers of intangibles are present within the boundaries of the firm, then one would expect the performance of the affiliate to respond to investments in intangibles from the parent, and vice versa. As such, one should use a controlled Markov process in both (4) and (3) to explicitly allow for other elements of $\mathscr{I}_{gt-1}$ to affect TFP. Taking this into account, Bilir and Morales (2019) examine the impact of innovation in multinational firms by considering an empirical model where the Markov process of affiliate TFP can be shifted by both affiliate and headquarter R&D, i.e. equation (4) becomes: $\omega_{git} = E[\omega_{git}|\omega_{git-1}, R\&D_{git-1}, R\&D_{g0t-1}] + \xi_{git}$. While R&D spending is an important driver of proprietary knowledge, it represents only one element of the broad set of intangibles, ranging from R&D and software to design, branding, organizational capital, and social relations.

In an ideal world, researchers would observe all actions related to intangibles. However, in the real world this is rather infeasible. If anything, one can limit the analysis to some very special cases of observed intangibles, e.g. R&D, patents, etc. This brings us back to the inherent difficulty of measuring and evaluating intangibles (Haskel and Westlake 2018).

Irrespective of how it is estimated, empirical TFP is not identical to disembodied technological change, known as the 'Solow Residual' (Solow 1957). Indeed, the Solow Residual refers to everything that the firm observes but cannot quantify with scientific objectivity, e.g. innate characteristics of workers, know-how, etc. Instead, TFP also includes the impact of factors that are quantifiable with scientific objectivity from the firm, but not available in the data for the researcher, e.g. management practices, acquired characteristics of workers, innovation, mailing list of clients etc. Therefore, the remaining output variation after conditioning for observed tangible inputs—known as a "measure of our ignorance" (Abramovitz 1956)—is expected to be informative about the unobserved intangible aspects of the firm.

Combining this with the fact that ownership links are observed in the data, we consider the TFP of the ownership-linked firm as a composite measure of intangible transfers which is allowed to determine the productivity evolution of the firm, such that:

$$\omega_{g0t} = E[\omega_{g0t}|\omega_{g0t-1}, \omega_{git-1}] + \xi_{g0t} \tag{5}$$

and

$$\omega_{git} = E[\omega_{git}|\omega_{git-1}, \omega_{g0t-1}] + \xi_{git} \tag{6}$$

Apart from the variables which can be hypothesized to affect each other intertemporally, this specification does not require any prior knowledge about the forces influencing them. As such, estimates of equation (5) and (6) identify the potential presence and importance of intangible transfers within the boundaries of the firm.[17] One can think of random shocks creating persistent intertemporal feedback effects between ownership-linked firms. These shocks summarize all of the uncertainties related to the implementation and success of various actions.

Overall, this simple and internally consistent extension of a production function specification provides a natural and intuitive way of analysing the importance of intangible transfers within firm boundaries.

4 Identification and Estimation

We now present how the model in Section 3 is brought to the data to capture the effects of interest. In what follows we describe the identification strategy, underlying assumptions, and choice of functional forms to estimate the 'baseline model.'

4.1 Identification Strategy

A well-know challenge when estimating equations (1) and (2) is the endogeneity of inputs, also known as 'simultaneity' or 'transmission bias.' Such bias originates from the fact that firms know their productivity level when they decide which inputs to use (Marschak and Andrews 1944; Griliches and Mairesse 1999).[18] To circumvent this bias, we follow the nonparametric identification strategy developed by Gandhi, Navarro, and Rivers (2020) (herein GNR). GNR propose a simple estimator for gross output production functions under the commonly employed model structure in proxy variable methods, i.e. at least one flexible production input.

Identification is established by exploiting information in the first order condition with respect to the flexible input from the firm's static profit maximisation problem. In addition to the transmission bias, this flexible estimation approach also controls for the value-added bias that arises from estimating a value-added rather than a gross output production function.[19] In line

[17]Note that this model is silent about the underline structure of intangibles, e.g. technological versus non-technological elements (Hulten 2010; Haskel and Westlake 2018), and any potential differential effects on productivity. Therefore, this model can only capture productivity effects from intangibles transferred between ownership-linked firms and not the productivity effects of intangibles within the same firm, e.g. innovation (Doraszelski and Jaumandreu 2013). To the extent that certain own-firm intangibles are correlated with tangibles, one should explicitly include them in the law of motion to avoid omitted variable bias (De Loecker 2013). For such an application, see Bilir and Morales (2019). However, intangibles (e.g. software, product recipe, etc.) are more likely to be 'scalable' (Haskel and Westlake 2018), i.e. used for an unlimited number of times with an infinitesimal cost increase, and thus not necessarily related to tangible inputs.

[18]The applied production function estimation literature has primarily employed structural approaches including both dynamic panel methods (Arellano and Bond 1991; Blundell and Bond 1998, 2000) and proxy variable methods (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2015). However, proxy variable methods have dominated in the empirical literature given dynamic panel methods' weak performance both at a theoretical and empirical level (Griliches and Mairesse 1999; Ackerberg et al. 2007).

[19]See Gandhi et al. (2017) for an exposition of the sizeable effects of value-added bias on TFP heterogeneity. Merlevede and Theodorakopoulos (2018) empirically assess the importance of such a misspecification in the context

with most of the proxy variable methods, the GNR procedure follows two steps and allows estimation of both the production function and the effects of interest from equations (5) and (6).

4.2 Timing of Inputs

Timing assumptions about when firms make choices and observe shocks are crucial to correctly identifying production functions using structural approaches (Ackerberg 2019). On the one hand, the replacement and installation of new capital is costly and time-consuming. On the other, rigidities in European labour market institutions often prevent labour adjustments within the (accounting) year. These factors translate to a one period lag between the choice of capital and labour and their realisation in the production process (hence in the accounting data). Therefore, in line with the literature, we assume that capital and labour are predetermined inputs which are chosen one period prior to the TFP realisation. Specifically, ownership groups (and thus the firms within the group) have information on these inputs and take them into account in the period's production process $\{l_{g0t}, k_{g0t}, l_{git}, k_{git}\} \in \mathscr{I}_{gt}$.

At least one production input must be fully flexible under the model structure of proxy variable methods. As such, following the literature, we assume that material is the only flexible input that freely adjusts in each period, $\{m_{g0t}, m_{git}\} \notin \mathscr{I}_{gt}$, and has no dynamic implications, $\partial m_{g0t}/\partial m_{g0t-1} = \partial m_{git}/\partial m_{git-1} = 0$. First, this assumption implies that there is a spot market for commodities that are up for immediate trade. Second, it implies that firms can freely choose material inputs and are unaffected by their previous sourcing decisions.[20]

4.3 Functional Forms

A common practice in the empirical literature is to separately estimate both the production function and effects of interest for each meaningful granular set of firms, e.g. by pooling all parent firms at the country-industry level. In practice, however, performing separate estimations in this context raises two concerns about the identifying variation.

First, the number of firms becomes very small (if not zero) for sufficiently granular sets of firms when allowing for different production technologies between the parent and affiliate.[21] Second, the estimation of equation (5) or (6) identifies the production technologies of the sets of firms used in the estimation as well as of all other sets of ownership-linked firms.[22] This

of their research application.

[20]The input is no longer flexible if the firm is constrained or faces market distortions that affect its input choices. In this case, one needs to apply an alternative identification strategy, such as dynamic panel methods. Shenoy (2018) provides an extensive discussion on this topic. However, our sample focuses on larger firms that, if anything, are less constrained by market imperfections relative to smaller-sized firms (Beck et al. 2005). Nonetheless, we provide robustness over the alternative assumption that material is a non-flexible input, i.e. either predetermined and/or dynamic.

[21]For example, looking at Appendix Table C.3 We find limited parent-year observations in any manufacturing industry in Estonia.

[22]For example, estimation of the production technology of parent firms in the Romanian Manufacture of electrical equipment should also deliver estimates for the production technology of their ownership-linked affiliates in four

is important because considering each set of firms separately disregards relevant and sizable identifying variation within the sets of ownership-linked firms that are, in turn, linked to other sets of firms.[23] Both cases above result in sample selection issues as certain groups do not have a sufficient number of observations to identify the group-specific production function. This is especially the case for smaller countries. As such, consistent estimation requires not only sufficient variation within each group of firms but also for all other groups of firms linked with ownership.

We implement three concrete steps to evade the sample selection issues described above. First, we pool firms across all manufacturing industries and European countries in the data. Thus, instead of estimating the model for each set of firms separately, we include all information from the baseline sample. Subsequently, we allow the production functions (1) and (2) to vary across industries j to account for heterogeneity in production technologies. This implies that firms across all EU countries in the sample share the same production technology within a given manufacturing industry. This assumption is consistent with increased production integration in the EU (Nordström and Flam 2018) and allows for sufficient identifying variation within each industry in the data (see Appendix Table C.3 and C.4).[24] Finally, with this data structure in mind, we use simple parametric functional forms for the baseline model to avoid depleting the degrees of freedom and impeding the estimation routine. More specifically, for the production technologies in (1) and (2) we rely on industry-j specific Cobb-Douglas specifications for both the parent:

$$h_j\left(k_{g0t}, l_{g0t}, m_{g0t}; \pi\right) = \sum_j \left(\pi_{cj} + \pi_{kj} k_{g0t} + \pi_{lj} l_{g0t} + \pi_{mj} m_{g0t}\right) \odot d_j \tag{7}$$

and the affiliate:

$$f_j\left(k_{git}, l_{git}, m_{git}; \alpha\right) = \sum_j \left(\alpha_{cj} + \alpha_{kj} k_{git} + \alpha_{lj} l_{git} + \alpha_{mj} m_{git}\right) \odot d_j \tag{8}$$

where π and α are vectors with the industry-j specific parameters of the parent's and affiliate's production technology, respectively, d_j is a dummy variable equal to one when a firm is in industry j and zero otherwise, and $\odot$ represents the element-wise (Hadamard) product. This is the simplest and most commonly used specification in the literature, albeit at the expense of restricting the elasticities of substitution between inputs to unity.[25]

industries in Romania. Those industries include: Manufacture of basic metals and fabricated metal products, except machinery and equipment; Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c.; and Other manufacturing, and repair and installation of machinery and equipment.

[23] Adding to the previous example, this refers to affiliate firms owned by parent firms not in the Romanian Manufacture of electrical equipment, which actually constitutes the bulk of information for those groups.

[24] Acknowledging that this approach might mask further heterogeneous effects across countries and/or industries, we later try to uncover these with additional checks.

[25] Alternatively, one could allow for more flexible substitution patterns between inputs, i.e. translog functional form. Such a choice comes with typical trade-offs faced by empirical researchers: increased parameter space and

Similarly, we rely on linear specifications for the evolution of productivities[26] with:

$$\omega_{g0t} = \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\rho}_{fe} + \xi_{g0t} \tag{9}$$

and

$$\omega_{git} = \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \rho_{fe} + \xi_{git} \tag{10}$$

where $\bar{\omega}_{git-1} \equiv \sum_i \omega_{git-1}/I_g$ is the mean lagged productivity from all affiliates linked to the parent within each ownership group g.[27] $\rho_{fe} \equiv \rho^a_{cj} + \rho^a_{ct} + \rho^a_{jt} + \rho^p_{cj} + \rho^p_{ct} + \rho^p_{jt}$ is a set of additive fixed effects, i.e. unobserved terms reflecting shocks/characteristics that vary across the country-industry (cj), country-year (ct) and industry-year (jt) of the affiliate (a) and parent (p), respectively. $\tilde{\rho}_{fe}$ refers to the same set of fixed effects which are now collapsed to the parent-year dimension, since a parent can have many affiliates.[28] These controls account for various macroeconomic shocks, cyclical variation and structural differences at the country and/or industry level. At the same time, including these fixed effects at the parent and affiliate level in each equation controls for business cycle synchronisation and persistent shocks which propagate through the ownership structure and which could falsely appear as productivity effects.

Under these simple formulations, equations (9) and (10) now closely resemble panel Vector Autoregression (VAR) models (Holtz-Eakin et al. 1988) which capture interdependencies among two stochastic processes. Note that these specifications are not industry-specific as in the case of the production functions, but their simplicity allows us to control for additional dimensions in the data, i.e. fixed effects, without imposing a computationally intensive estimation routine. Therefore, the estimated parameters deliver an average effect across all manufacturing industries.[29] In addition, both equations account for a global constant which is not separately identified and is thus subsumed in the fixed effects.

Combining (1) and (2) with (5) and (6), respectively, along with their parametric functional forms mentioned above, results in the following estimating baseline equations which constitute the baseline model:

$$y_{g0t} = \sum_j \left(\pi_{kj}k_{g0t} + \pi_{lj}l_{g0t} + \pi_{mj}m_{g0t}\right) \odot d_j + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + \xi_{g0t} + \varepsilon_{g0t} \tag{11}$$

computationally intensive estimation routines. However, for robustness, we explore this alternative.

[26] Alternatively, a more general functional form can be used by introducing a sieve of relevant controls. This case should be considered with caution since non-linearities, even in the case where fixed effects enter linearly, would result in a computationally very intense estimation.

[27] Recall that the parent can have multiple affiliates, but such cases represent only a small fraction of the baseline data (see Section 2). However, we provide additional robustness when we instead choose the minimum, maximum or median value from the multi-affiliates' productivities.

[28] For the multi-affiliate parent firms we use the maximum column value when collapsing the affiliate fixed effects at the parent-year level.

[29] To unmask potential heterogeneity across industries, we also provide industry-specific estimates.

and

$$y_{git} = \sum_j \left(\alpha_{kj}k_{git} + \alpha_{lj}l_{git} + \alpha_{mj}m_{git}\right) \odot d_j + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + \xi_{git} + \varepsilon_{git} \quad (12)$$

where the industry specific production function constants π_{cj} and α_{cj} cannot be separately identified from the fixed effects (and the constant in the markov process) and are thus subsumed in $\widetilde{\phi}_{fe}$ and ϕ_{fe}, respectively. Overall, the estimated parameters of interest ρ_{pa} and ρ_{ap} give the average short-run effect of ownership-linked productivity with its long-run impact emerging through the persistence parameters ρ_{pp} and ρ_{aa}, respectively.

4.4 Estimation

Estimation of baseline equations (11) and (12) follows directly from the nonparametric identification strategy of GNR. Below, we outline the relevant assumptions made and steps followed, while we refer the interested reader to Appendix A for a detailed overview over the nonparametric identification of our empirical model.

The static profit maximisation problem yields the first order condition with respect to the flexible input, material, for both the parent and affiliate. Combining these optimality conditions with the relevant production functions and re-arranging terms delivers the following material cost share regression equations:

$$s_{g0t} = ln\left(\sum_j \pi'_{mj} \odot d_j\right) - \varepsilon_{g0t} \quad (13)$$

and

$$s_{git} = ln\left(\sum_j \alpha'_{mj} \odot d_j\right) - \varepsilon_{git} \quad (14)$$

where s_{g0t} and s_{git} are the log of the nominal share of material costs over sales for the parent and the affiliate, respectively. The terms $\pi'_{mj} \equiv \pi_{mj}\mathscr{E}_p$ and $\alpha'_{mj} \equiv \alpha_{mj}\mathscr{E}_a$ are the industry-j specific output elasticities of material up to a nuisance constant $\mathscr{E}_p$ and $\mathscr{E}_a$, respectively. By the time firms make their annual decisions, ex-post shocks ε_{g0t} and ε_{git} are not in their information set and therefore $\mathscr{E}_p = E(e^{\varepsilon_{g0t}})$ and $\mathscr{E}_a = E(e^{\varepsilon_{git}})$.[30] Note that TFP is dropped from both share equations. This follows the identification insight of GNR where the TFP term which induced the transmission bias is eliminated from the share equation due to assumed Hicks-neutrality, i.e. additive.[31]

[30]To derive these share equations that treat $\mathscr{E}_p$ and $\mathscr{E}_a$ as constants when brought to the data, we need to assume that the ex-post shocks to production are independent of the firm's information set. See Appendix A for a discussion over of this assumption, possibilities to relax it to mean independence and the importance of accounting for the term $\mathscr{E}_p$ and $\mathscr{E}_a$.

[31]Also see Doraszelski and Jaumandreu (2013) for an application exploiting the same structural link between the first order condition of the flexible input and the production function.

It is important to mention that, for the optimality conditions to hold, an additional restriction must be imposed on the drivers of material usage beyond the implied assumptions from the timing of flexible inputs discussed in subsection 4.2. This includes the absence of any type of interdependencies in the sourcing decisions across firms within the same ownership group, irrespective of the centralisation level of decision-making.[32] We relax this assumption in Section 6 and employ an alternate estimation strategy to alleviate concerns about its restrictiveness. On the other hand, such assumptions are irrelevant for capital and labour inputs since the identification strategy does not need to take a stand on their optimality conditions. Therefore, this estimation is consistent with any type of model structure describing the determinants of capital and labour usage.

Under the assumption that ex-post shocks to production are independent of the firm's information set, a Non Linear Least Squares (NLLS) estimation of (13) and (14) is applied. For this simple parametric case we regress the log of material costs share on the log of a full set of industry-specific dummy variables d_j. This step identifies ε_{g0t} and ε_{git}—the sample analogue of $\mathscr{E}_p$ and $\mathscr{E}_a$—and a vector of industry-j specific output elasticities of material for both the parent (π_m) and affiliate (α_m).[33]

Up to this stage, the production functions are partly identified with the remaining elements of the estimating equations expressed as:

$$\begin{aligned}\widehat{\mathscr{Y}}_{g0t} &= \sum_j \left(\pi_{kj}k_{g0t} + \pi_{lj}l_{g0t}\right) \odot d_j + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + \xi_{g0t} \\ &= \sum_j \left(\pi_{kj}k_{g0t} + \pi_{lj}l_{g0t}\right) \odot d_j + \rho_{pp}\Big(\hat{\mathscr{Y}}_{g0t-1} - \sum_j \left(\pi_{kj}k_{g0t-1} + \pi_{lj}l_{g0t-1}\right) \odot d_j\Big) \\ &\qquad + \rho_{pa}\overline{\Big(\hat{\mathscr{Y}}_{git-1} - \sum_j \left(\alpha_{kj}k_{git-1} + \alpha_{lj}l_{git-1}\right) \odot d_j\Big)} + \widetilde{\phi}_{fe} + \xi_{g0t}\end{aligned} \tag{15}$$

and

$$\begin{aligned}\hat{\mathscr{Y}}_{git} &= \sum_j \left(\alpha_{kj}k_{git} + \alpha_{lj}l_{git}\right) \odot d_j + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + \xi_{git} \\ &= \sum_j \left(\alpha_{kj}k_{git} + \alpha_{lj}l_{git}\right) \odot d_j + \rho_{aa}\Big(\hat{\mathscr{Y}}_{git-1} - \sum_j \left(\alpha_{kj}k_{git-1} + \alpha_{lj}l_{git-1}\right) \odot d_j\Big) \\ &\qquad + \rho_{ap}\Big(\hat{\mathscr{Y}}_{g0t-1} - \sum_j \left(\pi_{kj}k_{g0t-1} + \pi_{lj}l_{g0t-1}\right) \odot d_j\Big) + \phi_{fe} + \xi_{git}\end{aligned} \tag{16}$$

[32]In principle, the estimation strategy could account for such interdependencies to the extent that they are intratemporal, do not invalidate the assumption over the flexible nature of material inputs and can be explicitly modeled in the firms optimality conditions. For a closely related modelling approach where the global sourcing decisions interact through the firm's cost function see Antràs et al. (2017).

[33]Alternatively, at this stage, one can estimate each equation for each industry j separately since all interdependencies through the productivity term are by construction eliminated. Therefore, the share equations are not bounded by the limitations discussed in subsection 4.3 that would require pooling all available firms in the data.

where $\widehat{\mathscr{Y}_{g0t}} \equiv y_{g0t} - \sum_j \widehat{\pi}_{mj} m_{g0t} \odot d_j - \widehat{\varepsilon}_{g0t}$ and $\widehat{\mathscr{Y}_{git}} \equiv y_{git} - \sum_j \widehat{\alpha}_{mj} m_{git} \odot d_j - \widehat{\varepsilon}_{git}$ are the log of the expected output net of the computed part of production from the first step.

