FDI and Superstar Spillovers: Evidence from firm-to-firm transactions*

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Abstract

Despite competition concerns over the increasing dominance of global corporations, many argue that productivity spillovers from multinationals to domestic firms justify pro-FDI policies. For the first time, we use firm-to-firm transaction data in a *developed* country to examine the impact of forming a new relationship with a multinational, and find a TFP increase of about 8% three or more years after the event. Sales to other buyers, trade and customer quality also increase. However, we also document that starting to supply other "superstar firms" such as those who heavily export or are very large *also* increases performance by similar amounts, even if the superstar is a non-multinational. Placebos on starting relationships with smaller firms and novel identification strategies relying solely on demand shocks to superstar firms support a causal interpretation. A model of technology transfer rationalizes these effects and also correctly predicts (i) falls in post-event markups; (ii) the type of firms who form superstar relationships and (iii) bigger treatment effects from superstars intensive in R&D, IT and/or human capital. In addition to productivity spillovers, we document the transmission of "relationship capabilities" and "dating agency" effects as the increase in new buyers is particularly strong within the superstar firm's existing network. These results suggest an important role for raising productivity through the supply chains of superstar firms regardless of their multinational status.

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1 Introduction

Do superstar firms generate positive spillovers? The increasing dominance of large firms in developed countries in recent decades has attracted much attention (Autor et al. (2020), Bajgar et al. (2020), De Loecker, Eeckhout, and Unger (2020)), mostly focused on the potential costs of these trends (Philippon (2019) and White House (2021)Akcigit and Ates (forthcoming)). Although there may be benefits from reallocating output to more efficient firms, there are fears over their monopoly and monopsony power () as well as lobbying strength (Eeckhout (2022), Wu (2018)). Despite these fears, governments spend large sums of money to attract one particular type of superstar firm: foreign multinationals. A large literature has tried to assess the benefits of such policies. Although it is well established that a multinational enterprise (MNE) has better performance than a typical domestic firm (e.g. higher productivity and wages), it is less clear that there are spillover benefits to local firms from Foreign Direct Investment (FDI). Many case studies argue for positive effects of foreign new entrants on the domestic suppliers to these multinationals. Iacovone et al. (2015), for example, discuss the impact of Walmart's entry into Mexico. Firms who started supplying "Wal-Mex" experienced large increases in their productivity, sales and innovation due to pressure from their superstar customer. Similarly, Sutton (2004) documents how the entry of multinational auto manufacturers into China and India had a positive effect on the productivity of their domestic auto parts suppliers. The multinationals worked extensively with local suppliers to upgrade their managerial and technological practices through transferring know-how. Similarly, Bloom, Van Reenen, and Melvin (2013) discuss how Indian shoe supplier Godalkas was helped by their main customer Nike to upgrade their productivity through extensive managerial training

Despite this case study evidence, the econometric literature has found mixed results on FDI spillovers. Aitken and Harrison (1999) found negative productivity effects on domestic firms from FDI in the same industry in Venezuela, whereas Keller and Yeaple (2009) find positive effects in the US. Javorcik (2004) emphasizes the empirical and theoretical ambiguity of the own industry "horizontal" FDI, and instead documents positive spillovers in Lithuania from multinational enterprises in the downstream sector. As with the case studies, the main positive mechanism postulated is that a multinational transfers technological and/or managerial know-how to its suppliers. However, because these econometric studies have had to rely on industry-level measures of FDI, it is challenging both to credibly identify the causal effects and to understand the mechanisms. In particular, do spillovers require that local firms form a direct trading relationship to benefit from these spillover effects through becoming integrated with the multinational's global supply chain?