Following dynamic panel and proxy variable methods, the second step exploits the assumption over the law of motion of TFP and proceeds with a standard iterative Generalised Method of Moments (GMM). We simultaneously estimate the model by stacking equation (15) and (16) and imposing the cross-equation constraints on the remaining industry-specific parameters of the production technologies ($\widetilde{\pi} \equiv \{\pi_k, \pi_l\}$) and ($\widetilde{\alpha} \equiv \{\alpha_k, \alpha_l\}$) that appear through the interdependencies of TFP in the Markov process.[34] By distinctly instrumenting each of the stacked equations, we form a GMM criterion function based on the following moment conditions:

$$E\left[\begin{pmatrix} \mathscr{Z}_j^p & \omega_{g0t-1}(\widetilde{\pi}) & \bar{\omega}_{git-1}(\widetilde{\alpha}) & \widetilde{d}_{fe} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathscr{Z}_j^a & \omega_{git-1}(\widetilde{\alpha}) & \omega_{g0t-1}(\widetilde{\pi}) & d_{fe} \end{pmatrix}' \begin{pmatrix} \xi_{g0t} \\ \xi_{git} \end{pmatrix}\right] = 0 \tag{17}$$

where $\mathscr{Z}_j^p \equiv \left(\{k_{g0jt}\}, \{l_{g0jt}\}\right)$ and $\mathscr{Z}_j^a \equiv \left(\{k_{gijt}\}, \{l_{gijt}\}\right)$ are the 'instrument sub-matrices' with the terms in brackets denoting a full set of industry-j specific variables. The orthogonality conditions directly depend on the timing assumptions of inputs in subsection 4.2. Predeterminedness of current values of capital and labour make them orthogonal to the productivity innovations and thus help to identify the remaining part of the production technology of the parent ($\widetilde{\pi}$) and affiliate ($\widetilde{\alpha}$). Continuing, to identify the Markov process parameters ρ_{pp}, ρ_{pa} and ρ_{aa}, ρ_{ap}, for a guess of $\widetilde{\pi}$ and $\widetilde{\alpha}$, we form $\omega_{g0t-1}(\widetilde{\pi})$ and $\omega_{git-1}(\widetilde{\alpha})$ $\left(\text{hence } \bar{\omega}_{git-1}(\widetilde{\alpha})\right)$, respectively, which are by construction orthogonal to the TFP innovations. Finally, for the fixed effects $\widetilde{\phi}_{fe}$ and ϕ_{fe} defined in subsection 4.3 we use a full set of dummy variables $\widetilde{d}_{fe}$ and d_{fe}, respectively. These are assumed to be exogenous and thus uncorrelated with the unanticipated innovations to productivity. This is an exactly identified model where the number of instruments is the same as the number of parameters.[35]

By minimising the squared Euclidean length of the sample analogue of (17), we retrieve estimates for parameters of the production technology of the parent ($\widetilde{\pi}$) and affiliate ($\widetilde{\alpha}$). We also retrieve estimates for the persistence of firms' TFP (ρ_{pp} and ρ_{aa}), the productivity effects from the linked firms' TFP (ρ_{pa} and ρ_{ap}) and all of the fixed-effects considered ($\widetilde{\phi}_{fe}$ and ϕ_{fe}). Based on these estimates, we can now compute other relevant variables, e.g. TFP and returns to

[34]The main distinction from a standard production function setup is that each specification from above identifies not only the own remaining part of the production technology and Markov process, but also the remaining part of the production technology of ownership-linked firms. For example, equation (15) identifies both the production technology ($\widetilde{\pi}$) and Markov process (ρ_{pp}, ρ_{pa}) of parent firms, but also the production technology of affiliates ($\widetilde{\alpha}$). Therefore, we exploit this structure of the model and estimate it jointly in order to improve efficiency. Alternatively, one can estimate each equation separately with the relevant adjustment to the instrument matrix such that the remaining parameters of the production technology of ownership-linked firms are identified from each estimating equation separately.

[35]The estimation is still consistent when allowing for productivity innovations to be arbitrarily correlated across firms within the same cluster, e.g. ownership groups, followed by the appropriate correction of standard errors. However, if serial correlation in the productivity innovations is suspected, depending on the assumptions over the autocorrelation structure, deeper lags of the instrument matrix can be used to consistently estimate the model.

scale (RTS), for both the parent and the affiliate, using equations (11) and (12), respectively.

4.5 Statistical Inference

In order to compute standard errors that ensure estimator precision, we implement a pairs cluster bootstrap method.[36] Taking this approach is important for two reasons. First, the estimation described above follows two steps. As such, closed form solutions for the variance-covariance matrices are not apparent. Second, the potential presence of within-cluster error correlation could lead to biased standard errors if not taken into account (see Cameron and Miller 2015).[37]

We first define clusters C at the ownership group level g, allowing firm-year observations to be arbitrarily correlated within but independent across clusters.[38] Importantly, we form clusters at level of the ownership group g (and not at the level of the ownership group-year gt) to ensure that the full time-series of each firm is retained when creating the bootstrap samples below. We then randomly draw with replacement G times over entire clusters, i.e. blocks of ownership-linked parent and affiliate firms (not observations), from the original sample and generate the b^{th} bootstrap sample, where $b = 1 \ldots B$. We repeat this step for $B = 100$ times. For each parameter estimate from the original sample $\widehat{\theta}$, $\widehat{\theta}_b$ is the estimate from the b^{th} bootstrap replication and $\bar{\theta}$ is the mean of all the $\widehat{\theta}_b$s. As such, the bootstrap standard error is computed as follows:

$$se(\widehat{\theta}) = \left(\frac{1}{B-1} \sum_{b=1}^{B} (\widehat{\theta}_b - \bar{\theta})^2 \right)^{1/2} \tag{18}$$

Calculated as such, the computed standard errors can be used for statistical inference similar to any other asymptotically valid standard errors.

[36] For bootstrap methods see Efron (1979), Efron (1982), Horowitz (2001) and Davidson and MacKinnon (2004). For a complete review on cluster-robust inference see Cameron and Miller (2015).

[37] More precisely, we refer to cross-sectional correlation across firms within the cluster and not to serial correlation. The latter would result in standard endogeneity issues in dynamic panel methods which, depending on the autocorrelation structure of the error, could be accounted for using deeper lags in the instrument matrix.

[38] For the baseline sample, 12,665 clusters are formed which drop to 9,405 in the second step of the estimation.

5 Results

In this section we first present the baseline results which assess the extent to which intangible transfers from ownership-linked firms constitute as potential determinants of the firm's TFP evolution. Subsequently, by uncovering heterogeneity in the baseline results, we point to potential mechanisms in place. Finally, we support the validity of the baseline methodological approach through: (a) an extension of the baseline model by introducing a specific form of intangibles reported in the data, i.e. patents; and (b) conducting a falsification exercise.

Table 2: Baseline estimates

	Affiliate			Parent	
	(1a)	(2a)		(1b)	(2b)
Technology	Baseline	Interaction		Baseline	Interaction
$\bar{\alpha}_k$	0.090***	0.090***	$\bar{\pi}_k$	0.097***	0.096***
	(0.007)	(0.007)		(0.008)	(0.008)
$\bar{\alpha}_l$	0.383***	0.383***	$\bar{\pi}_l$	0.366***	0.366***
	(0.015)	(0.015)		(0.016)	(0.016)
$\bar{\alpha}_m$	0.421***	0.421***	$\bar{\pi}_m$	0.467***	0.467***
	(0.003)	(0.003)		(0.002)	(0.002)
Markov					
ρ_{aa}	0.921***	0.920***	ρ_{pp}	0.936***	0.936***
	(0.003)	(0.003)		(0.004)	(0.004)
ρ_{ap}	0.034***	0.034***	ρ_{pa}	0.013***	0.013***
	(0.003)	(0.003)		(0.002)	(0.002)
ρ_{a*p}		0.004**	ρ_{p*a}		-0.003
		(0.002)			(0.002)
Obs.	48,572	48,572	Obs.	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1a) and (1b) report results from the joint estimation of equations (16) and (15), respectively (Baseline). Column (2a) and (2b) report results from an extension of Baseline where $\rho_{a*p}\omega_{git-1}\omega_{g0t-1}$ and $\rho_{p*a}\omega_{g0t-1}\bar{\omega}_{git-1}$ are added in (16) and (15), respectively (Interaction). All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. Top panel reports the average of the industry specific output elasticities of capital, labour and material, respectively (see Appendix Table C.7 for industry-specific estimates). ρ_{ap} and ρ_{pa} in column (2a) and (2b), respectively, reports the unconditional mean elasticity of ownership-linked lagged TFP. Last row reports the observations used in the second-step of each estimation.

5.1 Baseline

Columns 1a and 1b in Table 2 report estimates of the baseline model (Baseline) for the affiliate (left panel) and parent (right panel), respectively. The top panel reports the average of the industry-specific output elasticities of capital, labour, and material, respectively. These are both economically sensible for both the parent and affiliate, and in line with what is reported in the empirical literature.[39] These estimates act as a first pass over the reasonable performance of the baseline model.

The bottom panel reports the estimated parameters of the Markov processes. A positive and statistically significant estimate for ρ_{ap} in column (1a) suggests that lagged parent TFP is an important determinant of affiliate TFP. Qualitatively, results are in line with recent estimates by Bilir and Morales (2019) who find a statistically significant positive effect of lagged parent R&D spending on affiliate TFP. Quantitatively, the estimated elasticity here is approximately three times larger.[40] This suggests that lagged parent TFP also accounts for variation in parent intangibles beyond R&D.

Similarly, a positive and statistically significant estimate of ρ_{pa} in column 1b suggests that lagged affiliate TFP is also an important determinant of parent productivity. This is a novel finding which points to the presence of feedback effects from intangible transfers between the parent and affiliate. It adds to existing empirical evidence supporting the importance of intangibles in explaining common ownership (Atalay et al. 2014; Bilir and Morales 2019). Moreover, for the special case of R&D investment, Bilir and Morales (2019) do not find such an effect for US parent firms. This highlights the importance of considering a broader definition of intangibles.

Results complement the findings of a spatial (regional or international) disconnect between the costs and gains of policies which stimulate innovation through R&D spending (Bilir and Morales 2019). However, to the extent that TFP captures all other intangibles, the size of this disconnect clearly depends on the relative importance of the efficiency gains from intangible transfers between ownership-linked firms. The estimated short run TFP elasticity of ownership-linked TFP is approximately three times larger for the affiliate (ρ_{ap}) than for the parent (ρ_{pa}). Yet, the contribution of ownership-linked TFP to long-run firm performance is also driven by the persistence of TFP (ρ_{aa}, ρ_{pp}). Specifically, the long-run 'absorptive capacity' of the affiliate-from-parent TFP is more than double what the parent absorbs from any change in affiliate TFP (42% and 20%, respectively). On the basis of a one standard deviation increase in lagged parent TFP, affiliate TFP increases by 0.4% in the short run and 5.2% in the long run on average. From the parent's perspective, a one standard deviation increase in lagged (group-g) average affiliate TFP leads to an average increase in parent TFP of 0.2% in the short run and 3.0% in the long run.[41]

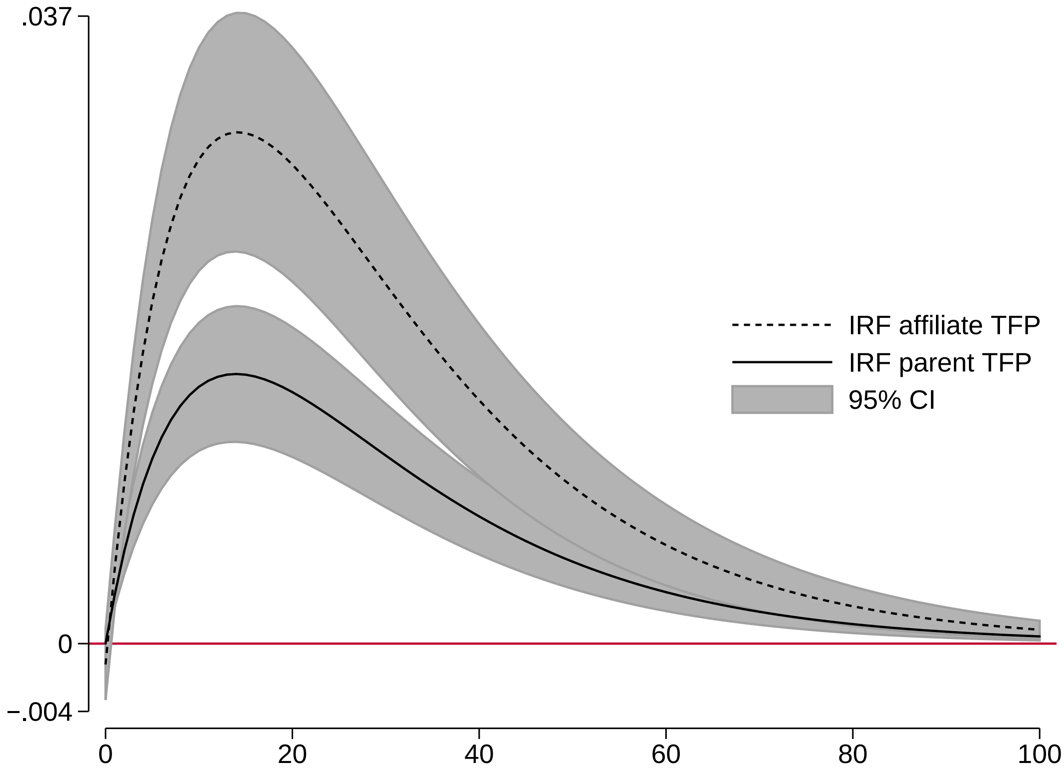
The long run effects above are computed under the assumption that TFPs are taken as given

[39]See Appendix Table C.7 for industry-specific estimates and Figures C.1-C.2 for their respective standard errors.

[40]We compare with the parent R&D elasticity of 0.0122 in column 2 of Table 6 in Bilir and Morales (2019).

[41]The affiliate short-run effect is computed using the formula: $\rho_{ap} * sd(\omega_{j0t-1}) * 100$ and the long-run effect using: $\left(1/(1-\rho_{aa})\right) * \rho_{ap} * sd(\omega_{j0t-1}) * 100$, where ρ_{ap} and ρ_{aa} are point estimates from the baseline equation (16), and $sd(\omega_{j0t-1})$ is one within standard deviation of the lagged value of estimated parent TFP. Similarly, the parent short-run effect is computed based on: $\rho_{pa} * sd(\bar{\omega}_{jit-1}) * 100$ and the long-run effect using: $\left(1/(1-\rho_{pp})\right) * \rho_{pa} * sd(\bar{\omega}_{jit-1}) * 100$, where ρ_{pa} and ρ_{pp} are point estimates from the baseline equation (15), and $sd(\bar{\omega}_{jit-1})$ is one within standard deviation of the lagged value of estimated average (group g) affiliate TFP. The long-run absorptive capacities, follow from the same formulas when $sd(\cdot) = 1$.

Figure 1: Impulse Response Functions - IRF



Source: Author's calculations using estimates from baseline model.
Notes: Orthogonalised impulse response functions (vertical axis) over a 100 year horizon (horizontal axis). IRFs are computed using estimates of the parameters and cross-equation error variance–covariance matrix from baseline equations (16) and (15). The dashed line is the response of affiliate TFP over time from a one standard deviation structural shock on parent TFP. The solid line is the response of parent TFP over time from a one standard deviation structural shock on affiliate TFP. The variance-covariance matrix is decomposed in a lower triangular matrix with positive diagonal elements using Cholesky decomposition under the following assumption over the ordering of variables: parent TFP; and affiliate TFP. 95% confidence intervals (CI) are computed using Gaussian approximation based on Monte Carlo simulation with 100 draws.

at each point in time. However, as discussed above, equations (9) and (10) resemble a panel VAR model with two endogenous variables, i.e. a model which allows for ownership-based dynamic interdependencies among the productivities of the parent and affiliate which evolve stochastically. The baseline results highlight that the coefficients on the reduced-form VAR equations cannot be interpreted causally unless further identifying restrictions are imposed on the model's parameters.[42] Assuming that the model is stable and thus invertible (Lütkepohl 2005), it can be rewritten as an infinite order vector moving-average representation. This formulation permits the computation of impulse response functions (IRFs). IRFs help analyse the response of endogenous variables in the VAR model (e.g. affiliate TFP) due to an impulse to one of the innovations (e.g. parent productivity shock). To guarantee the exogeneity of the impulse (and thus the causal interpretation) otrhogonalised IRFs are computed following Sims (1980).[43]

[42] However, lagged parent TFP can be said to Granger-cause affiliate TFP and vice versa (Granger 1969, 1980).
[43] This includes a Cholesky decomposition of the reduced-form variance-covariance matrix assuming the follow-

Figure 1 plots the orthogonalised IRFs, which represent the percentage point changes in affiliate TFP (dotted line) and parent TFP (solid line) over a 100 year time horizon after an exogenous shock in parent and affiliate TFP, respectively. Intuitively, one can think of such shocks as: unexpected inventions; degree of applicability; and other uncertainties related to intangibles. The IRFs suggest a statistically significant positive nonlinear response that peaks after 20 periods and then slowly dies out, both for the parent and the affiliate. However, the efficiency gains for the affiliate are twice as large as those for the parent (see Appendix Figure C.3 for cumulative IRFs) for the manufacturing sector. As such, accounting for the relative importance of such dynamic relationships between the parent and affiliate is key to understanding the distribution of economic activity both across space and time.

We next explore the process through which the transfer of intangibles via ownership-linked firms generates efficiency gains. In particular, to provide some guidance over the possible mechanisms in place, we extend the baseline model to include the interaction term $\rho_{a*p}\omega_{git-1} * \omega_{g0t-1}$ and $\rho_{p*a}\omega_{g0t-1} * \bar{\omega}_{git-1}$ in estimating equations (16) and (15), respectively (Interaction).[44] A positive and statistically significant interaction term (ρ_{a*p}) in column 2a, supports the presence of strong complementarities. This finding qualitatively verifies recent estimates from the literature, where the impact of parent R&D on affiliate TFP is larger for innovative affiliates relative to non-innovative ones (Bilir and Morales 2019). It also supports the notion that intangibles exert valuable synergies amongst themselves (Haskel and Westlake 2018). Such synergies induce relationship-specific learning when production requires coordination with other firms (Kellogg 2011). This includes both knowledge accumulation and personal interactions between the affiliate and its parent who work together within the boundaries of the firm. Overall, while affiliates can benefit from performing their own tasks (Arrow 1962; Stokey 1988; Parente 1994; Jovanovic and Nyarko 1996), our results suggest that they benefit more through learning when combining tasks performed from the parent. These can include, among others: organisational restructuring; network sharing; revamping technical and managerial practices; and transferring knowledge.

In column 2b, a negative but statistically insignificant interaction term suggests the absence of similar learning mechanisms for the parent. This result complements both theories and empirical findings which suggest that firms expand their boundaries to exploit intangible assets both at home and abroad (Grubaugh 1987; Markusen 1995). Specifically, it suggests that parent firms are pure recipients of affiliate-specific intangibles and—importantly—helps understand the true motives of firm ownership (Teece 1982; Atalay et al. 2014).

ing ordering of the variables: parent TFP first and then affiliate TFP (Sims 1980). Note that results remain virtually the same when assuming the reverse ordering.

[44] Equation (17) now also includes $\omega_{git-1} * \omega_{g0t-1}$ and $\omega_{g0t-1} * \bar{\omega}_{git-1}$ as additional instruments identifying the parameters ρ_{a*p} and ρ_{p*a}, respectively.

5.2 Heterogeneity

Results for the interaction terms above raise the question as to whether the baseline results are applicable to all groups of firms. To explore heterogeneity in the baseline results, we test for differential effects by interacting the ownership-linked productivities with a dummy variable D_{gt-1} that is equal to one when the firm belongs to the group defined at the top of each column in Table 3 and zero otherwise. Specifically, we extend the baseline model to the following estimating equations:

$$y_{git} = \sum_j \left(\alpha_{kj} k_{git} + \alpha_{lj} l_{git} + \alpha_{mj} m_{git}\right) \odot d_j + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + \xi_{git} + \varepsilon_{git} + \rho_{ap*D}\omega_{g0t-1} * D_{gt-1} + \rho_{Da} D_{gt-1} + \phi_{fe} \odot D_{gt-1} \tag{19}$$

and

$$y_{g0t} = \sum_j \left(\pi_{kj} k_{g0t} + \pi_{lj} l_{g0t} + \pi_{mj} m_{g0t}\right) \odot d_j + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + \xi_{g0t} + \varepsilon_{g0t} + \rho_{pa*D}\bar{\omega}_{git-1} * \widetilde{D}_{gt-1} + \rho_{Dp}\widetilde{D}_{gt-1} + \widetilde{\phi}_{fe} \odot \widetilde{D}_{gt-1} \tag{20}$$

where $\widetilde{D}_{gt-1}$ takes the maximum value of D_{gt-1} across affiliates within each ownership group. Estimation follows directly from the baseline model, with the instrument matrix in equation (17) now also including $(\omega_{git-1} * D_{gt-1}, D_{gt-1}, \phi_{fe} \odot D_{gt-1})$ and $(\omega_{g0t-1} * \widetilde{D}_{gt-1}, \widetilde{D}_{gt-1}, \widetilde{\phi}_{fe} \odot \widetilde{D}_{gt-1})$ that help to identify the parameters $(\rho_{ap*D}, \rho_{Da}, \rho_{pa*D}, \rho_{Da})$ as well as the relevant fixed effects.[45] Table 3 reports the estimates from the Markov process.[46] To ease comparison with the baseline results, columns 1a and 1b repeat columns 1a and 1b from Table 2.

Multinationals.—Gumpert (2018) uses a theoretical model to show that cross-border communication costs dampen communication between a foreign affiliate and its parent, forcing it to depend on learning practices.[47] To test for this, in columns 2a and 2b we define the dummy variable as equal to one when the ownership link is cross-border and zero otherwise (MNC). Results show no significant difference between foreign owned and domestically owned firms. Specifically, the foreign ownership premium in TFP effects from ownership-linked firms—while positive—are not statistically significant for either the affiliate or the parent.

Western vs. Eastern Europe.—In the European context where economies are fairly inte-

[45] The identifying assumption is that D_{gt-1} is orthogonal to current period productivity innovations.

[46] Estimates for the production technology parameters provide no additional insights and are thus only reported in Appendix Figures C.4 and C.5.

[47] In this model of optimal knowledge the parent avoids such communication costs by assigning more knowledge to their foreign affiliates. This also helps explain why foreign affiliates have higher wages and sales relative to domestic ones. We confirm that such differences are prevalent in the data and also exist across other dimensions of the firm, i.e. labour, capital and materials, when comparing Appendix Tables C.5 and C.6.

grated and benefit from the single market, boarders and thus communication costs are harder to distinguish. Therefore, in columns 3a and 3b we define boarders to meaningfully and clearly capture differences in communication costs. Specifically, the dummy variable takes a unit value if the parent is in a Western European Country (WEC) and the affiliate in a Central Eastern European Country (CEEC) and zero otherwise.[48] The idea is grounded in the fact that the process of industrial, economic, social and cultural integration of CEECs with EU is relatively recent. Thus, during the sample period cross-border communication costs for parents in WEC are larger when affiliates are in CEEC. Defining the dummy variable in this way, we find a positive and statistically significant interaction effect for the affiliates. This finding further validates the results from the previous section, which suggest that learning mechanisms are important for understanding the underlying drivers of baseline results for the affiliate. Intuitively, high cross-border communication costs cause parent firms to communicate less but assign more knowledge to their affiliates, which in turn makes the affiliates to master a higher share of the production process by themselves (Gumpert 2018).

Table 3: Heterogeneity: baseline model with interactions

	Affiliate					Parent			
	(1a)	(2a)	(3a)	(4a)		(1b)	(2b)	(3b)	(4b)
		D=1 if in group below, else 0					D=1 if in group below, else 0		
Markov	Baseline	MNC	CEEC	Vertical		Baseline	MNC	CEEC	Vertical
ρ_{aa}	0.921***	0.922***	0.924***	0.924***	ρ_{pp}	0.936***	0.940***	0.940***	0.938***
	(0.003)	(0.003)	(0.003)	(0.003)		(0.004)	(0.005)	(0.004)	(0.005)
ρ_{ap}	0.034***	0.032***	0.031***	0.033***	ρ_{pa}	0.013***	0.012***	0.013***	0.015***
	(0.003)	(0.004)	(0.004)	(0.004)		(0.002)	(0.002)	(0.002)	(0.002)
ρ_{ap*D}		0.010	0.027**	-0.003	ρ_{pa*D}		0.001	-0.006	-0.009**
		(0.009)	(0.013)	(0.007)			(0.005)	(0.009)	(0.004)
Obs.	48,572	48,572	48,572	48,572	Obs.	37,524	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1a) and (1b) report results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2a)-(4a) and (2b)-(4b) report results from an extension of Baseline where $\rho_{ap*D}D_{gt-1}\omega_{g0t-1}$ and $\rho_{pa*D}D_{gt-1}\bar{\omega}_{git-1}$ are added in (16) and (15), respectively. D_{gt-1} is a dummy variable with zeros unless it takes unit values for the group of firms where: country of parent is other than the affiliate's (MNC); parent is from Western Europe and affiliate from Central Eastern Europe (CEEC); parent industry is other than the affiliate's (Vertical). All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Last 3 columns in both panels also include the D_{gt-1} and its interaction with the fixed effects described above. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. The last row reports the observations used in the second-step of each estimation.

Vertical.—While learning mechanisms appear to be important in explaining the TFP effects from intangible transfers for the affiliate, this is not the case for the parent. To assess potential

[48]WEC cover: Austria; Belgium; Finland; France; Germany; Italy; Norway; Portugal; Spain; and Sweden, while CEEC cover: Bulgaria; Croatia; Czech Republic; Estonia; Hungary; Poland; Romania; Slovakia; and Slovenia. This split also follows the level of economic development of these countries (UNCTAD 2019) and is in line with the different phases of EU enlargement.

mechanisms behind such TFP effects for the parent, we exploit variation in the industrial activity of the firms given that the technological and non-technological components of intangibles are not fully compatible across industries. In columns 3a and 3b, the dummy variable thus takes unit values when both the parent and affiliate are in different industries and zero otherwise. We find a negative and statistically significant (at 5% level) interaction effect for the parent. This suggests that it is harder for parent firms to adopt the technological and non technological components of intangibles from affiliates in different industries. This result supports the notion that parent firms are pure recipients of affiliate technology, and is in line with the motives of a parent to control an affiliate in the first place.

5.3 Patents

We next extend the empirical model by introducing a firm-year variable on the number of granted patent applications. Extending the model in this way supports the validity of the methodological approach by including a measure of a specific intangible which is directly reported in the Amadeus database by BvDEP. Following Stiebale (2016), we use this information to construct a patent stock dummy variable (herein PAT) equal to unity if a firm has a positive, not yet depreciated (at a 15% rate), stock of granted patent applications and zero otherwise.[49] Table 4 shows that parent firms are relatively more involved in patenting activity: 25% of parents have at least one granted patent application compared to 7.6% of affiliates.

Table 4: Summary statistics of patent stock dummy (PAT)

	Obs.	Mean	St.Dev.	p25	p50	p75
Affiliate	71,119	.076	.26	0	0	0
Parent	54,098	.25	.43	0	0	1

Notes: PAT is a dummy variable with unit values if a firm has a positive (not yet depreciated) stock of granted patent applications and zero otherwise. PAT is constructed following Stiebale (2016) with the underline data sourced from Amadeus database by BvDEP.

Table 5 reports simple correlations between the observed (in the data) PAT and the unobserved (but estimated from the baseline specification) TFP for both parent and affiliate firms. We find a positive association and low strength. This suggests that the TFP measures contain meaningful information for patenting activity that can safely be considered as intangibles. Moreover, the low strength of the correlation suggests that patents are likely not the most significant determinants in the intangible space, and that the TFP measure contains meaningful information for other intangible inputs. On a more empirical note, this table also hints at the possibility of omitted variable bias even in if one directly observes some intangibles. Specifically, the variables of

[49]For uniformity and to avoid double counting, we focus only on patents reported in European Patent Office (EPO) and not from other sources, such as: national authorities and WIPO.

interest would be biased if the observed intangibles are correlated with other highly relevant unobserved intangibles. Including the lagged productivity of ownership linked firms as an additional term in the markov process can partly account for such mispecifications.

Table 5: Correlation of TFP and Patents

	ω_{git}	ω_{g0t}	PAT$_{git}$	PAT$_{g0t}$
ω_{git}	1.000			
ω_{g0t}	0.468	1.000		
PAT$_{git}$	0.135	0.081	1.000	
PAT$_{g0t}$	0.146	0.148	0.204	1.000

Notes: PAT is a dummy variable taking unit values if a firm has positive undepreciated stock of granted patent applications and zero otherwise. ω is the estimated TFP from the baseline model.

We now extend the baseline empirical model by allowing the patent activity of both the firm itself and the ownership-linked firm to be a potential determinant of the firm's future productivity. This results in the following estimating equations:

$$y_{git} = \sum_j \left(\alpha_{kj}k_{git} + \alpha_{lj}l_{git} + \alpha_{mj}m_{git}\right) \odot d_j + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + \xi_{git} + \varepsilon_{git} + \rho_{PATaa}PAT_{git-1} + \rho_{PATap}PAT_{g0t-1} \tag{21}$$

and

$$y_{g0t} = \sum_j \left(\pi_{kj}k_{g0t} + \pi_{lj}l_{g0t} + \pi_{mj}m_{g0t}\right) \odot d_j + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + \xi_{g0t} + \varepsilon_{g0t} + \rho_{PATpp}PAT_{g0t-1} + \rho_{PATpa}\widetilde{PAT}_{git-1} \tag{22}$$

where $\widetilde{PAT}_{git-1}$ takes the maximum value of PAT_{git-1} across affiliates within each ownership group, i.e. at least one affiliate has a positive patent stock within the group, and zero otherwise. Estimation follows directly from the baseline model. We adjust the instrument matrix in equation (17) by including the instruments $\left(PAT_{git-1}, PAT_{g0t-1}\right)$ and $\left(PAT_{g0t-1}, \widetilde{PAT}_{git-1}\right)$. These serve to identify the parameters $\left(\rho_{PATaa}, \rho_{PATap}\right)$ and $\left(\rho_{PATpp}, \rho_{PATpa}\right)$, respectively.[50]

Table 6 presents estimates of the markov process parameters both for the affiliate (left panel) and parent (right panel).[51] The table consists of 3 principal columns. As before, columns 1a and 1b report the baseline estimates. The remaining columns present estimates for different model specifications when considering the patent application stock variable with or without the lagged productivity of the ownership-linked firm. Columns 2a and 2b impose the parameter restrictions

[50]The identifying assumption is that last period patent stock is orthogonal to current productivity innovations.

[51]Estimates of the production technology parameters are virtually the same across columns and for space considerations only report them in Appendix Figures C.6 and C.7.

$\rho_{ap} = \rho_{pa} = 0$ in (21) and (22), respectively. Results suggest that, on top of firm level patents $(\rho_{PATaa}, \rho_{PATpp})$, ownership linked patents $(\rho_{PATap}, \rho_{PATpa})$ are significant determinants of firm TFP for both the parent and affiliate. This lends support to the baseline results.

Table 6: Patents: baseline model with patent information

	Affiliate				Parent		
	(1a)	(2a)	(3a)		(1b)	(2b)	(3b)
	Baseline	Patent Dummy			Baseline	Patent Dummy	
		Only	&Baseline			Only	&Baseline
ρ_{aa}	0.921***	0.928***	0.921***	ρ_{pp}	0.936***	0.942***	0.937***
	(0.003)	(0.003)	(0.003)		(0.004)	(0.004)	(0.004)
ρ_{ap}	0.034***		0.034***	ρ_{pa}	0.013***		0.013***
	(0.003)		(0.003)		(0.002)		(0.002)
ρ_{PATaa}		0.010***	0.011***	ρ_{PATpp}		0.007***	0.008***
		(0.004)	(0.004)			(0.003)	(0.002)
ρ_{PATap}		0.007**	0.006*	ρ_{PATpa}		0.008***	0.006**
		(0.003)	(0.003)			(0.003)	(0.003)
Obs.	48,572	48,572	48,572	Obs.	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1a) and (1b) report results from the joint estimation of equations (16) and (15), respectively (Baseline). Column (2a)-(3a) and (2b)-(3b) report results from the extension of Baseline where $\rho_{PATaa}PAT_{git-1} + \rho_{PATap}PAT_{g0t-1}$ and $\rho_{PATpp}PAT_{g0t-1} + \rho_{PATpa}PAT_{git-1}$ are included as additional terms in equations (16) and (15), respectively. PAT_{git-1} and PAT_{g0t-1} are dummy variables that take unit values if the parent and affiliate firm, respectively, has positive (not yet depreciated) stock of granted patent applications. (2a) and (2b) impose the parameter restrictions: $\rho_{ap} = \rho_{pa} = 0$. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. Last row reports the observations used in the second-step of each estimation. Appendix Figures C.6 and C.7 report the industry-specific estimates of the production technology for each model.

It is important to mention at this stage that this specification is closely related to that of Bilir and Morales (2019), who use information on R&D spending instead of patents.[52] On the one hand, they find that parent R&D spending is a significant determinant of foreign affiliate TFP evolution. This is line with results presented in column 2a. However, they find no such effect for the parent, i.e. affiliate R&D investment leads to productivity improvements for the parent. This suggests that while affiliate R&D spending might not be a relevant determinant for the parent there are other intangibles—usually unobserved in the data—that are highly relevant (e.g. patents). In contrast, our baseline model nests approaches where only certain types of

[52]In practice, this is a more flexible approach since it also allows for different production technologies between the parent and affiliate, controls for fixed effects both at the parent and affiliate level and estimates a gross-output instead of a value-added production function.

intangibles are observed in the data.[53]

In columns 3a and 3b, we now also include the ownership-linked TFP as specified in (21) and (22). Results suggest that while ownership-linked patents still carry weight in explaining future productivity evolution, there are other relevant forms of ownership linked intangibles that need to be considered. Discrepancies in point estimates and precision between columns (2) and (3) touch upon the importance of controlling for ownership-linked TFP in order to account for possible non-causal correlation between the observed controls and other unobserved intangibles.

Overall, this subsection provides supportive evidence that linked firm TFP contains/controls for variation in intangibles. As such, it is a meaningful composite index for intangibles which should be considered accordingly.

5.4 Falsification Exercise

This subsection validates the results by performing a set of pseudo-placebo tests. The rationale behind this exercise is straightforward. If efficiency gains from ownership-linked TFP (as found in the baseline model) are also present outside firm boundaries, similar effects stemming from non-ownership-linked firms should be present as well. To perform this exercise, we employ an additional dataset sourced directly from the Amadeus database by BvDEP which contains information on purely 'local firms.' Put succinctly, local firms do not report any type of ownership link, at any level of control and at any point in time observed in the dataset. We process the data following the steps described in Section 2 to generate a dataset which contains balance sheet information for local firms in all countries and industries observed in the baseline sample.

The falsification exercise has two closely related parts. First, we randomly replace affiliate or parent firms with local firms and re-estimate the baseline model. Second, we closely match the affiliate or parent firms with local firms based on observed characteristics and re-estimate the baseline model. Table 7 presents estimates of the markov process parameters for both the affiliate (top panel) and parent (bottom panel). The table consists of 7 columns with the column 1 reporting the baseline estimates. Columns 2 and 5 report estimates of the baseline model using sub-samples of the baseline sample (randomly assigned and closest match wrt. Y, respectively).

In column 3 (for the original set of parent firms) we replace each affiliate by randomly drawing with replacement from the group of local firms observed in the same country, industry, initial year and number of surviving periods as the affiliate. Subsequently, we re-run the baseline estimation procedure using the randomly replaced sample and compare estimated outcomes in column 3 with those in column 2 using the baseline sample but with the same number of observations. In column 4 we conduct the reverse exercise by randomly replacing each parent with a local firm and keeping the original set of affiliates. In both columns, estimated results for ownership-linked TPF are statistically and economically insignificant. This validates that such

[53] This comes at the expense of being agnostic about the relative importance of each type of intangible.

effects cannot arbitrarily exist in the local economy. Results also exclude potential spurious estimates from unobserved market conditions and shocks in the group of local firms upon which we draw with replacement and which are not controlled for in the baseline model.

Table 7: Markov process estimates for falsification excercise

	(1) Baseline	(2) Restricted Sample	(3) Randomly Assign Affiliate	(4) Randomly Assign Parent	(5) Restricted Sample	(6) Closest Match wrt. Y Affiliate	(7) Closest Match wrt. Y Parent
Affiliate							
ρ_{aa}	0.921***	0.918***	0.873***	0.925***	0.923***	0.896***	0.930***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
ρ_{ap}	0.034***	0.040***	0.002	0.002	0.038***	0.011***	0.006
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Parent							
ρ_{pp}	0.936***	0.935***	0.938***	0.878***	0.936***	0.940***	0.913***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)
ρ_{pa}	0.013***	0.011***	0.003	-0.003	0.013***	0.005**	0.004
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)
Obs.	37,524	21,691	21,691	21,691	22,049	22,049	22,049

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Column (2) and (5) report estimates from the baseline model when using sub-samples of the baseline sample that match the number of observations in the falsification tests in columns (3)-(4) (Randomly Assign) and (6)-(7) (Closest Match wrt. Y), respectively. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. Last row reports the observations used in the second-step of each estimation. Appendix Table C.8 reports industry-specific estimates of the production technology for each model.

Nonetheless, non-random links of parent and affiliate firms with the local economy could also generate similar network effects, e.g. through domestic buyer-supplier relationships. In column 6, for the original set of parent firms, we thus replace each affiliate with a local firm by performing a nearest-neighbor Mahanalobis' distance matching (with replacement). The matching is based on the output observed for the group of local firms in the same country, industry, initial year, and number of surviving periods as the affiliate. Subsequently, we re-run the baseline estimation procedure using the matched sample and compare estimated outcomes in column 6 with those in column 5 using the baseline sample but with the same number of observations. Similarly, in column 7, we conduct the reverse exercise by matching each parent with a local firm and keeping the original set of affiliates as is.

Column 6 presents a statistically significant effect from ownership linked TPF both for the parent and affiliate which amounts to approximately one third of the baseline estimated elasticities in column 5. Although any significant result may seem counter-intuitive at first, it can be explained by spillovers and/or indirect effects, as well-established in the literature.[54] The absence of significant estimates in column 7 excludes the potential presence of unobserved persistent factors in the local economy that could be driving the results. This strengthens the interpretation of earlier findings as spillover effects.[55] Specifically, the last two columns suggest that, if anything, affiliates act as intermediaries of spillover effects that flow both back and forth between the parent and the local firms.

In short, this subsection lends support to the main findings in this paper and suggests that approximately two thirds of the baseline effects are actually internalised within the boundaries of the firm. Moreover, these findings open the door to further research on the relative importance and direction of technology transfers across the boundaries of the firm.

6 Robustness

We conduct a battery of additional checks to test the robustness of the baseline model. These include: alternative markov process specifications (Table 8 and Figure 2); additional fixed effects; flexible production technologies; alternative estimators; and cases of imperfect competition in the output market (Table 9). Finally, we provide additional robustness over the sensitivity of standard errors and alternative ways of processing the baseline data (Appendix Table C.11). Results presented in this section refer to estimates of the Markov process parameters. For conciseness, Appendix C contains estimates of the respective production technology parameters and they are referenced where relevant. As above, to facilitate comparison between the baseline and robustness models, the first column in each table reports the baseline estimates (Baseline).

Markov Process (Table 8).—Columns 2-4 in Table 8 report estimates from the baseline model where, instead of the mean ($\bar{\omega}_{git-1}$) in equation (15), we use the minimum, median and maximum lag affiliate TFP within each ownership group, respectively. While an expected increase is observed in the estimated coefficient (ρ_{pa}) the differences between columns 2, 3, and 4 are statistically insignificant. Column 5 tests for the potential presence of spillover effects from other affiliates within the same ownership group. Here, the baseline model is extended by including $\rho_{aa\_}\bar{\omega}_{gi\_t-1}$ from equation (16), which captures the affiliate TFP effect from the mean TFP of other affiliates within each group g. A statistically significant and positive effect is estimated, but with limited economic relevance since its point estimate is approximately 1/23 of ρ_{ap} and 1/10 of ρ_{pa}. Note that Bilir and Morales (2019) do not find such an effect when considering R&D. This further supports the notion that focusing on a specific type of intangibles obscures our understanding about their overall importance. Therefore, while novel, such an

[54]See Javorcik (2010) for a literature review on technology/knowledge spillovers to domestic firms from foreign direct investment, i.e. foreign affiliates of multinational companies. Also, see Merlevede and Theodorakopoulos (2018) for indirect effects of internationalisation occurring through the domestic supply chain.

[55]Estimates of the production technology parameters presented in Appendix Table C.8 remain within economically meaningful bounds and thus bring confidence over the sensible performance of the falsification exercise.

effect can only qualify as second order.