To address these issues, we use data on firm-to-firm sales to show that domestic firms selling directly to a multinational experience higher Total Factor Productivity (TFP) after a new relationship is established. The only other paper that has implemented this test is the seminal paper by Alfaro-Ureña, Manelici, and Vasquez (2022) who use firm transaction data from Costa Rica. We know of no econometric study that has used the value of firm-to-firm transaction data to look at these issues in a developed country.[1] Our data include the annual sales values for the universe of transactions between all firms located in Belgium. Specifically, we analyze whether the spillovers arise only from selling to multinationals or if they are present when selling to any successful "superstar" firm. Using an event study methodology we find that firms who start a serious relationship (i.e. start selling a significant amount to a multinational) increase their TFP by eight percent three or more years after the relationship forms. This is consistent with the idea that forming a direct relationship with a superstar provides additional benefits, rather than just being in the same industry or local area. However, we also examine forming serious relationships with other superstar firms defined as heavy exporters and/or large firms (our baseline definition is the largest 0.1% of firms in the sales distribution). We find that there are productivity impacts of similar magnitudes when a firm starts supplying superstars, even if the large firm is neither part of a multinational nor an exporter. This is, to our knowledge, the first time this has been documented and suggests the spillover benefits are not from a partner firm being a multinational *per se*, but rather from the superstar firm being more productive and successful. These are not the same. In our data, one third of the firms in the top 0.1% of the size distribution are neither multinationals nor intensive exporters. In addition to a positive growth in TFP, partnering with a superstar firms leads to growth in outputs, inputs (labor, capital and intermediates), the number of buyers, engagement in international trade and survival.

To make sure that our effects are not driven by any type of new relationships (e.g. starting to sell to smaller firms), we run various placebo tests that show no productivity effects from new relationships with non-superstars. Furthermore, we do not observe pre-trends for our firms who form serious relationships with superstars which goes against the idea that these firms were already on a positive productivity trajectory prior to forming a relationship with a superstar. To address the concern that there may be a contemporaneous positive productivity shock generating both the superstar relationship and future performance increase, we propose and execute econometric designs to isolate variation arising purely from shocks to superstar firms using a control function approach that leverages our knowledge of the population of buyer-seller networks (building on Amiti and Weinstein (2018)) and an IV approach that interacts lagged demand shocks from superstars with the the prior "distance" between superstars and potential suppliers in product and geographic space.

What are the mechanism underlying our superstar spillover effects? We specify a model that has productivity spillovers from superstars and endogenous matches between suppliers and superstars modeled as an auction process. The model predicts the patterns we see on superstar relationships and performance, but also generates auxiliary predictions. First, although new suppliers to superstars enjoy (weakly) higher profits, they should see falls in their average price cost margin as superstars will capture some of the relationship rents through a lower price in the auction (although they will not in

1. Some datasets track whether a relationship exists (extensive margin), but not how much was transacted - which we show below is empirically important. Iyoha (2021) uses publicly listed US firms which record the identity of the most important customers and suppliers (but not the amount bought or sold). Bernard, Moxnes, and Saito (2019) use Japanese firm data that lists the twenty largest suppliers (but not how much is transacted) to exploit the opening of a high-speed train line - credit agencies also record the most important buyer-seller links.

general capture all of it, as the number of bidders is finite, partly due to the benefits of geographic and product proximity). Second, suppliers will tend to be larger and more productive. Third, spillovers will be greater when the superstar has more know-how (e.g. higher R&D, IT and/or skills) or when the supplier has more to learn (as proxied by whether it is young or old). We confirm all three additional predictions in the data.

We then go beyond the productivity channels of our model to document two other dimensions to superstar spillovers that have not to our knowledge been explored in the literature. First, superstars that have high "relationship capability" (in the sense of Bernard et al. (2022)) confer some of this customer acquisition ability to their suppliers. Second, we find a particularly strong effect on increasing the number of buyers within a superstar's network (the firms who buy from the superstar). This may be because of reduced informational frictions in finding new partners or the quality signal of obtaining a contract with a top firm. We label this force the "dating agency" mechanism.

Although our findings are positive rather than explicitly normative, they do have policy implications that we return to in the conclusions. Specifically, the case for treating multinationals more generously than local non-multinationals is weak given the symmetry of superstar spillovers regardless of foreign ownership. Furthermore, there are serious costs to making it hard for firms to become superstars (or breaking up existing superstars), due to the spillovers we document here.

The next subsection offers a brief survey of the literature before moving on to describe the data (Section 2), Model (Section 3), Empirical Strategy (Section 4), Results (Section 5), Mechanisms (Section 6), Endogeneity (Section 7), Robustness (8) and Conclusions (Sections 9). Online Appendices go into more detail on Data (A), Econometrics (B), Theory (C) and Additional Results (D).