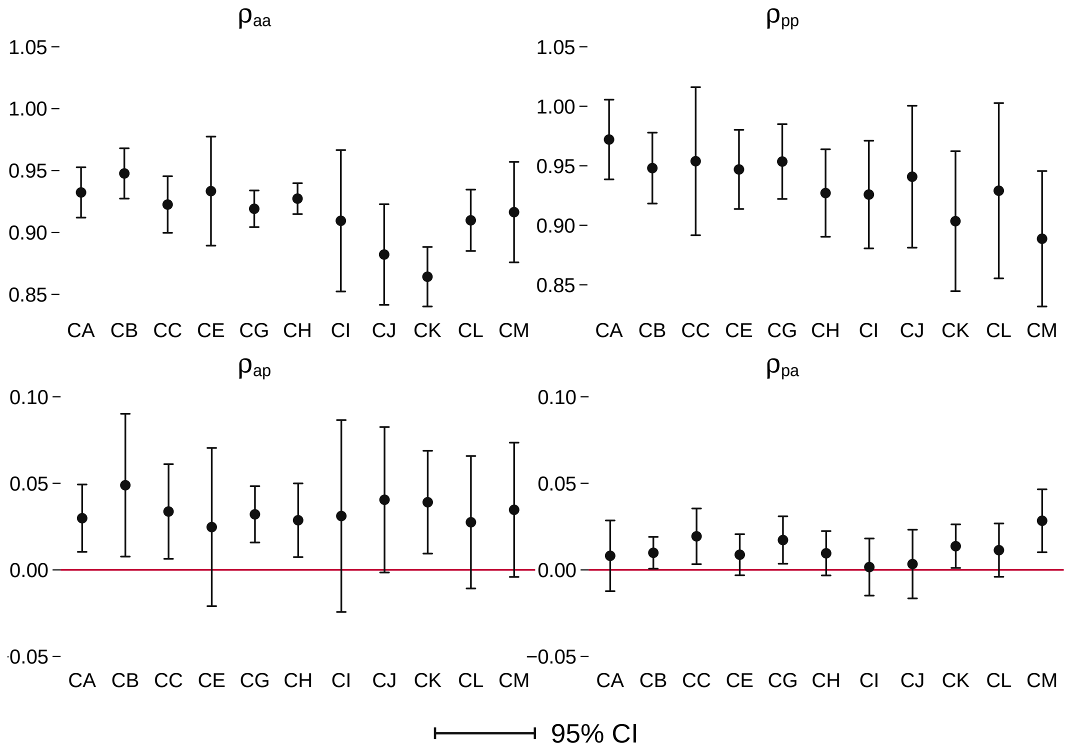
Table 8: Robustness to alternative markov processes

	(1)	(2)	(3)	(4)	(5)
	Baseline	Multiple affiliates			Other
Affiliate		Minimum	Median	Maximum	Affiliates
ρ_{aa}	0.9209***	0.9209***	0.9209***	0.9208***	0.9208***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
ρ_{ap}	0.0335***	0.0333***	0.0335***	0.0337***	0.0320***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0035)
$\rho_{aa\_}$					0.0014***
					(0.0004)
Parent					
ρ_{pp}	0.9365***	0.9374***	0.9365***	0.9362***	0.9365***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
ρ_{pa}	0.0130***	0.0108***	0.0128***	0.0133***	0.0131***
	(0.0019)	(0.0018)	(0.0019)	(0.0018)	(0.0019)
Obs.	37,524	37,524	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(4) report estimates from Baseline when instead of the mean ($\bar{\omega}_{git-1}$) in equation (15) we use the minimum, median and maximum lagged affiliate TFP within each g-group, respectively. Column (5) reports estimates from Baseline when $\rho_{aa\_}\bar{\omega}_{gi\_t-1}$ is added in equation (16) to capture the affiliate TFP effect from the mean TFP of other affiliates in the group. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. Last row reports the observations used in the second-step of each estimation. Appendix Table C.9 reports industry-specific estimates of the production technology for each model.

Continuing, Figure 2 reports the Markov process estimates when allowing the parameters to be industry specific both for the parent and affiliate. While all of the effects remain positive across industries, results for certain industries become statically insignificant. This can be explained by limited identifying variation (see Appendix Tables C.3 and C.4). Nonetheless, across all industries, the relative importance of ρ_{ap} over ρ_{pa} remains in line with the Baseline model. Overall, results remain robust to the alternative considerations of the Markov process.

Figure 2: Industry specific markov processes



Source: Author's estimates from Baseline Model with interaction terms.
Notes: Baseline model with industry specific Markov processes. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. See Appendix Table C.1 for a description of the A*38 industry code.

Fixed Effects (Table 9).—To exclude the possibility that results are driven by any type of country-industry specific growth trends, we next augment the baseline model with country-industry-time (cjt) fixed effects, both at the parent and affiliate level (column 2).[56] Interconnections across Europe suggest that responses to business cycle conditions might depend on complex network structures. For example, industry specific shocks which propagate through supply chain links could result in non-uniform responses across industries. One might therefore be concerned that the baseline results reflect bilateral cyclical variations at the country and industry level. To control for this, on top of the cjt fixed effects in column 2, we augment the baseline model with bilateral country-time, industry-time and country-industry fixed effects both at the parent and affiliate level (column 3).[57] In both columns, results remain similar to column 1 and thus alleviate concerns that aggregate persistent unobserved factors drive results.

Continuing, we augment the production functions (1) and (2) with parent-level (ϕ_{g0}) and affiliate-level (ϕ_{gi}) fixed effects, respectively (column 4). Adding these fixed effects controls for potential correlation between the variables of interest and any unobserved time-invariant

[56]This implies that the set of fixed effects defined in equations (9) and (10) becomes $\rho_{fe} \equiv \rho^{a}_{cjt} + \rho^{p}_{cjt}$.
[57]The set of fixed effects defined in equations (9) and (10) now becomes $\rho_{fe} \equiv \rho^{a}_{cjt} + \rho^{p}_{cjt} + \rho^{ap}_{cj} + \rho^{ap}_{ct} + \rho^{ap}_{jt}$.

Table 9: Robustness to additional fixed effects, production technologies, alternative estimators and imperfect competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Fixed Effects			Technology		Other Estimators		Imperfect Competition	
Affiliate		cjt	Bilateral	Firm	Translog	NP	ACF	Dynamic	CES	FGT
ρ_{aa}	0.921***	0.924***	0.916***	0.733***	0.912***	0.890***	0.906***	0.915***	0.921***	0.930***
	(0.003)	(0.003)	(0.003)	(0.026)	(0.003)	(0.005)	(0.004)	(0.011)	(0.003)	(0.006)
ρ_{ap}	0.034***	0.033***	0.033***	0.067***	0.035***	0.032***	0.035***	0.033***	0.033***	0.097***
	(0.003)	(0.003)	(0.004)	(0.020)	(0.004)	(0.004)	(0.004)	(0.008)	(0.004)	(0.019)
Parent										
ρ_{pp}	0.936***	0.940***	0.934***	0.779***	0.929***	0.916***	0.923***	0.968***	0.933***	0.942***
	(0.004)	(0.004)	(0.005)	(0.024)	(0.004)	(0.004)	(0.006)	(0.020)	(0.006)	(0.007)
ρ_{pa}	0.013***	0.012***	0.014***	0.040***	0.010***	0.005***	0.019***	0.022*	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.015)	(0.002)	(0.001)	(0.003)	(0.013)	(0.002)	(0.003)
Obs.	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(4) report estimates from Baseline accounting for additional fixed effects. Columns (5) and (6) report estimates from an extension of Baseline with a translog and nonparametric production technology, respectively. Columns (7) and (8) report estimates when using alternative estimators for Baseline. Columns (9) and (10) report estimates when accounting for certain types of imperfect competition in Baseline. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Columns (2)-(4) control for additional fixed effects. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. Last row reports the observations used in the second-step of each estimation. Appendix Table C.10 reports industry-specific estimates of the production technology for each model.

characteristics at both the parent and affiliate level. To estimate this model we augment the extension to account for firm fixed effects proposed by GNR (see Appendix A.3 for a detailed description of the estimable equations and estimation strategy).[58] In column 4, the obtained point estimates for the variables of interest have larger magnitudes compared to those in column 1, but remain qualitatively similar in terms of their relative importance between the parent and affiliate.[59]

Production Technology (Table 9).—We next introduce more general functional forms for the production technology to allow for flexible substitution patterns between inputs (columns 5 and 6). Column 5 relies on a relatively flexible parametric form, i.e. translog, which is frequently applied in empirical research.[60] On the other hand, in column 6 we rely on the nonparametric estimation (NP) of the production technologies following the identification strategy of GNR (see Appendix A). In both cases, estimated results are in line with the baseline estimates in column 1. As such, we exclude the possibility that baseline results are driven by unobserved heterogeneity in production technology.[61]

Alternative Estimators (Table 9).—Following the applied production function estimation literature, we check the sensitivity of the baseline results against alternative commonly used structural approaches. These include proxy variable methods (column 7) (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2015) and dynamic panel methods (column8) (Arellano and Bond 1991; Blundell and Bond 1998, 2000). Following the identification insights of Ackerberg, Caves, and Frazer (2015) (herein ACF), we estimate a version of the baseline model using a restricted profit value added instead of a gross output production function. In this case, the empirical measures of value added are now expressed as: $va_{g0t} \equiv ln(Y_{g0t} - M_{g0t})$ and $va_{git} \equiv ln(Y_{git} - M_{git})$ (see Appendix B). Results presented in column 7 remain in line with those in column 1.[62]

In column 8, we consider a simple version of dynamic panel methods without firm fixed effects (see Shenoy (2018) for an extended discussion on these methods in the context of production functions). Despite additional linearity restrictions imposed on the markov process,

[58]For a similar application see Merlevede and Theodorakopoulos (2018).

[59]The decrease in the point estimates of the persistence parameters is expected, since we now control for the upward bias originating from the positive correlation between the persistence term and firm fixed effects (Arellano 2003). In addition, in Appendix Table C.10, we retrieve economically sensible estimates for the output elasticities of inputs and returns to scale. This brings confidence over the reasonable performance of this estimator. However, additional restrictions over the linearity of the Markov process and the stationarity on the initial conditions process need to be imposed.

[60]Equations 7 and 8 are now represented as: $h_j(k_{g0t}, l_{g0t}, m_{g0t}; \pi) = \sum_j \left(\sum_{r_k+r_l+r_m \leq 2} \pi_{r_k,r_l,r_m} k_{g0t}^{r_k} l_{g0t}^{r_l} m_{g0t}^{r_m} \right) \odot d_j$ and $f_j(k_{git}, l_{git}, m_{git}; \alpha) = \sum_j \left(\sum_{r_k+r_l+r_m \leq 2} \alpha_{r_k,r_l,r_m} k_{git}^{r_k} l_{git}^{r_l} m_{git}^{r_m} \right) \odot d_j$, with $r_k, r_l, r_m \geq 0$.

[61]However, more flexible functional forms come with typical trade-offs faced by empirical researchers: increased parameter space; insufficient number of observations for certain groups; and computationally intensive estimation routines. Therefore, we abstain from using any of the two as a baseline.

[62]This estimation approach comes with the additional assumption of scalar unobservability to invert the proxy demand function (e.g. Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg et al. 2007, 2015).

this approach considers the case where material is a non-flexible input, e.g. due to financial constrains, and thus allows for any possible interdependencies and dynamic elements. In addition, we account for the presence of classical measurement error in both the output and input variables (e.g. from misreporting) by using two-period lags as instruments. Results remain robust against these alternative considerations, with an expected increase in standard errors due to the deeper lag structure of the instrument matrix (Ackerberg 2019).

Imperfect Competition (Table 9).—Since we observe monetary values deflated at the country-industry-year level (and not physical output), baseline results should be interpreted as revenue based (Klette and Griliches 1996). This could induce bias into the estimates to the extent that output prices also vary within a country-industry-year. While ideally we could account for such variation by observing physical quantities at the firm-year level, such information is not available and rather infeasible to collect in this multi-country context. As such, in column 9 we follow standard practices in the literature to extend the baseline empirical model by including further structure and assumptions. This includes an iso-elastic demand system coupled with monopolistic competition, similar to Klette and Griliches (1996) and De Loecker (2011), following the methodology proposed by GNR. An exact description of the estimation procedure can be found in Appendix O5-4 of GNR.[63]

In a similar context, column 10 proceeds with the idenitfication strategy proposed by Flynn et al. (2019) (herein FGT). This is intended to solve for the non-identification issue of standard proxy variable techniques, as shown by GNR, when measuring markups with production data and one of the input is flexible. By imposing the returns to scale, FGT show that production functions are identified. However, in both columns 9 and 10 the production function is only partially identified. While estimators deliver the true production technology parameters (see Appendix Table C.10) the Markov process parameters only reflect those from a revenue-based production function. More specifically, estimated productivity $\widetilde{\omega} = k(\omega, \xi)$ is a function of true productivity (ω) and demand shocks (ξ). Therefore, it is not possible to tell whether the larger $\widetilde{\omega}$ is because the firm is more productive (ω) or because it can charge a higher price (ξ). More detailed data is needed to answer that question, which is not currently available for such an extensive cross-country dataset.

Additional Robustness.—To further support the validity of the baseline results we proceed with a battery of additional robustness checks presented in Appendix Table C.11. In columns 2 and 3 we use the BACON procedure and relax the threshold for dropping outliers from the 30$^{\text{th}}$ to the 20$^{\text{th}}$ and 10$^{\text{th}}$ percentile of the distribution of nominated outliers, respectively. Column 4 repeats the baseline estimation procedure when treating the production error terms as classical measurement error in output and not as ex-post shocks to production. This implies that there is

[63]On top of the estimated effects of interest, we are also able to identify aggregate time-varying markups (see Appendix Figure C.9). This is expected to be insightful to the extent to which, on average, firms adjust their markups over time. Therefore, effects presented in column 6 remain similar to the baseline in column 2 with an expected increase in magnitudes of the estimated production technology parameters.

no need for the $\mathscr{E}$ correction, i.e. $\mathscr{E}_a = \mathscr{E}_p = 1$. In column 5, we repeat the baseline estimation but include the industries dropped from the baseline sample.[64] Columns 6 and 7 estimate the baseline model considering the more detailed industry (j) classifications CPA and NACE, respectively (see Appendix Table C.1). In column 8 we bootstrap the baseline specification for 1000 replications, while in columns 9 and 10 we pairs bootstrap the standard errors at the country-industry (cj) and country (c) cluster, respectively.

Results are robust in all of the above cases. Finally, unimodality in the distribution of bootstrapped values (see Appendix Figure C.8) suggests that standard errors are robust to the presence of potential outlier clusters. This is especially true for cases where the cluster size is small (Cameron and Miller 2015).

7 Conclusion

A large literature has tried to understand the role of firm boundaries. Suggestive empirical evidence points to the theoretically based argument that firm boundaries exist to facilitate the transfer of intangible inputs. In this paper we identify and quantify transfers of intangibles, and how they determine the productivity evolution of the firm.

We use a carefully constructed European panel of majority owned parent-affiliate groups with full balance sheet information on both sides for the period 2004-2015 and extend a typical production function estimation procedure. Due to a well-known lack of data on intangible inputs, we devise an empirical method that allows us to characterise the full set of intangibles transferred between parent and affiliate firms.

We identify, at the firm level, the importance of intangible transfers between ownership-linked firms. While affiliates benefit from their parents' intangibles, these benefits also run the other way around. This finding is new to the literature, lending validation to theories which explain the motives of firm ownership.

The results presented in this paper are particularly poignant due to inherent difficulties in measuring intangible assets and their relative impact across space and time. Therefore, they are of high relevance to policymakers and institutions in their efforts to quantify the costs and benefits of policies related to intangible investment.

[64]These include sectors NACE 19 - Manufacture of coke and refined petroleum products and NACE 21 - Manufacture of rubber and plastic products.

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Appendices

A GNR Two-step Estimation Procedure

This section serves as an overview of the basic steps and assumptions of the GNR non-parametric estimation procedure applied to the empirical model in Section 3. For a detailed and complete description refer to GNR. For notation simplicity and without loss of generality, we disregard the country c and industry j dimensions. The estimation is directly extended by allowing the functional forms of the production technology $h(\cdot)$ and $f(\cdot)$ to vary by industry j.

To recap the main assumptions, this case considers the classic environment of perfect competition in both input and output markets. Capital and labour are predetermined inputs and therefore chosen one year prior to the realisation of productivity, i.e. at $(t-1)$. The only flexible input 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, the static profit maximisation problem yields the first order condition with respect to the flexible input for the parent:

$$P_t^M = P_t \frac{\partial}{\partial M_t} H(K_{g0t}, L_{g0t}, M_{g0t}) \mathrm{e}^{\omega_{g0t}} \mathscr{E}_p \tag{A.1}$$

and the affiliate:

$$P_t^M = P_t \frac{\partial}{\partial M_t} F(K_{git}, L_{git}, M_{git}) \mathrm{e}^{\omega_{git}} \mathscr{E}_a \tag{A.2}$$

where P_t^M and P_t are the price of material and output, respectively. Under perfect competition in input and output markets, they are constant across parent and affiliates within the same country and industry, but can vary over time. By the time firms make their annual decisions, ex-post shocks ε_{g0t} and ε_{git} are not in their information set and therefore $\mathscr{E}_p = E(\mathrm{e}^{\varepsilon_{g0t}})$ and $\mathscr{E}_a = E(\mathrm{e}^{\varepsilon_{git}})$.[65] To derive (A.1) and (A.2) one needs to assume that the distributions of the ex-post shocks are independent of the within period variation in the firm's information set, i.e. $P_\varepsilon\big(\varepsilon_{g0t}|\mathscr{I}_{gt}\big) = P_\varepsilon\big(\varepsilon_{g0t}\big)$ and $P_\varepsilon\big(\varepsilon_{git}|\mathscr{I}_{gt}\big) = P_\varepsilon\big(\varepsilon_{git}\big)$. Alternatively, as commonly used in the proxy variable setup, mean independence $\big(E[\varepsilon_{g0t}|\mathscr{I}_{gt}] = E[\varepsilon_{git}|\mathscr{I}_{gt}] = 0\big)$ would not suffice to treat $\mathscr{E}$'s as constants since from the firm's problem they will now become some function of the information set, i.e. $\mathscr{E}_a\big(\mathscr{I}_{gt}\big)$ and $\mathscr{E}_p\big(\mathscr{I}_{gt}\big)$. See GNR for a detailed discussion on this topic and alternative ways to relax this assumption to mean independence.[66]

We retrieve a material costs share equation for the parent by combining (A.1) with (1) and re-arranging terms:

$$s_{g0t} = ln\Big(\widetilde{h}(k_{g0t}, l_{g0t}, m_{g0t})\Big) + ln\mathscr{E}_p - \varepsilon_{g0t} \tag{A.3}$$

[65] It is important to account and correct for this nuisance term since ignoring it, i.e. $\mathscr{E}_p = \mathscr{E}_a = 1$, inherently implies that we move from the mean to the median central tendency of $\mathrm{e}^{\varepsilon_{git}}$ (see Goldberger 1968).

[66] Note that if εs are treated as classical measurement error then one can use the weaker assumption of mean independence and skip the correction described above.

Similarly, we retrieve a material costs share equation for the affiliate by combining (A.2) with (2):

$$s_{git} = ln\left(\widetilde{f}(k_{git}, l_{git}, m_{git})\right) + ln\mathscr{E}_a - \varepsilon_{git} \tag{A.4}$$

In the above, s_{g0t} and s_{git} are the log of the nominal share of material costs for the parent and the affiliate, respectively. $\widetilde{h}(k_{g0t}, l_{g0t}, m_{g0t}) = \frac{\partial}{\partial m_{g0t}} h(k_{g0t}, l_{g0t}, m_{g0t})$ and $\widetilde{f}(k_{git}, l_{git}, m_{git}) = \frac{\partial}{\partial m_{git}} f(k_{git}, l_{git}, m_{git})$ are the output elasticities of the flexible input. Notice that in both share equations, TFP is not present anymore. This follows the identification insight of GNR where the TFP term inducing the transmission bias is eliminated from the share equation due to the assumed Hicks-neutrality, i.e. additive. The idea here is that the share equation helps to recover the output elasticity of the flexible input and in turn allows for the nonparametric identification of the rest of the production function and Markov process. GNR propose a simple nonparametric estimator using sieve estimators and, in line with proxy variable methods, follows two steps.

A.1 Step One

In the first step, a Non Linear Least Squares (NLLS) estimation for each of the share equations (A.3) and (A.4) is applied, with:

$$\widetilde{h}(k_{g0t}, l_{g0t}, m_{g0t})\mathscr{E}_p = \sum_{r_k + r_l + r_m \leq r} \gamma'_{r_k, r_l, r_m} k_{g0t}^{r_k} l_{g0t}^{r_l} m_{g0t}^{r_m}, \ with \ r_k, r_l, r_m \geq 0 \tag{A.5}$$

and

$$\widetilde{f}(k_{git}, l_{git}, m_{git})\mathscr{E}_a = \sum_{r_k + r_l + r_m \leq r} \delta'_{r_k, r_l, r_m} k_{git}^{r_k} l_{git}^{r_l} m_{git}^{r_m}, \ with \ r_k, r_l, r_m \geq 0 \tag{A.6}$$

approximated by a polynomial series estimator of order r. The independence assumption of the ex post shocks to production imply the conditional moments $E[\varepsilon_{g0t}|k_{g0t}, l_{g0t}, m_{g0t}] = E[\varepsilon_{git}|k_{git}, l_{git}, m_{git}] = 0$ allowing to form the unconditional moments $E\left[\varepsilon_{g0t}(\partial \widetilde{h}(k_{g0t}, l_{g0t}, m_{g0t})/\partial\gamma)\right] = E\left[\varepsilon_{git}(\partial \widetilde{f}(k_{git}, l_{git}, m_{git})/\partial\delta)\right] = 0$. This step exactly identifies ε_{g0t} and ε_{git} (hence $\widehat{\mathscr{E}_p} = \frac{1}{GT}\sum_{g,t} e^{\widehat{\varepsilon}_{g0t}}$ and $\widehat{\mathscr{E}_a} = \frac{1}{IT}\sum_{gi,t} e^{\widehat{\varepsilon}_{git}}$), $\gamma \equiv \gamma'/\mathscr{E}_p$, $\delta \equiv \delta'/\mathscr{E}_a$) and thus the output elasticities of the flexible input, i.e. material, for both the parent $\left(\widetilde{h}(\cdot)\right)$ and affiliate $\left(\widetilde{f}(\cdot)\right)$.

A.2 Step Two

By integrating up the output elasticity of the flexible input for the parent:

$$\int \widetilde{h}(k_{g0t}, l_{g0t}, m_{g0t}) dm_{g0t} = h(k_{g0t}, l_{g0t}, m_{g0t}) + \mathscr{H}(k_{g0t}, l_{g0t}) \tag{A.7}$$

and the affiliate:

$$\int \widetilde{f}(k_{git}, l_{git}, m_{git}) dm_{git} = f(k_{git}, l_{git}, m_{git}) + \mathscr{F}(k_{git}, l_{git}) \tag{A.8}$$

We identify the production function of the parent and affiliate up to an unknown constant of integration $\mathscr{H}(k_{g0t}, l_{g0t})$ and $\mathscr{F}(k_{git}, l_{git})$, respectively. By subtracting the production functions (1) and (2) from equations (A.7) and (A.8), respectively, we retrieve the following expressions for parent TFP:

$$\omega_{g0t} = \hat{\mathscr{Y}}_{g0t} + \mathscr{H}(k_{g0t}, l_{g0t}) \tag{A.9}$$

and affiliate TFP:

$$\omega_{git} = \hat{\mathscr{Y}}_{git} + \mathscr{F}(k_{git}, l_{git}) \tag{A.10}$$

where $\hat{\mathscr{Y}}_{g0t}$ and $\hat{\mathscr{Y}}_{git}$ are the log of the expected output net of the computed integral of the output elasticity of materials for the parent (A.7) and affiliate (A.8), respectively, as estimated from the first step. $\mathscr{H}(k_{g0t}, l_{g0t})$ and $\mathscr{F}(k_{git}, l_{git})$ represent the remaining part of the production function to be identified for the parent and affiliate, respectively, and approximated by a polynomial of degree r both for the parent:

$$\mathscr{H}(k_{g0t}, l_{g0t}) = \sum_{0<r_k+r_l\leq\nu} \pi_{r_k,r_l} k_{g0t}^{r_k} l_{g0t}^{r_l}, \; with \;\; r_k, r_l \geq 0 \tag{A.11}$$

and the affiliate:

$$\mathscr{F}(k_{git}, l_{git}) = \sum_{0<r_k+r_l\leq\nu} \alpha_{r_k,r_l} k_{git}^{r_k} l_{git}^{r_l}, \; with \;\; r_k, r_l \geq 0 \tag{A.12}$$

Note that both parent and affiliate TFP are now expressed as functions of variables observed in the data (l and k), variables generated ($\hat{\mathscr{Y}}$), and parameters to be estimated $\pi_\nu = (\pi_{1,0}, \pi_{0,1}, \ldots, \pi_{r_k,r_l})$ and $\alpha_\nu = (\alpha_{1,0}, \alpha_{0,1}, \ldots, \alpha_{r_k,r_l})$.

Following the dynamic panel literature, the second step exploits the assumption over the law of motion of TFP. Without loss of generality, we combine (A.9) and (A.10) with the conditional linear first-order Markov processes from the baseline model in (9) and (10),[67] resulting in the estimating equations:

$$\begin{aligned}
\hat{\mathscr{Y}}_{g0t} &= -\mathscr{H}(k_{g0t}, l_{g0t}) + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + \xi_{g0t} \\
&= -\mathscr{H}(k_{g0t}, l_{g0t}) + \rho_{pp}\Big(\hat{\mathscr{Y}}_{g0t-1} + \mathscr{H}(k_{g0t-1}, l_{g0t-1})\Big) \\
&\quad + \rho_{pa}\overline{\Big(\hat{\mathscr{Y}}_{git-1} + \mathscr{F}(k_{g0t-1}, l_{g0t-1})\Big)} + \widetilde{\phi}_{fe} + \xi_{g0t}
\end{aligned} \tag{A.13}$$

and

$$\begin{aligned}
\hat{\mathscr{Y}}_{git} &= -\mathscr{F}(k_{git}, l_{git}) + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + \xi_{git} \\
&= -\mathscr{F}(k_{g0t}, l_{g0t}) + \rho_{aa}\Big(\hat{\mathscr{Y}}_{git-1} + \mathscr{F}(k_{git-1}, l_{git-1})\Big) \\
&\quad + \rho_{ap}\Big(\hat{\mathscr{Y}}_{g0t-1} + \mathscr{H}(k_{g0t-1}, l_{g0t-1})\Big) + \phi_{fe} + \xi_{git}
\end{aligned} \tag{A.14}$$

[67] Alternatively, with the data constraints and parameter space in mind, a more flexible functional form can be considered where: $\omega_{g0t} = g\big(\omega_{g0t-1}, \omega_{git-1}\big) + \widetilde{\phi}_{fe} + \xi_{it}$ and $\omega_{git} = d\big(\omega_{git-1}, \omega_{g0t-1}\big) + \phi_{fe} + \xi_{it}$.

The main difference from a standard production function is that each specification identifies not only the own production technology and Markov process, but also the production technology of the ownership-linked firms. For example, equation (A.13) identifies not only the production technology $\left(\mathscr{H}(\cdot)\right)$ and Markov process (ρ_{pp}, ρ_{pa}) of parent firms, but also the production technology of affiliates $\mathscr{F}(\cdot)$.

The step proceeds with a standard iterative Generalised Method of Moments (GMM). We simultaneously estimate the model by stacking equation (A.13) and (A.14) and imposing the cross-equation constraints on the parameters of the production technologies that appear through the interdependencies of TFP in the Markov process. By distinctly instrumenting each of the stacked equations, we form a GMM criterion function based on the following moment conditions:

$$E\left[\begin{pmatrix} \mathscr{Z}_r^p & \omega_{g0t-1}(\pi_r) & \bar{\omega}_{git-1}(\alpha_r) & \widetilde{d}_{fe} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathscr{Z}_r^a & \omega_{git-1}(\alpha_r) & \omega_{g0t-1}(\pi_r) & d_{fe} \end{pmatrix}' \begin{pmatrix} \xi_{g0t} \\ \xi_{git} \end{pmatrix}\right] = 0 \tag{A.15}$$

where $\mathscr{Z}_r^p = \left(k_{g0t}, l_{g0t}, \ldots, k_{g0t}^{r_k} l_{g0t}^{r_l}\right)$ and $\mathscr{Z}_r^a = \left(k_{git}, l_{git}, \ldots, k_{git}^{r_k} l_{git}^{r_l}\right)$ are the 'instrument sub-matrices' with their column space dimensions depending on the degree r of the polynomials used to approximate the constants of integration in (A.11) and (A.12). The orthogonality conditions directly depend on the timing assumptions of inputs. Capital and labour, both for the parent and affiliate, are predetermined and thus orthogonal to the productivity innovations.[68] These instruments are typical in the literature and help to identify the π's and α's for capital and labour. Continuing, to identify the Markov process parameters ρ_{pp}, ρ_{pa} and ρ_{aa}, ρ_{ap}, for a guess of π_r and α_r, we form $\omega_{g0t-1}(\pi_r)$ and $\omega_{git-1}(\alpha_r)$ $\left(\text{hence } \bar{\omega}_{git-1}(\alpha_r)\right)$ based on (A.9) and (A.10), respectively, which are by construction orthogonal to the TFP innovations.[69] Finally, for the fixed effects $\widetilde{\phi}_{fe}$ and ϕ_{fe} we use a full set of dummy variables $\widetilde{d}_{fe}$ and d_{fe}, respectively, as defined in Section 4.3 which are assumed to be exogenous and thus uncorrelated with the unanticipated innovations to productivity. This is an exactly identified model where the number of instruments is the same as the number of parameters.[70]

By minimising the squared Euclidean length of the sample analogue of (A.15), we retrieve estimates for parameters of the production technology of the parent (π_r) and affiliate (α_r). We also retrieve estimates for the persistence of firms' TFP (ρ_{pp} and ρ_{aa}), the productivity effects from the linked firms' TFP (ρ_{pa} and ρ_{ap}) and all of the fixed-effects considered ($\widetilde{\phi}_{fe}$ and ϕ_{fe}).

As discussed in subsection 4.3, for the baseline model we apply industry-specific Cobb-Douglass specifications for $H(\cdot)$ and $F(\cdot)$ in (1) and (2), respectively, to control for growth differentials across industries. This is equivalent to a polynomial of degree zero for the elasticities

[68] However, if labour is assumed to be a dynamic input then current labour and productivity are correlated and thus thus instrument with lagged values of labour instead.

[69] Alternatively, one can use values of $\mathscr{Y}_{g0t}$ and $\mathscr{Y}_{git}$ generated from the first step.

[70] Estimating each equation separately requires additional instruments to identify the production technology of ownership-linked firms. For example, for (A.13) $E\left[(\mathscr{Z}_r^p, \omega_{g0t-1}(\pi_r), \omega_{git-1}(\alpha_r), \widetilde{d}_{fe}, \mathscr{Z}_r^a)' \xi_{g0t}\right] = 0$ and for (A.14) $E\left[(\mathscr{Z}_r^a, \omega_{git-1}(\alpha_r), \omega_{g0t-1}(\rho_r), d_{fe}, \mathscr{Z}_r^p)' \xi_{git}\right] = 0$.

of material, $r = 0$, i.e. industry dummies in the share equation regression, and a first order polynomial for the constants of integration, $r = 1$.

Based on estimates of the production function coefficients, we can now compute other relevant variables, i.e. TFP, output elasticities of inputs and returns to scale (RTS), for both the parent and the affiliate, using equations (1) and (2), respectively

A.3 Step Two with Firm Fixed Effects

In line with dynamic panel methods, GNR provide an extension of their estimation strategy that can easily account for firm fixed effects, something not possible in proxy variable methods.[71] Here we provide an augmented version of their extension applied to our empirical model. For the case of parent-level (ϕ_{g0}) and affiliate-level (ϕ_{gi}) fixed effects, the production functions (1) and (2) are now written as:

$$y_{g0t} = h(k_{g0t}, l_{g0t}, m_{g0t}) + \widetilde{\omega}_{g0t} + \varepsilon_{g0t} \tag{A.16}$$

and

$$y_{git} = f(k_{git}, l_{git}, m_{git}) + \widetilde{\omega}_{git} + \varepsilon_{git} \tag{A.17}$$

where $\widetilde{\omega}_{g0t} \equiv \omega_{g0t} + \phi_{g0}$ and $\widetilde{\omega}_{git} \equiv \omega_{git} + \phi_{gi}$. Since fixed effects enter log-additively, the first order conditions of the firm in (A.1) and (A.2), and the share equations in (A.3) and (A.4) remain the same, with $\widetilde{\omega}_{g0t}$ and $\widetilde{\omega}_{git}$ replacing ω_{g0t} and ω_{git}, respectively. Therefore, the first step described in Appendix A.1 is exactly the same.

In the second step, the estimating equations (A.13) and (A.14) are now augmented to:

$$\begin{aligned}\hat{\mathscr{Y}}_{g0t} &= -\mathscr{H}(k_{g0t}, l_{g0t}) + \rho_{pp}\omega_{g0t-1} + \rho_{pa}\bar{\omega}_{git-1} + \widetilde{\phi}_{fe} + (1-\rho_{pp})\phi_{g0} - \rho_{pa}\phi_{gi} + \xi_{g0t} \\ &= -\mathscr{H}(k_{g0t}, l_{g0t}) + \rho_{pp}\Big(\hat{\mathscr{Y}}_{g0t-1} + \mathscr{H}(k_{g0t-1}, l_{g0t-1})\Big) \\ &\qquad + \rho_{pa}\overline{\Big(\hat{\mathscr{Y}}_{git-1} + \mathscr{F}(k_{g0t-1}, l_{g0t-1})\Big)} + \widetilde{\phi}_{fe} + (1-\rho_{pp})\phi_{g0} - \rho_{pa}\phi_{gi} + \xi_{g0t}\end{aligned} \tag{A.18}$$

and

$$\begin{aligned}\hat{\mathscr{Y}}_{git} &= -\mathscr{F}(k_{git}, l_{git}) + \rho_{aa}\omega_{git-1} + \rho_{ap}\omega_{g0t-1} + \phi_{fe} + (1-\rho_{aa})\phi_{gi} - \rho_{ap}\phi_{g0} + \xi_{git} \\ &= -\mathscr{F}(k_{g0t}, l_{g0t}) + \rho_{aa}\Big(\hat{\mathscr{Y}}_{git-1} + \mathscr{F}(k_{git-1}, l_{git-1})\Big) \\ &\qquad + \rho_{ap}\Big(\hat{\mathscr{Y}}_{g0t-1} + \mathscr{H}(k_{g0t-1}, l_{g0t-1})\Big) + \phi_{fe} + (1-\rho_{aa})\phi_{gi} - \rho_{ap}\phi_{g0} + \xi_{git}\end{aligned} \tag{A.19}$$

[71] For a detailed description see Appendix O5-1 in GNR.

A.3.1 First Difference GMM (DIF)

Following the dynamic panel literature, GNR eliminate the fixed effects by first-differencing the above equations:

$$\Delta\hat{\mathscr{Y}}_{g0t} = -\Delta\mathscr{H}(k_{g0t}, l_{g0t}) + \rho_{pp}\Delta\omega_{g0t-1} + \rho_{pa}\Delta\bar{\omega}_{git-1} + \Delta\widetilde{\phi}_{fe} + \Delta\xi_{g0t} \tag{A.20}$$

and

$$\Delta\hat{\mathscr{Y}}_{git} = -\Delta\mathscr{F}(k_{git}, l_{git}) + \rho_{aa}\Delta\omega_{git-1} + \rho_{ap}\Delta\omega_{g0t-1} + \Delta\phi_{fe} + \Delta\xi_{git} \tag{A.21}$$

where Δ is the first difference operator. Note that as in dynamic panel methods, linearity of the Markov processes is necessary, since otherwise the fixed effects would enter nonlinearly in (A.18) and (A.19) and thus cannot difference them out. By construction, the above equation suffers from endogeneity induced by the correlation between first-differenced lagged productivities and $\Delta\xi$. To solve for this, one can instrument with deeper lags in levels à la Arellano and Bond (1991). However, as shown by Blundell and Bond (1998), first differencing in a dynamic panel setup performs poorly when TFP is close to a random walk because of weak instruments causing large finite sample bias. In a production function context, this results in empirical estimates of output elasticities and returns to scale which are imprecise and possess large standard errors (Griliches and Mairesse 1999; Blundell and Bond 2000). Therefore, to reduce such biases, we further augment the GNR estimation procedure with firm fixed effects borrowing from the "System GMM" estimator developed by Blundell and Bond (1998) and outlined by Arellano and Bover (1995).[72] For a similar application, see Merlevede and Theodorakopoulos (2018).

A.3.2 System GMM (SYS)

Following Blundell and Bond (1998), the SYS GMM approach augments the DIF GMM from the previous section by estimating simultaneously the equation in differences and levels in a single equation for the parent:

$$\begin{pmatrix}\Delta\hat{\mathscr{Y}}_{g0t}\\ \hat{\mathscr{Y}}_{g0t}\end{pmatrix} = -\begin{pmatrix}\Delta\mathscr{H}(k_{g0t}, l_{g0t})\\ \mathscr{H}(k_{g0t}, l_{g0t})\end{pmatrix} + \rho_{pp}\begin{pmatrix}\Delta\omega_{g0t-1}\\ \omega_{g0t-1}\end{pmatrix} + \rho_{pa}\begin{pmatrix}\Delta\bar{\omega}_{git-1}\\ \bar{\omega}_{git-1}\end{pmatrix} + \begin{pmatrix}\Delta\widetilde{\phi}_{fe}\\ \widetilde{\phi}_{fe}\end{pmatrix} + \begin{pmatrix}\Delta\xi_{g0t}\\ \xi_{g0t}\end{pmatrix} \tag{A.22}$$

and the affiliate:

$$\begin{pmatrix}\Delta\hat{\mathscr{Y}}_{git}\\ \hat{\mathscr{Y}}_{git}\end{pmatrix} = -\begin{pmatrix}\Delta\mathscr{F}(k_{git}, l_{git})\\ \mathscr{F}(k_{git}, l_{git})\end{pmatrix} + \rho_{pp}\begin{pmatrix}\Delta\omega_{git-1}\\ \omega_{git-1}\end{pmatrix} + \rho_{pa}\begin{pmatrix}\Delta\omega_{g0t-1}\\ \omega_{g0t-1}\end{pmatrix} + \begin{pmatrix}\Delta\phi_{fe}\\ \phi_{fe}\end{pmatrix} + \begin{pmatrix}\Delta\xi_{git}\\ \xi_{git}\end{pmatrix} \tag{A.23}$$

where the same linear relationship with the same coefficients applies, resulting in a stacked dataset with two times the amount of data and the same set of parameters used in levels for

[72] This approach does not come for free since we need to introduce stationarity restrictions on the initial conditions process (Arellano and Bover 1995).

the parent and affiliate, respectively. The remaining part of the procedure is the same as in Appendix A.2 with the only difference being in the instrument matrix used to form the moment conditions By distinctly instrumenting each of the stacked equations, we form the following moment conditions:

$$E\left[\begin{pmatrix} \mathscr{Z}_r^{DIF_p} & 0 & 0 & 0 \\ 0 & \mathscr{Z}_r^{LEV_p} & 0 & 0 \\ 0 & 0 & \mathscr{Z}_r^{DIF_a} & 0 \\ 0 & 0 & 0 & \mathscr{Z}_r^{LEV_a} \end{pmatrix}' \begin{pmatrix} \Delta\xi_{g0t} \\ \xi_{g0t} \\ \Delta\xi_{git} \\ \xi_{git} \end{pmatrix}\right] = 0 \tag{A.24}$$

where for the equation in first-differences we use deeper lags of values in levels:

$$\mathscr{Z}_r^{DIF_p} = \left(k_{g0t-1}, l_{g0t-1}, \ldots, k_{g0t-1}^{r_k} l_{g0t-1}^{r_l}, \omega_{g0t-2}(\pi_r), \bar{\omega}_{git-2}(\alpha_r), \Delta\widetilde{d}_{fe}\right)$$

and

$$\mathscr{Z}_r^{DIF_a} = \left(k_{git-1}, l_{git-1}, \ldots, k_{git-1}^{r_k} l_{git-1}^{r_l}, \omega_{git-2}(\alpha_r), \omega_{g0t-2}(\pi_r), \Delta d_{fe}\right)$$

For the equation in levels we exploit (deeper lags of) first-differenced values:[73]

$$\mathscr{Z}_r^{LEV_p} = \left(\Delta k_{g0t}, \Delta l_{g0t}, \ldots, \Delta k_{g0t}^{r_k} \Delta l_{g0t}^{r_l}, \Delta\omega_{g0t-1}(\pi_r), \Delta\bar{\omega}_{git-1}(\alpha_r), \widetilde{d}_{fe}\right)$$

and

$$\mathscr{Z}_r^{LEV_a} = \left(\Delta k_{git}, \Delta l_{git}, \ldots, \Delta k_{git}^{r_k} \Delta l_{git}^{r_l}, \Delta\omega_{git-1}(\alpha_r), \Delta\omega_{g0t-1}(\pi_r), d_{fe}\right)$$

As a choice of a weighting matrix to yield a consistent estimator, we follow, among others, Windmeijer (2000) by choosing the block diagonal matrix:

$$W = N\left(Z_r^{SYS\prime} \begin{pmatrix} H^{DIF_p} & D_p & 0 & 0 \\ D_p' & I_{T-2} & 0 & 0 \\ 0 & 0 & H^{DIF_a} & D_p \\ 0 & 0 & D_p' & I_{T-2} \end{pmatrix} Z_r^{SYS}\right)^{-1} \tag{A.25}$$

where Z_r^{SYS} is the instrument matrix described in (A.24). $H^{DIF_p} \equiv D_p D_p{}'$ and $H^{DIF_a} \equiv D_a D_a{}'$ are $T-2$ square matrices that have 2's on the main diagonal, -1s on the first subdiagonals, and zeros elsewhere. D_p and D_a are matrices with -1s in the diagonal, 1s in the first upper sub-diagonal, and zeros elsewhere. Finally, N contains the number of parent and affiliate firms,

[73]For the variables of interest, i.e. ownership-linked productivities, we use all possible lags as instruments in order to maintain maximal identifying variation, while for the rest of the variables we limit the instruments to include only the first lag. We abstain from using additional deeper lags for all variables in order to avoid potential biases generated by instrument proliferation (Roodman 2009). In the same spirit, we further limit the instrument count by using a collapsed version of the instrument matrix, as suggested by Roodman (2009) among others. Kiviet et al. (2017) demonstrate how the combination of these two instrument reduction methods can improve estimation precision.

respectively.