1.1 Existing Literature

Our work connects to many other papers in the literature. First, there is an extensive literature documenting that multinationals have higher productivity than domestic firms (see Keller (2021) for a general survey). A theory literature has taken these facts and argued for a hierarchy whereby the most productive firms will pay the fixed costs of having foreign establishments, the next most productive firms will be non-multinational exporters and the least productive firms will be purely domestic Helpman, Melitz, and Yeaple (2004). We build on this idea, as it suggests that multinationals and exporters should be more productive, so forming a relationship with such firms may confer spillover benefits. There is also a large literature on sourcing decisions in international trade, for example, Chaney (2014), Antràs and Chor (2013), Eaton, Kortum, and Kramarz (2011), Antràs, Fort, and Tintelnot (2017), Lim (2018), and Dhyne, Kikkawa, et al. (2021).

Second, there is a literature that looks at spillovers from multinationals. The empirical strategy is to examine whether a higher industry-level amount of FDI investment increases a firm's productivity. Early studies (e.g. Aitken and Harrison (1999) and Konings (2001)) looked at FDI in the firm's own industry ("horizontal FDI"), finding often negative effects. By contrast, Keller and Yeaple (2009) using US data and Alvarez and López (2008) using Chilean data found positive effects. A problem looking at horizontal FDI is that it confounds the positive effect from learning from a multinational with a product market competition effect which has ambiguous effects on measured productivity. Competition will tend to reduce price cost margins and if sales revenue is used instead of the volume of output, measured productivity will appear to fall (as revenue-based TFPR reflects margins as well as quantity-based TFPQ). Later studies looked at FDI in downstream and upstream industries and have tended to find more positive effects, especially in downstream (i.e. who you sell to) industries (e.g. Javorcik 2004) rather than upstream industries (i.e. who you buy from). Nonetheless, industry level data is coarse. Even if the econometric problem of correlated industry level shocks can be adequately controlled for, a question remains over whether the productivity benefits are enjoyed just from the firm who sells to a multinational firm or more widely to many firms with some degree of connection (e.g. geographically, technologically, through the product market or indirectly linked through the production network, etc.). Only Alfaro-Ureña, Manelici, and Vasquez (2022) have used firm-to-firm sales to show that domestic firms in Costa Rica selling directly to a foreign multinational experience a growth in TFP. In addition to analyzing this issue in a developed country (and also considering outward FDI), we extend their analysis by estimating spillovers from selling to exporters and to very large firms. The latter exercise turns out to be very important - almost all very large private sector firms in Costa Rica are multinationals, so it is not possible to perform such an analysis.

There is a wider literature looking at production networks for large firms regardless of multinational status. Greenstone, Hornbeck, and Moretti (2010) looked at spillover effects from "Million Dollar Plants" - large establishments of very big enterprises, some of whom were multinationals and some of whom were not. They looked at incumbent plants in counties when these Million Dollar Plants were set up and found that productivity rose relative to incumbents in runner-up counties. Bloom et al. (2019) revisited their design on more recent data, replicated the results and found that one mechanism behind the spillover effects was the transferal in managerial know-how between the Million Dollar Plants and the local incumbents. Neither paper observed direct firm-to-firm linkages as we do, however.

More generally, there has been a lot of renewed interest in firm-to-firm networks as vectors of transmission of shocks along complex supply chains (e.g. Acemoglu and Azar (2020), Acemoglu et al. (2012), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017), Liu (2019), Atalay et al. (2011), and Carvalho et al. (2021)). Nevertheless, none of these papers have been able to explicitly look at the sales of firm-to-firm buyer-seller relationships due to data constraints. Moreover, the spillovers through the production networks examined in these papers are fundamentally different from ours, looking at either customer demand linkages or the transmission of supplier productivity shocks through lower input prices. By contrast, we look at whether productivity increases for suppliers when forming relationships with high productivity superstars. Perhaps the closest paper is Iyoha (2021) who develops a methodology for examining productivity spillovers within production networks based on augmenting standard proxy variable production function estimation (beginning with Olley and Pakes (1996)). [2]Throughout this literature, the general empirical approach has been to condition on the existing

2. She applies this methodology to US Compustat firms from 1977 to 2016, exploiting the fact that SEC regulations

network, and examine how shocks to part of it reverberate across the supply chains. By contrast, we examine the dynamics of network formation, focusing on analyzing changing performance before and after a firm joins a network, in order to more credibly estimate the causal effects of selling to superstar firms.This is a complementary approach, which should help build a richer dynamic picture of changes along the extensive margin.

As noted in the introduction, there is a recent literature documenting the rise in industrial concentration in the US and many other advanced nations. The increased importance of dominant companies raises the question of the impact of these superstar firms on other companies. Often the debate is framed in terms of the negative impact of these firms by reducing competition and increasing lobbying. Our paper documents one positive mechanism on productivity spillovers from these superstar firms on their suppliers.