B ACF Two-step Estimation Procedure

This section provides an overview of the basic steps and assumptions in the ACF estimation procedure applied to the the baseline model under a value-added production function. For a detailed and complete description of the estimatio approach refer to ACF. This procedure controls for collinearity problems encountered in Levinsohn and Petrin (2003). Assumptions imposed about competition and timing of firms' decisions are as in the previous section. Similarly, for notation simplicity and without loss of generality, we disregard the country c and industry j dimensions. The estimation is directly extended by allowing the functional forms of the production technologies determined below to vary by industry j. The main difference with the baseline model is that we now use a restricted profit value-added production function both for the parent $VA_{g0t} = Y_{g0t} - M_{g0t} = H(K_{g0t}, L_{g0t})\mathrm{e}^{\omega_{g0t}}$ and affiliate $VA_{git} = Y_{git} - M_{git} = F(K_{git}, L_{git})\mathrm{e}^{\omega_{git}}$, which in logs is expressed as:

$$va_{g0t} = h(k_{g0t}, l_{g0t}) + \omega_{g0t} + \varepsilon_{g0t} \tag{B.1}$$

and

$$va_{git} = f(k_{git}, l_{git}) + \omega_{git} + \varepsilon_{git} \tag{B.2}$$

where va_{g0t} and va_{git} is the log of double deflated value-added the parent and affiliate, respectively.

Conditional on the state variables and other firm characteristics, firm's static profit maximisation yields material input demands $m_{g0t} = m_p(k_{g0t}, l_{g0t}, m_{g0t})$ and $m_{git} = m_a(k_{git}, l_{git}, m_{git})$. To control for the unobserved productivity of the parent and affiliate, we use the inverted intermediate input demand $\omega_{g0t} = m_p^{-1}(k_{g0t}, l_{g0t}, m_{g0t})$ and $\omega_{g0t} = m_a^{-1}(k_{git}, l_{git}, m_{git})$, respectively, under the assumption of monotonocity of m in ω.[74] Alternatively, we can rewrite (B.1) and (B.2) as:

$$va_{g0t} = u(k_{g0t}, l_{g0t}, m_{g0t}) + \varepsilon_{g0t} \tag{B.3}$$

and

$$va_{git} = v(k_{git}, l_{git}, m_{git}) + \varepsilon_{git} \tag{B.4}$$

B.1 Step One

For a polynomial approximation of order κ for both $u(\cdot)$ and $v(\cdot)$, an Ordinary Least Squares (OLS) regression on (B.3) and (B.4) delivers a measure of value-added purged from measurement

[74] To exclude the possibility of other unobservable factors that would violate the scalar unobservability assumption, one should use as many relevant observable variables as possible (with the parameter space restriction in mind) In addition, here we assume that there are no interdependencies in the decision making of material inputs. However, if this is not the case, at the minimum, ownership-linked material inputs should also be included in the control function.

error in output for the parent ($\hat{\mathscr{V}}_{g0t}$) and affiliate ($\hat{\mathscr{V}}_{git}$), respectively.[75]

B.2 Step Two

Productivities can now be re-written as: $\omega_{g0t} = \hat{u}_{g0t} - h(k_{g0t}, l_{g0t})$ and $\omega_{git} = \hat{v}_{git} - f(k_{git}, l_{git})$. For production functions approximated with a polynomial of order $\nu < \kappa$ the second step follows exactly the same estimation procedure as in Appendix A.2, but with ($\hat{\mathscr{Y}}_{g0t}$) and ($\hat{\mathscr{Y}}_{git}$) replaced by ($\hat{\mathscr{V}}_{g0t}$) and ($\hat{\mathscr{V}}_{git}$), respectively.[76]

[75]For our estimates, both $u(\cdot)$ and $v(\cdot)$ are approximated with a third order polynomial ($\kappa = 3$). Also note that ε, as typically treated in the literature, reflects only classical measurement error and not ex-post shocks to production. As such, the identifying assumption in this stage can be relaxed to mean independence instead of full independence needed in the baseline model.

[76]Recall that the baseline model assumes Cobb-Douglas production functions.

C Additional Figures and Tables

Table C.1: List of A*38, CPA and NACE 2-digit (Rev.2) industries for the manufacturing sector

A*38	CPA	NACE	Description
CA	5	10	Manufacture of food products
CA	5	11	Manufacture of beverages
CA	5	12	Manufacture of tobacco products
CB	6	13	Manufacture of textiles
CB	6	14	Manufacture of wearing apparel
CB	6	15	Manufacture of leather and related products
CC	7	16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
CC	8	17	Manufacture of paper and paper products
CC	9	18	Printing and reproduction of recorded media
CD	10	19	Manufacture of coke and refined petroleum products
CE	11	20	Manufacture of chemicals and chemical products
CF	12	21	Manufacture of basic pharmaceutical products and preparations
CG	13	22	Manufacture of rubber and plastic products
CG	14	23	Manufacture of other non-metallic mineral products
CH	15	24	Manufacture of basic metals
CH	16	25	Manufacture of fabricated metal products, excl. machinery & equip.
CI	17	26	Manufacture of computer, electronic and optical products
CJ	18	27	Manufacture of electrical equipment
CK	19	28	Manufacture of machinery and equipment n.e.c.
CL	20	29	Manufacture of motor vehicles, trailers and semi-trailers
CL	21	30	Manufacture of other transport equipment
CM	22	31	Manufacture of furniture
CM	22	32	Other manufacturing
CM	23	33	Repair and installation of machinery and equipment

Note: A*38 represents intermediate aggregation of the NACE Rev.2 2-digit classification (NACE) (Eurostat 2020). CPA represents the Classification of Products by Activity and is directly mapped to NACE since both classifications are completely aligned down to the class level (Eurostat 2019).

Table C.2: Data Representativeness

	Foreign affiliates in country				Country's affiliates abroad			
	Nº affiliates		Employment		Nº affiliates		Employment	
	n	share	*n*	share	*n*	share	*n*	share
AT	367	0.88	37,996	0.63	819	0.63	120,519	0.59
BE	344	1.13	55,566	0.72	652	0.58	48,866	0.54
BG	93	0.24	42,089	0.65	6	0.08	167	0.00
CZ	1,142	0.49	258,709	0.90	77	1.08	4,039	0.33
DE	1,184	0.53	152,578	0.29	2,589	0.38	422,789	0.39
EE	267	0.93	18,974	0.62	29	0.53	1,992	0.51
ES	742	0.46	121,756	0.45	577	0.64	66,609	1.10
FI	214	0.85	31,361	0.96	371	0.52	38,912	0.39
FR	771	0.41	49,492	0.21	1,181	0.51	227,717	0.42
HR	128	0.41	14,904	0.58	13	-	377	-
HU	263	0.21	81,542	0.57	33	0.33	4,927	0.62
IT	904	0.81	144,301	0.98	1,119	0.54	105,083	0.39
NO	160	0.44	12,187	0.39	208	0.45	22,748	0.43
PL	1,637	0.98	143,913	0.53	57	0.55	9,781	0.44
PT	292	0.46	39,533	0.48	72	0.49	7,617	0.56
RO	912	0.39	179,599	0.65	5	0.16	47	0.04
SE	239	0.36	37,774	0.44	770	0.66	78,734	0.48
SI	109	0.44	15,862	0.51	46	0.89	5,388	0.76
SK	303	0.45	77,714	0.59	56	0.36	5,033	0.32
Total	10,904	0.57	1,578,614	0.55	10,904	0.57	1,578,614	0.55

Notes: Number of firms and employees covered by our dataset both in levels (*n*) and as a share (share) of inward Foreign Affiliates Statistics (FATS) provided by Eurostat for the year 2012 (affiliates in manufacturing and parents in all industries - FATS does not provide parent industry).

Table C.3: Parent-year Observations by Country and Industry

	A*38 Industry Classification											
Country	CA	CB	CC	CE	CG	CH	CI	CJ	CK	CL	CM	Total
AT	72	58	100	57	179	177	37	81	104	37	21	923
BE	304	137	205	177	361	340	56	80	166	55	76	1,957
BG	131	75	51	24	54	119	4	16	56	0	56	586
CZ	165	49	85	49	222	193	62	37	247	95	97	1,301
DE	313	197	222	245	734	854	336	452	932	307	194	4,786
EE	9	4	38	1	8	16	0	3	0	11	16	106
ES	1,838	466	962	602	1,433	1,516	152	288	584	667	557	9,065
FI	194	82	447	25	220	483	63	72	299	103	183	2,171
FR	1,185	401	851	417	1,065	1,378	276	373	701	419	551	7,617
HR	129	41	98	16	98	42	1	30	30	19	47	551
HU	12	3	11	10	46	14	0	1	1	13	8	119
IT	1,349	1,784	1,045	853	2,469	3,586	589	1,099	3,221	677	1,140	17,812
NO	255	73	156	29	180	216	43	34	146	96	155	1,383
PL	79	13	57	54	105	37	6	18	53	31	38	491
PT	344	236	161	82	333	316	1	49	120	76	73	1,791
RO	224	190	143	38	194	226	30	48	65	75	101	1,334
SE	120	34	319	22	152	305	43	18	200	84	118	1,415
SI	68	36	55	15	91	85	24	51	29	33	16	503
SK	23	0	31	7	30	40	0	27	12	1	16	187
Total	6,814	3,879	5,037	2,723	7,974	9,943	1,723	2,777	6,966	2,799	3,463	54,098

Notes: Using baseline sample discussed in Section 2. Underline data sourced from Amadeus database by BvDEP.

Table C.4: Affiliate-year Observations by Country and Industry

	A*38 Industry Classification											
Country	CA	CB	CC	CE	CG	CH	CI	CJ	CK	CL	CM	Total
AT	44	26	64	18	80	113	38	27	68	25	25	528
BE	332	89	194	150	403	518	61	50	120	77	77	2,071
BG	180	104	63	31	119	193	10	40	73	24	45	882
CZ	233	112	155	142	602	584	74	203	380	249	214	2,948
DE	358	128	236	284	639	976	322	262	859	312	239	4,615
EE	45	45	119	7	60	163	29	25	33	32	68	626
ES	2,686	513	1,183	860	1,952	2,066	218	363	882	965	722	12,410
FI	191	50	461	27	272	470	53	86	276	100	190	2,176
FR	1,644	488	1,241	501	1,610	1,985	368	326	717	499	804	10,183
HR	201	78	134	48	206	152	5	95	70	42	65	1,096
HU	37	20	24	55	80	100	38	33	30	40	17	474
IT	1,680	1,657	1,042	855	2,866	4,528	774	1,168	3,399	812	1,436	20,217
NO	350	57	268	53	213	279	45	48	224	99	170	1,806
PL	149	43	141	110	366	251	43	108	160	182	132	1,685
PT	497	342	250	211	444	421	14	104	169	208	122	2,782
RO	325	661	344	102	464	753	92	125	263	268	208	3,605
SE	144	21	374	31	136	358	36	44	197	99	126	1,566
SI	70	32	87	34	115	100	14	29	62	34	47	624
SK	61	51	37	14	124	201	9	47	122	91	68	825
Total	9,227	4,517	6,417	3,533	10,751	14,211	2,243	3,183	8,104	4,158	4,775	71,119

Notes: Using baseline sample discussed in Section 2. Underline data sourced from Amadeus database by BvDEP.

Table C.5: Summary Statistics with Domestic Ownership

Affiliates' …	Obs.	Mean	St.Dev.	p25	p50	p75
Output†	56,363	25	172	1.7	5.2	16
Capital†	56,363	5.3	36	.15	.83	3.5
Material†	56,363	15	116	.67	2.5	8.7
Labour	56,363	88	407	11	29	78
Wage	56,258	41,771	45,478	27,592	37,465	47,614
Parents' …						
Output†	44,395	130	1,202	6.5	20	63
Capital†	44,395	23	146	.89	3.5	12
Material†	44,395	84	912	2.9	10	35
Labour	44,395	357	2,192	34	88	246
Wage	44,350	46,537	573,890	30,643	41,106	51,799
$N^{\underline{o}}$ Affiliates	44,395	1.3	.77	1	1	1

Notes: † Monetary variables in millions of Euro. Unbalanced panel of 10,575 parent and 14,246 affiliate firms in 22 NACE 2-digit manufacturing industries and across 19 EU countries over the period 2004 to 2015. Underline data sourced from Amadeus database by BvDEP.

Table C.6: Summary Statistics with Foreign Ownership

Affiliates' …	Obs.	Mean	St.Dev.	p25	p50	p75
Output†	14,756	54	318	3.7	11	32
Capital†	14,756	14	324	.44	2.1	7.1
Material†	14,756	36	225	1.9	6.4	19
Labour	14,756	198	591	28	75	180
Wage	14,742	33,877	65,968	11,828	25,948	47,503
Parents' …						
Output†	12,382	288	2,028	21	54	140
Capital†	12,382	40	216	2.2	7.9	23
Material†	12,382	193	1,531	10	28	78
Labour	12,382	704	3,719	89	220	535
Wage	12,363	51,339	40,974	38,248	47,786	59,085
$N^{\underline{o}}$ Affiliates	12,382	1.2	.56	1	1	1

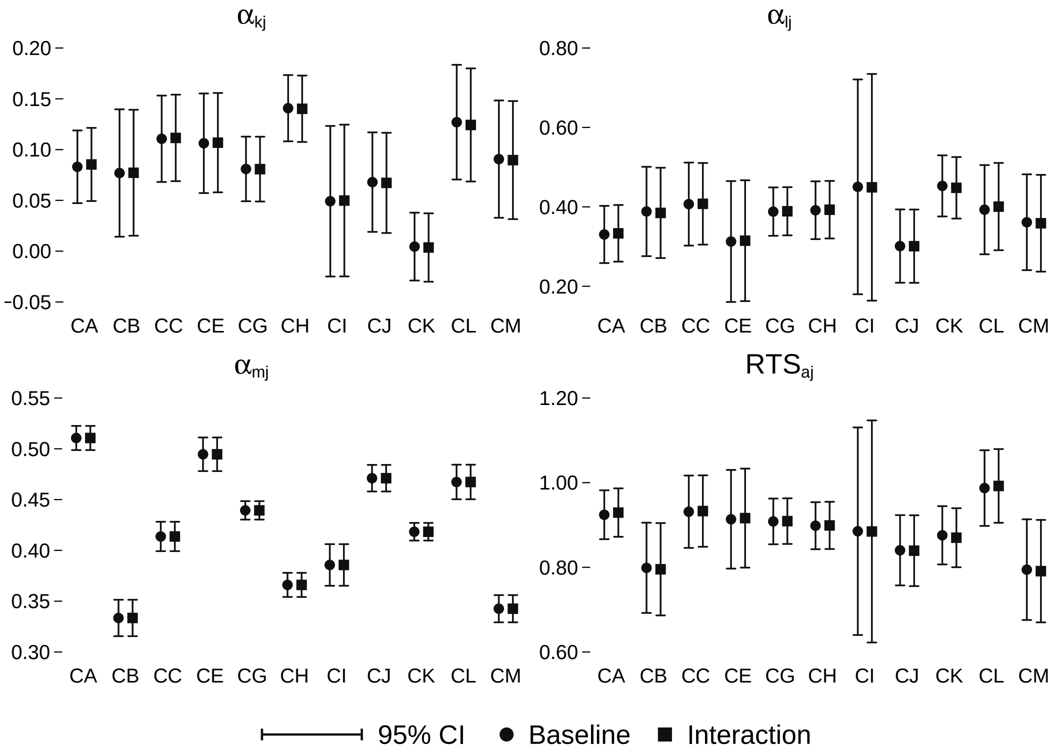
Notes: † Monetary variables in millions of Euro. Unbalanced panel of 2,591 parent and 3,459 affiliate firms in 22 NACE 2-digit manufacturing industries and across 19 EU countries over the period 2004 to 2015. Underline data sourced from Amadeus database by BvDEP.

Table C.7: Industry specific output elasticities of inputs and returns to scale for baseline and interaction model

A*38 Industry	Baseline Model								Interaction Model							
	Affiliate				Parent				Affiliate				Parent			
Classification	α_{kj}	α_{lj}	α_{mj}	RTS_{aj}	π_{kj}	π_{lj}	π_{mj}	RTS_{pj}	α_{kj}	α_{lj}	α_{mj}	RTS_{aj}	π_{kj}	π_{lj}	π_{mj}	RTS_{pj}
CA	0.083	0.331	0.511	0.924	0.085	0.333	0.511	0.929	0.083	0.282	0.548	0.913	0.080	0.282	0.548	0.910
CB	0.077	0.388	0.333	0.799	0.077	0.385	0.333	0.795	0.107	0.261	0.445	0.813	0.107	0.265	0.445	0.817
CC	0.111	0.407	0.414	0.931	0.111	0.408	0.414	0.933	0.134	0.366	0.451	0.951	0.133	0.365	0.451	0.949
CE	0.106	0.313	0.495	0.914	0.107	0.315	0.495	0.916	0.066	0.338	0.495	0.900	0.066	0.337	0.495	0.898
CG	0.081	0.388	0.439	0.908	0.081	0.389	0.439	0.909	0.104	0.362	0.454	0.921	0.104	0.362	0.454	0.920
CH	0.141	0.392	0.366	0.898	0.140	0.393	0.366	0.899	0.120	0.390	0.447	0.957	0.120	0.389	0.447	0.957
CI	0.068	0.301	0.471	0.840	0.067	0.301	0.471	0.839	0.062	0.408	0.475	0.944	0.062	0.408	0.475	0.944
CK	0.005	0.453	0.418	0.876	0.004	0.448	0.418	0.870	0.072	0.411	0.453	0.936	0.072	0.413	0.453	0.937
CL	0.127	0.393	0.467	0.987	0.124	0.401	0.467	0.992	0.128	0.363	0.493	0.984	0.128	0.360	0.493	0.981
CM	0.091	0.361	0.343	0.795	0.090	0.359	0.343	0.791	0.053	0.444	0.431	0.928	0.053	0.446	0.431	0.930
All-mean	0.090	0.383	0.421	0.894	0.090	0.383	0.421	0.894	0.097	0.365	0.468	0.930	0.097	0.366	0.468	0.930
All-median	0.083	0.388	0.418	0.898	0.085	0.389	0.418	0.899	0.109	0.363	0.451	0.926	0.109	0.361	0.451	0.929
All-st.dev.	0.040	0.041	0.056	0.047	0.040	0.040	0.056	0.049	0.043	0.065	0.042	0.049	0.043	0.065	0.042	0.047

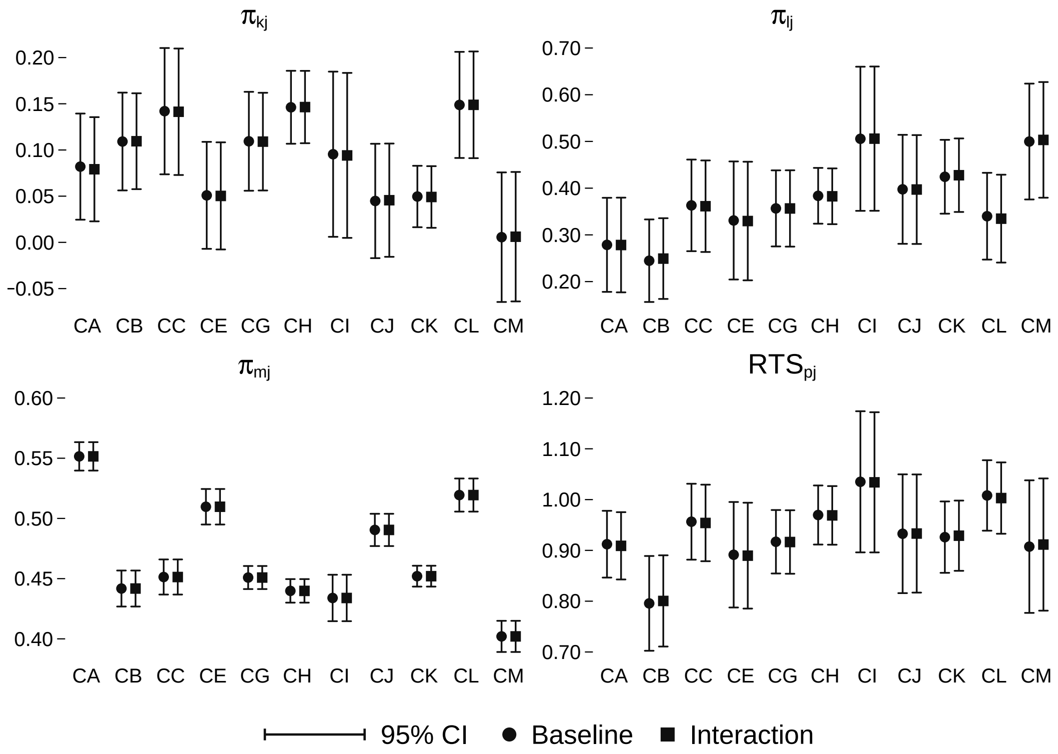
Notes: Results under the Baseline Model refer to the joint estimation of baseline equations (16) and (15). Results under the Interaction Model refer to the joint estimation of an extension of the Baseline Model where $\rho_{a*p}\omega_{git-1}\omega_{g0t-1}$ and $\rho_{p*a}\omega_{g0t-1}\bar{\omega}_{git-1}$ are included as additional terms in equations (16) and (15), respectively. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. α_{kj}, α_{lj}, α_{mj} are affiliate industry-j specific point estimates of the output elasticities of capital, labour and material, respectively. Similarly, α_{kj}, α_{lj}, α_{mj} are parent A*38 industry-j specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{aj} \equiv \alpha_{kj} + \alpha_{lj} + \alpha_{mj}$ and $RTS_{pj} \equiv \alpha_{kj} + \alpha_{lj} + \alpha_{mj}$ represent the returns to scale of production for the parent and affiliate, respectively. The last three rows report the mean, median and standard deviation of the point estimates across all industries.

Figure C.1: Affiliate industry specific output elasticities of inputs and RTS



Source: Author's estimates from Baseline and Interaction model.
Notes: Baseline refers to the joint estimation of equations (16) and (15). Interaction refers to an extension of Baseline where $\rho_{a*p}\omega_{git-1}\omega_{g0t-1}$ and $\rho_{p*a}\omega_{g0t-1}\bar{\omega}_{git-1}$ are added in equations (16) and (15), respectively. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. α_{kj}, α_{lj}, α_{mj} are affiliate industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{aj} \equiv \alpha_{kj} + \alpha_{lj} + \alpha_{mj}$ represent the returns to scale of production for the affiliate.

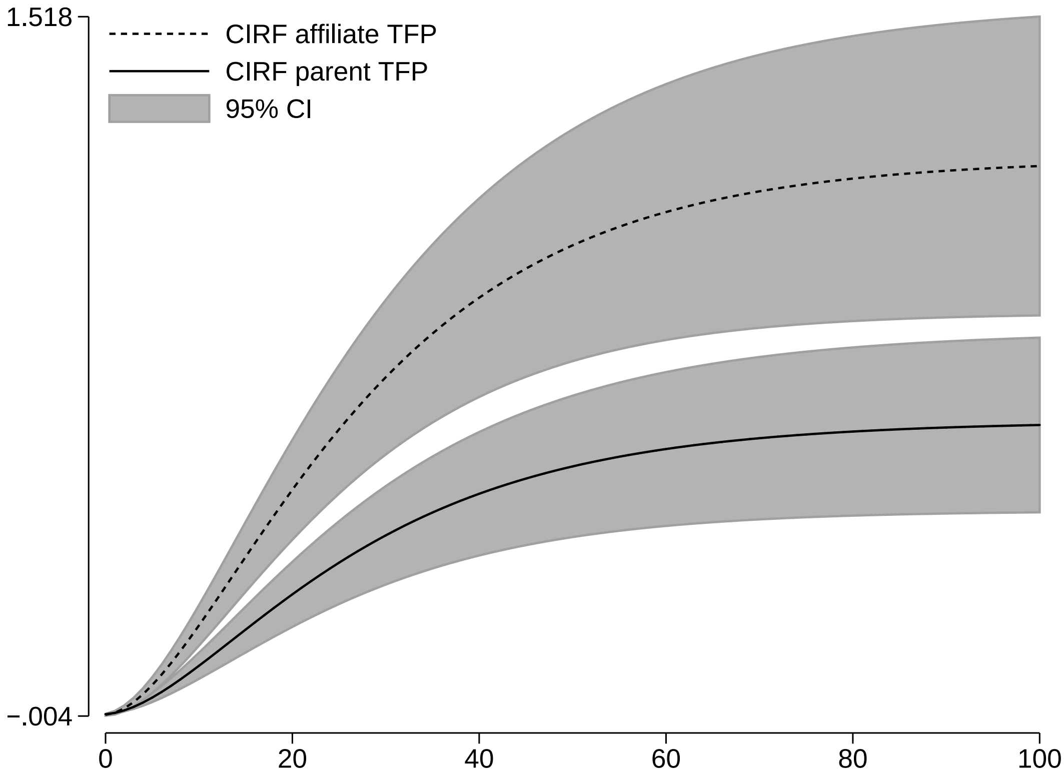
Figure C.2: Parent industry specific output elasticities of inputs and RTS



Source: Author's estimates from Baseline and Interaction model.

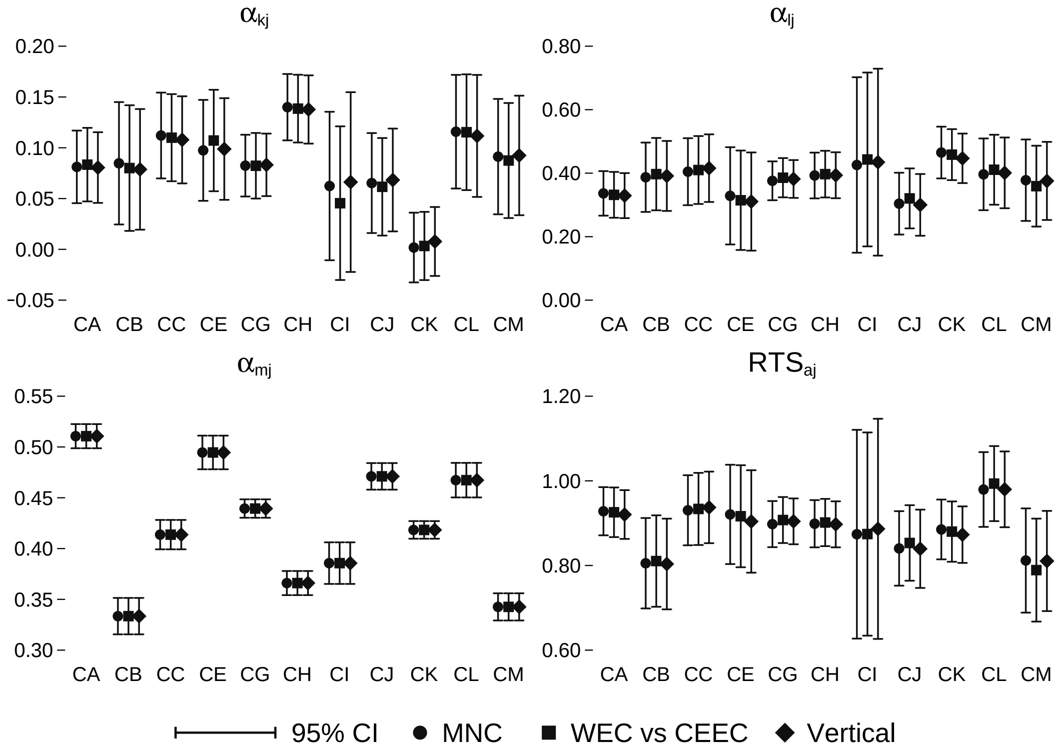
Notes: Baseline refers to the joint estimation of equations (16) and (15). Interaction refers to an extension of Baseline where $\rho_{a*p}\omega_{git-1}\omega_{g0t-1}$ and $\rho_{p*a}\omega_{g0t-1}\bar{\omega}_{git-1}$ are added in equations (16) and (15), respectively. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. π_{kj}, π_{lj}, π_{mj} are parent industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{pj} \equiv \pi_{kj} + \pi_{lj} + \pi_{mj}$ represent the returns to scale of production for the parent.

Figure C.3: Cumulative Impulse Response Functions - CIRF



Source: Author's calculations using estimates from baseline model.
Notes: Orthogonalised cumulative impulse response functions (vertical axis) over a 100 year horizon (horizontal axis). CIRFs are computed using estimates of the parameters and cross-equation error variance–covariance matrix from equations (16) and (15). The dashed line is the cumulative response of affiliate TFP over time from a one standard deviation structural shock on parent TFP. The solid line is the cumulative response of parent TFP over time from a one standard deviation structural shock on affiliate TFP. The variance-covariance matrix is decomposed in a lower triangular matrix with positive diagonal elements using Choleski decomposition under the following assumption over the ordering of variables: parent TFP; and affiliate TFP. 95% confidence intervals (CI) are computed using Gaussian approximation based on Monte Carlo simulation with 100 draws.

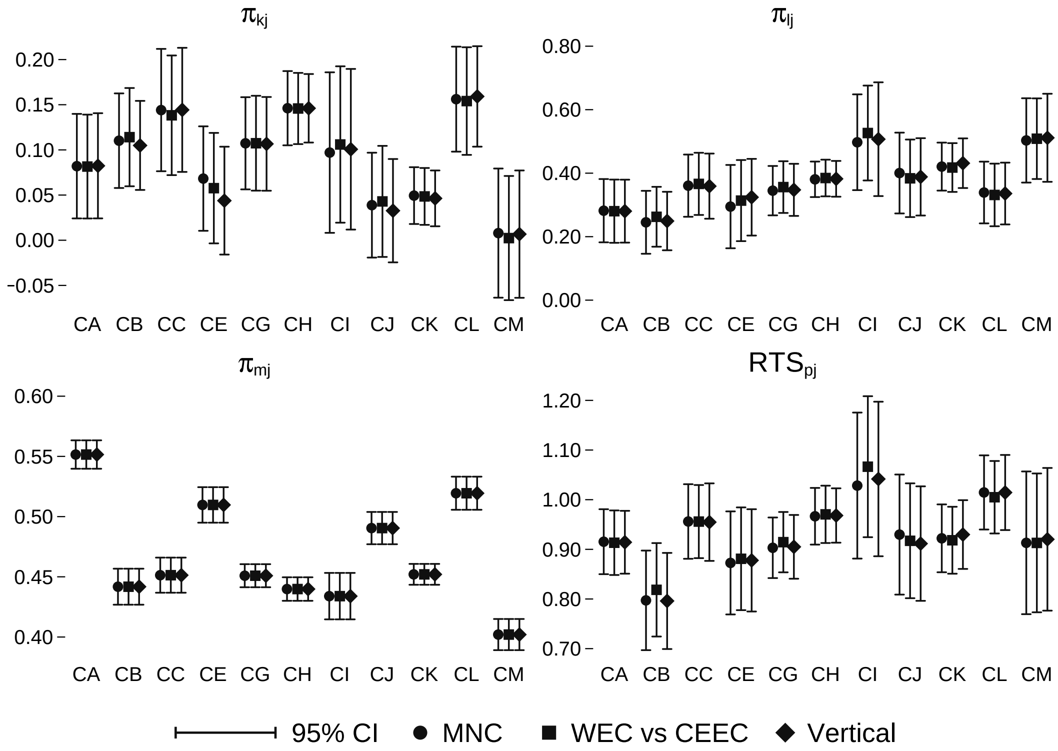
Figure C.4: Affiliate industry specific output elasticities of inputs and RTS



Source: Author's estimates from Baseline Model with interaction terms.

Notes: Each marker reports results from an extension of baseline model where $\rho_{ap*D} D_{gt-1} \omega_{g0t-1}$ and $\rho_{pa*D} D_{gt-1} \bar{\omega}_{git-1}$ are added in equations (16) and (15), respectively. D_{gt-1} is a dummy variable with zeros unless it takes unit values for the group of firms where: country of parent is other than that of the affiliate's (MNC); parent is from Western Europe and affiliate from Central Eastern Europe (CEEC); parent industry is other than the affiliate's (Vertical). All regressions include: dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level; the dummy variable D_{gt-1}; and its interaction with the fixed effects. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. α_{kj}, α_{lj}, α_{mj} are affiliate industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{aj} \equiv \alpha_{kj} + \alpha_{lj} + \alpha_{mj}$ represent the returns to scale of production for the affiliate.

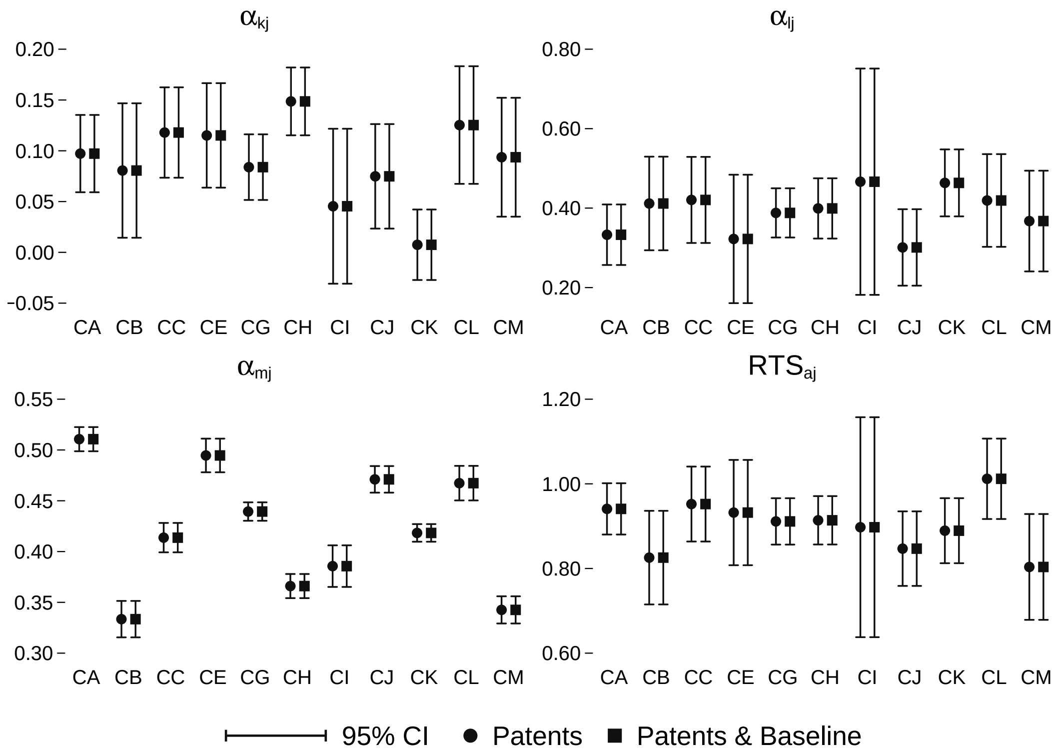
Figure C.5: Parent industry specific output elasticities of inputs and RTS



Source: Author's estimates from Baseline and Interaction model.

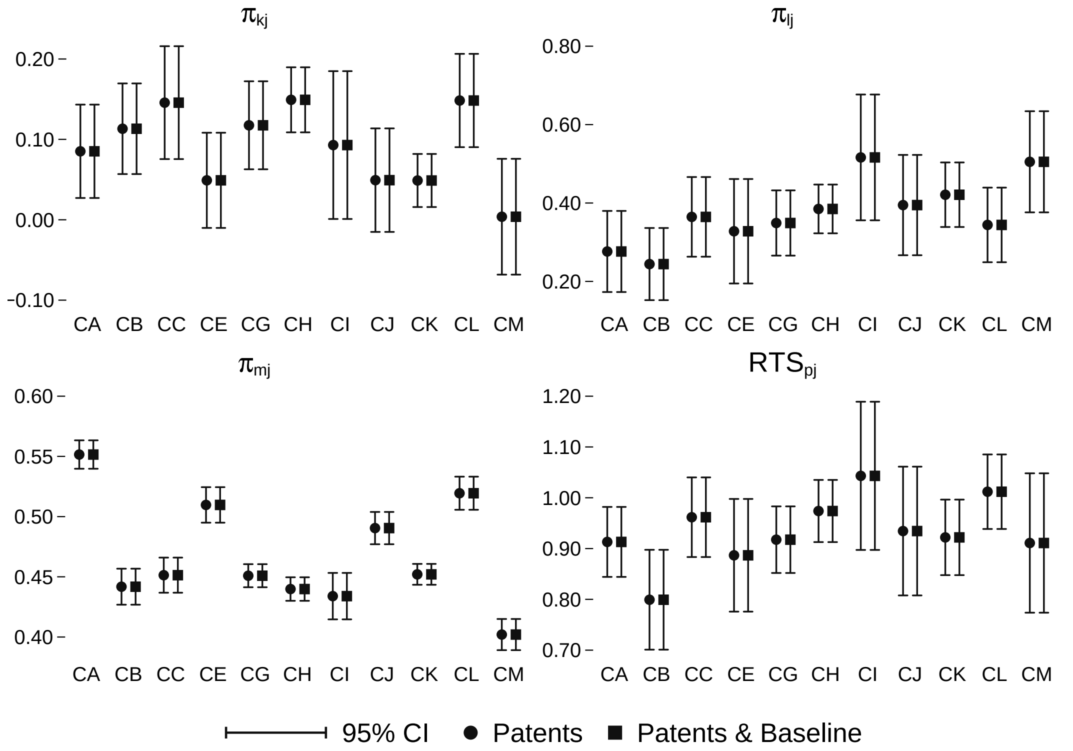
Notes: Each marker reports results from an extension of baseline model where $\rho_{ap*D} D_{gt-1} \omega_{g0t-1}$ and $\rho_{pa*D} D_{gt-1} \bar{\omega}_{git-1}$ are added in equations (16) and (15), respectively. D_{gt-1} is a dummy variable with zeros unless it takes unit values for the group of firms where: country of parent is other than that of the affiliate's (MNC); parent is from Western Europe and affiliate from Central Eastern Europe (CEEC); parent industry other than the affiliate's (Vertical). All regressions include: dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level; the dummy variable D_{gt-1}; and its interaction with the fixed effects. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. π_{kj}, π_{lj}, π_{mj} are parent industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{pj} \equiv \pi_{kj} + \pi_{lj} + \pi_{mj}$ represent the returns to scale of production for the parent.

Figure C.6: Affiliate industry specific output elasticities of inputs and RTS



Source: Author's estimates from variants of the Baseline Model with information on patents.
Notes: Each model reports results from an extension of the baseline model where $\rho_{PATaa}PAT_{git-1} + \rho_{PATap}PAT_{g0t-1}$ and $\rho_{PATpp}PAT_{g0t-1} + \rho_{PATpa}PAT_{git-1}$ are added in equations (16) and (15), respectively. PAT_{git-1} and PAT_{g0t-1} are dummy variables that take unit values if the parent and affiliate firm, respectively, has positive (not yet depreciated) stock of granted patent applications. Patent model imposes the parameter restriction: $\rho_{ap} = \rho_{pa} = 0$. All regressions include: dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level; the dummy variable D_{gt-1}; and its interaction with the fixed effects. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. α_{kj}, α_{lj}, α_{mj} are affiliate industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{aj} \equiv \alpha_{kj} + \alpha_{lj} + \alpha_{mj}$ represent the returns to scale of production for affiliate.

Figure C.7: Parent industry specific output elasticities of inputs and RTS



Source: Author's estimates from variants of the Baseline Model with information on patents.
Notes: Each model reports results from an extension of the baseline model where $\rho_{PATaa}PAT_{git-1} + \rho_{PATap}PAT_{g0t-1}$ and $\rho_{PATpp}PAT_{g0t-1} + \rho_{PATpa}PAT_{git-1}$ are added in equations (16) and (15), respectively. PAT_{git-1} and PAT_{g0t-1} are dummy variables that take unit values if the parent and affiliate firm, respectively, has positive (not yet depreciated) stock of granted patent applications. Patent model imposes the parameter restriction: $\rho_{ap} = \rho_{pa} = 0$. All regressions include: dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level; the dummy variable D_{gt-1}; and its interaction with the fixed effects. 95% confidence intervals are computed using the normal-approximation method after a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure. π_{kj}, π_{lj}, π_{mj} are parent industry-A*38 specific point estimates of the output elasticities of capital, labour and material, respectively. $RTS_{pj} \equiv \pi_{kj} + \pi_{lj} + \pi_{mj}$ represent the returns to scale of production for the parent.

Table C.8: Output eslasticities of inputs for falsification excercise

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Restricted	Randomly Assign		Restricted	Closest Match wrt. Y	
Affiliate		Sample	Affiliate	Parent	Sample	Affiliate	Parent
$\bar{\alpha}_k$	0.090***	0.097***	0.117***	0.104***	0.087***	0.121***	0.093***
	(0.007)	(0.010)	(0.008)	(0.010)	(0.010)	(0.008)	(0.011)
$\bar{\alpha}_l$	0.383***	0.381***	0.484***	0.399***	0.383***	0.392***	0.401***
	(0.015)	(0.018)	(0.020)	(0.018)	(0.022)	(0.017)	(0.022)
$\bar{\alpha}_m$	0.421***	0.419***	0.333***	0.419***	0.419***	0.429***	0.419***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Parent							
$\bar{\pi}_k$	0.097***	0.109***	0.114***	0.115***	0.106***	0.112***	0.129***
	(0.008)	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)
$\bar{\pi}_l$	0.366***	0.372***	0.380***	0.492***	0.354***	0.361***	0.341***
	(0.016)	(0.023)	(0.023)	(0.021)	(0.024)	(0.024)	(0.019)
$\bar{\pi}_m$	0.467***	0.468***	0.468***	0.337***	0.469***	0.469***	0.464***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Obs.	37,524	21,691	21,691	21,691	22,049	22,049	22,049

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Column (2) and (5) report estimates from the baseline model when using sub-samples of the baseline sample (used in column (1)) that match the number of observations used when conducting the falsification tests in columns (3)-(4) (Randomly Assign) and (6)-(7) (Closest Match wrt. Y), respectively. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. This table reports the average of the industry specific output elasticities of capital, labour and material, respectively, both for the affiliate (top panel) and parent (bottom panel). Last row reports the observations used in the second-step of each estimation.

Table C.9: Output eslasticities of inputs for robustness to alternative markov processes

	(1)	(2)	(3)	(4)	(5)
	Baseline	Multiple affiliates			Other
Affiliate		Min	Median	Max	Affiliates
$\bar{\alpha}_k$	0.0900***	0.0902***	0.0900***	0.0899***	0.0890***
	(0.0067)	(0.0067)	(0.0067)	(0.0067)	(0.0067)
$\bar{\alpha}_l$	0.3827***	0.3833***	0.3828***	0.3824***	0.3775***
	(0.0151)	(0.0151)	(0.0151)	(0.0151)	(0.0152)
$\bar{\alpha}_m$	0.4210***	0.4210***	0.4210***	0.4210***	0.4210***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Parent					
$\bar{\pi}_k$	0.0969***	0.0980***	0.0970***	0.0963***	0.0967***
	(0.0082)	(0.0083)	(0.0082)	(0.0081)	(0.0082)
$\bar{\pi}_l$	0.3658***	0.3681***	0.3659***	0.3645***	0.3654***
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0159)
$\bar{\pi}_m$	0.4665***	0.4665***	0.4665***	0.4665***	0.4665***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Obs.	37,524	37,524	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(4) report estimates from Baseline when instead of the mean ($\bar{\omega}_{git-1}$) in equation (15) we use the minimum, median and maximum lagged TFP from all affiliates linked to the parent within the same ownership group, respectively. Column (5) reports estimates from an extension of Baseline when $\rho_{aa\_}\bar{\omega}_{gi\_t-1}$ is added in equation (16) to capture the affiliate TFP effect from the mean TFP of other affiliates in within the group. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. This table reports the average of the industry specific output elasticities of capital, labour and material, respectively, both for the affiliate (top panel) and parent (bottom panel). Last row reports the observations used in the second-step of each estimation.

Table C.10: Output eslasticities of inputs for robustness to alternative fixed effects, production technologies, alternative estimators and imperfect competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Fixed Effects			Technology		Other Estimators		Imperfect Competition	
Affiliate		cjt	Bilateral	g0 & gi	Translog	NP	ACF	Dynamic	CES	FGT
$\bar{\alpha}_k$	0.090***	0.091***	0.088***	0.067***	0.091***	0.096***	0.145***	0.037***	0.096***	0.019***
	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.008)	(0.014)	(0.007)	(0.003)
$\bar{\alpha}_l$	0.383***	0.383***	0.390***	0.231***	0.370***	0.361***	0.707***	0.232***	0.402***	0.120***
	(0.015)	(0.016)	(0.016)	(0.013)	(0.009)	(0.008)	(0.017)	(0.041)	(0.016)	(0.009)
$\bar{\alpha}_m$	0.421***	0.421***	0.421***	0.421***	0.466***	0.481***		0.696***	0.436***	0.861***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.020)	(0.007)	(0.010)
Parent										
$\bar{\pi}_k$	0.097***	0.098***	0.097***	0.057***	0.104***	0.099***	0.173***	0.032*	0.103***	0.028***
	(0.008)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.011)	(0.019)	(0.010)	(0.003)
$\bar{\pi}_l$	0.366***	0.369***	0.364***	0.153***	0.376***	0.385***	0.759***	0.142***	0.391***	0.141***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.009)	(0.010)	(0.020)	(0.035)	(0.024)	(0.010)
$\bar{\pi}_m$	0.467***	0.467***	0.467***	0.467***	0.495***	0.501***		0.758***	0.490***	0.832***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)		(0.027)	(0.021)	(0.011)
Obs.	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524	37,524

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(4) report estimates from Baseline accounting for additional fixed effects. Columns (5) and (6) report estimates from an extension of Baseline with a translog and nonparametric production technology, respectively. Columns (7) and (8) report estimates when using alternative estimators for Baseline. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Columns (2)-(4) control for additional fixed effects. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications over the two-step estimation procedure and reported in parentheses below point estimates. This table reports the average of the industry specific output elasticities of capital, labour and material, respectively, both for the affiliate (top panel) and parent (bottom panel). Last row reports the observations used in the second-step of each estimation.

Table C.11: Robustness to alternative selection and aggregation of data, and bootstraped standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Trim		No $\mathscr{E}$	Industry Aggregation			Bootstrap	Clustering	
Affiliate		p20	p10	correction	All j	CPA	NACE 2	B=500	cj	c
ρ_{aa}	0.921***	0.922***	0.921***	0.921***	0.921***	0.917***	0.914***	0.921***	0.921***	0.921***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.011)	(0.003)	(0.007)	(0.008)
ρ_{ap}	0.034***	0.033***	0.033***	0.032***	0.033***	0.033***	0.033***	0.034***	0.034***	0.034***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Parent										
ρ_{pp}	0.936***	0.931***	0.928***	0.936***	0.937***	0.933***	0.932***	0.936***	0.936***	0.936***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.010)	(0.004)	(0.005)	(0.005)
ρ_{pa}	0.013***	0.010***	0.007***	0.013***	0.013***	0.013***	0.012***	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Obs.	37,524	40,207	42,171	37,524	38,252	37,524	37,524	37,524	37,524	37,524

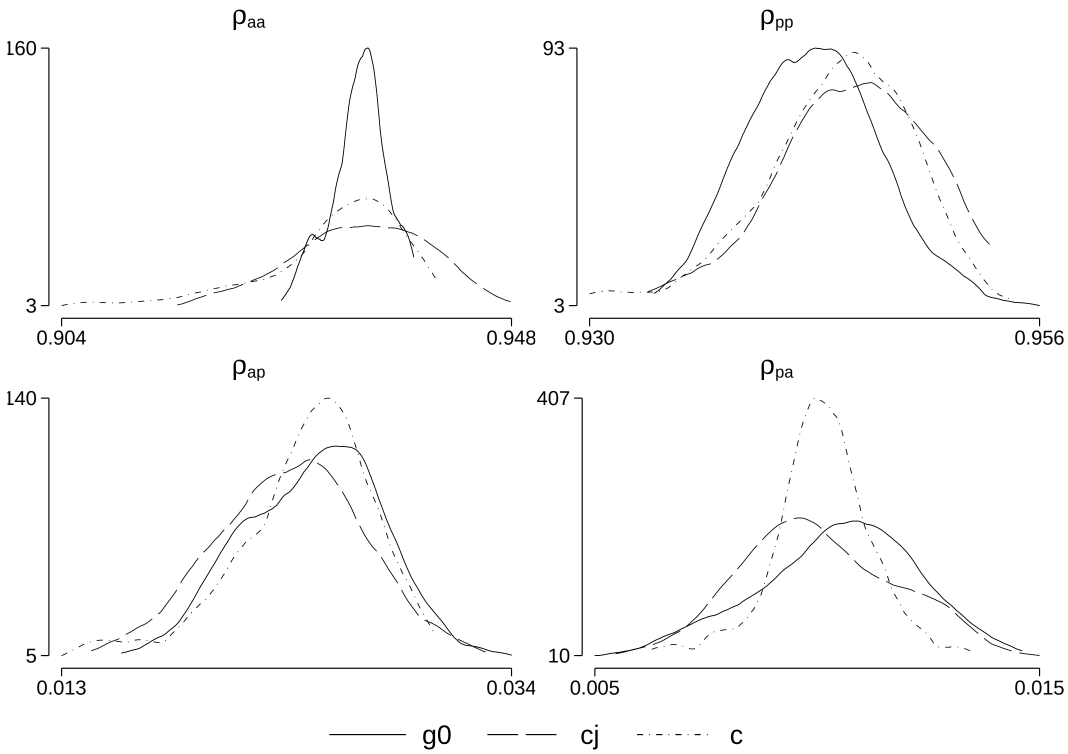
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(7) report estimates from Baseline for different treatment of the data. Columns (8) and (10) report estimates from Baseline for different treatment of bootstrapped standard errors. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications (in (8) with 500) over the two-step estimation procedure and reported in parentheses below point estimates. Columns (9) and (10) cluster at the country-industry and country of the parent, respectively. Last row reports the observations used in the second-step of each estimation. Appendix Table C.12 reports industry-specific estimates of the production technology for each model.

Table C.12: Output elasticities of inputs for robustness to alternative selection and aggregation of data, and bootstraped standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Trim		No $\mathscr{E}$	Industry Aggregation			Bootstrap	Clustering	
Affiliate		p20	p10	correction	All j	CPA	NACE 2	B=500	cj	c
$\bar{\alpha}_k$	0.090***	0.109***	0.147***	0.081***	0.089***	0.086***	0.087	0.090***	0.090***	0.090***
	(0.007)	(0.009)	(0.011)	(0.006)	(0.007)	(0.007)	(265.985)	(0.007)	(0.007)	(0.008)
$\bar{\alpha}_l$	0.383***	0.464***	0.592***	0.345***	0.385***	0.374***	0.373	0.383***	0.383***	0.383***
	(0.015)	(0.017)	(0.026)	(0.014)	(0.015)	(0.015)	(512.949)	(0.016)	(0.017)	(0.024)
$\bar{\alpha}_m$	0.421***	0.340***	0.196***	0.478***	0.420***	0.426***	0.427***	0.421***	0.421***	0.421***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.009)	(0.011)
Parent										
$\bar{\pi}_k$	0.097***	0.108***	0.113***	0.091***	0.095***	0.094***	0.095	0.097***	0.097***	0.097***
	(0.008)	(0.010)	(0.011)	(0.008)	(0.010)	(0.008)	(313.110)	(0.009)	(0.011)	(0.012)
$\bar{\pi}_l$	0.366***	0.394***	0.436***	0.342***	0.369***	0.361***	0.361	0.366***	0.366***	0.366***
	(0.016)	(0.016)	(0.019)	(0.015)	(0.016)	(0.016)	(1031.948)	(0.015)	(0.016)	(0.016)
$\bar{\pi}_m$	0.467***	0.440***	0.405***	0.501***	0.465***	0.471***	0.472***	0.467***	0.467***	0.467***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.013)
Obs.	37,524	40,207	42,171	37,524	38,252	37,524	37,524	37,524	37,524	37,524

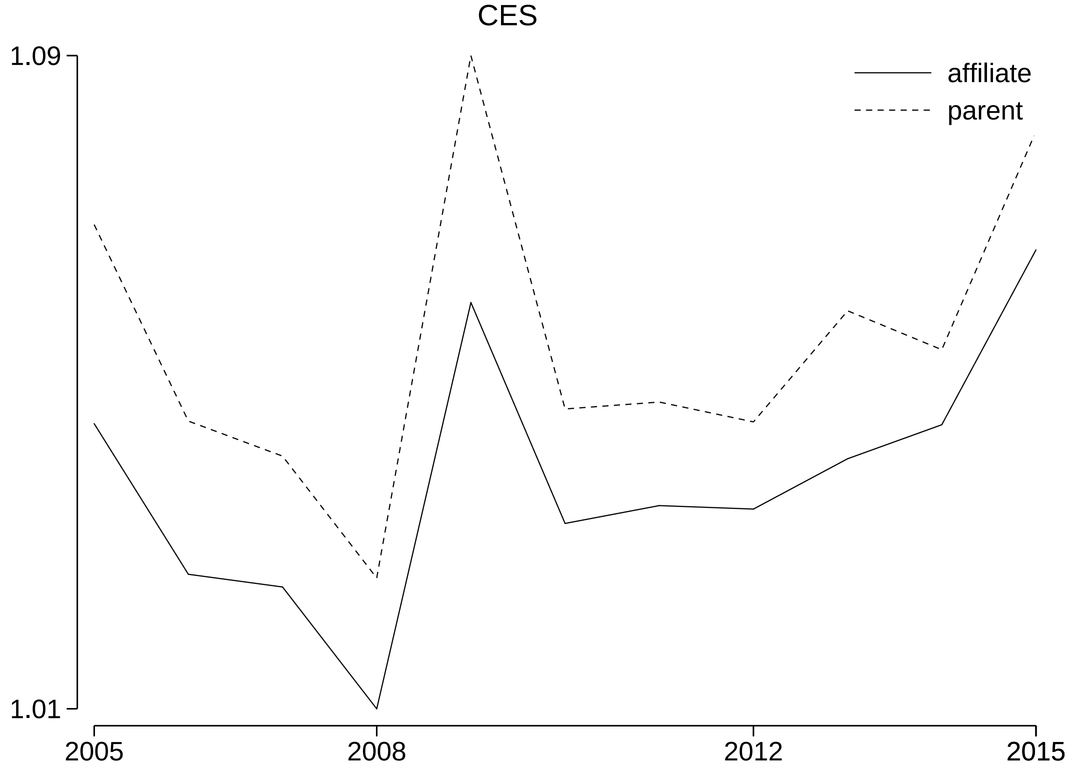
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column (1) reports results from the joint estimation of equations (16) and (15), respectively (Baseline). Columns (2)-(7) report estimates from Baseline for different treatment of the data. Columns (8) and (10) report estimates from Baseline for different treatment of bootstrapped standard errors. All regressions include dummies for country-industry, country-year and industry-year fixed effects, both at the parent and affiliate level. Standard errors are computed using a pairs cluster (at the ownership group) bootstrap with 100 replications (in (8) with 500) over the two-step estimation procedure and reported in parentheses below point estimates. Columns (9) and (10) cluster at the country-industry and country of the parent, respectively. This table reports the average of the industry specific output elasticities of capital, labour and material, respectively, both for the affiliate (top panel) and parent (bottom panel). Last row reports the observations used in the second-step of each estimation.

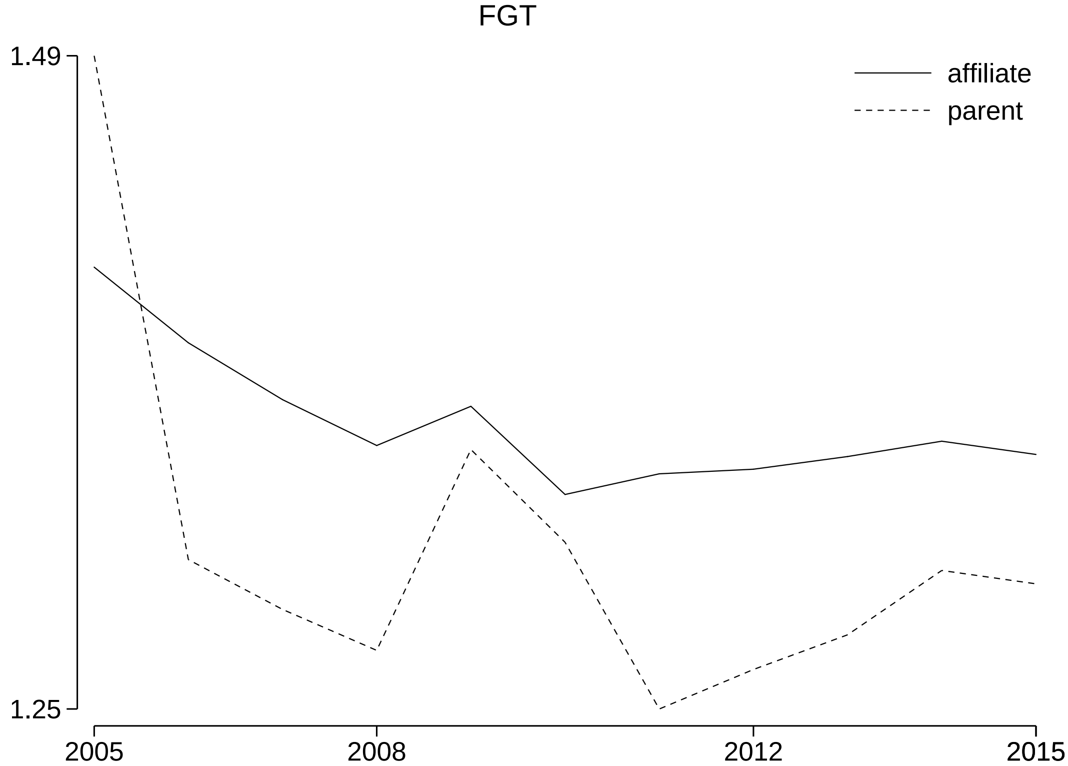
Figure C.8: Distributions of bootstraped values for different clustering levels



Source: Author's calculations based on estimates from the Baseline model.
Notes: For each estimated parameter of interest, the plotted distributions represent the kernel densities of the point estimates from the 100 replications of the pairs cluster bootstrap for different types of clustering, i.e. parent ($g0$) country-industry (cj) and country (c).

Figure C.9: Markup by year





Source: Author's calculations based on estimates from the CES and FGT model.
Notes: CES refers to yearly point estimates of markups from the extension of the Baseline model with CES preferences and monopolistic competition, following GNR. FGT to yearly markups computed as the material cost weighted average of firm-year estimated following FGT.