Finally, we connect with a voluminous literature examining productivity spillovers generated from R&D, IT and human capital. We also find evidence for the importance of these indicators of know-how, but distinct from the existing work, we show that firm to firm supply linkages are an important conduit of these spillovers.

2 Data

The critical data source for our analysis is the Business-To-Business (B2B) transactions dataset from the National Bank of Belgium (NBB). This records the value of annual sales between all domestic supplier-buyer relationships in Belgium for the period 2002 to 2014, based on their value-added tax (VAT) declarations. Sales refer to the sum of all invoices from firm i to firm j, net of the VAT amount due, in a given year. As every firm in Belgium is required to report VAT on all sales of at least 250 euros, the data has universal coverage of all businesses active in Belgium. More details of the B2B and other data are provided in Appendix A (and also in Dhyne, Magerman, and Rubínová (2015)).

We supplement the B2B data with company accounts data on firm characteristics, administered by the Central Balance Sheet office at the NBB. All incorporated companies with limited legal liability are required to file their annual accounts at the NBB for tax compliance purposes. This gives additional financial and operational characteristics of each firm, comprising information on value added, labor costs, employment, intermediate inputs of goods and services, and capital stocks and expenditures, which enables us to estimate Total Factor Productivity (TFP) for each firm. Fiscal years have been annualized to calendar years to match the unit of observation in the NBB B2B data. We limit the sample of B2B transactions to firms that are in the accounts data (the main effect of this selection is to drop the self-employed). Our analysis only includes firm i's that report positive full-time equivalent

oblige firms to reveal their most important customers and suppliers, and finds that the average firm is 16% more productive due to these spillovers across the network. From a data point of view, we are able to look at both private and public firms, examine heterogeneity by FDI, exporting and size and leverage the intensity of the relationship (i.e. how much firm i sells to firm j) rather than just the existence of the relationship. This is also an advantage over papers such as Atalay et al. (2011), that use the Commodity Flows Survey, which does not precisely identify whether a shipment is between firms or within the same firm (and is also only available for manufacturing rather than whole economy).

employees at the beginning of the sample in order to be able to estimate TFP. For our main analysis, we also drop any firm i that does not sell to any Belgium firm j, and thus exclude firm i that only sell directly to final Belgian or foreign consumers, as our objective is to understand whether selling to superstar firms generates spillovers.

We consider three types of superstar firms: (i) multinationals; (ii) exporters; and (iii) large firms. First, we define a multinational as any firm that has inward or outward foreign direct investment of at least ten percent on average over the sample period. To do this, we draw on the NBB annual Foreign Direct Investment (FDI) survey, which is organized within the framework of the statistical obligations of Belgium to the international bodies of which it is a member, such as the IMF and the European Commission (Eurostat). These obligations relate both to the balance of payments statistics and to the overall foreign investment statistics. The inward and outward FDI data records the share of direct ownership by country of origin. Second, we define a firm as an exporter if it exports an average of at least ten percent of its sales over the sample period and it is not in the wholesale sector.[3] The export status of firms is based on the Intrastat trade survey for transactions within the EU and the customs trade data for transactions outside the EU, also accessed through the NBB. Third, we define a firm as being large if it is in the top 0.1 percentile of the sales distribution, based on the firm's total average sales over the sample period. We provide additional details on these data in the Appendix A and show extensive robustness to exact definitions of these thresholds.

We construct various measures of TFP. For our baseline we use the Wooldridge (2009) method, and include robustness checks with alternative approaches, such as Ackerberg, Caves, and Frazer (2015) and Gandhi, Navarro, and Rivers (2020). Details on estimation methods are provided in the Appendix B.1.

Table A1 shows the effects of our cleaning procedures on sample size (we cover about 82 percent of all jobs in employer firms) and shows averages (and variances) for the main variables in our baseline analysis sample of about 133,000 companies. Most firms are small: the mean is just over four full-time equivalent employees. Table A2 breaks down the means of variable of treatment firms before and after forming a serious relationship with a superstar firm as well as for controls. It is clear that firms appear to grow across many measures of performance comparing their raw means before and after the event (e.g. after selling to a multinational sales more than doubles and TFP jumps by 18 log points).

3 Model

In Appendix C we detail a simple model of superstar spillovers. There are N upstream firms with heterogeneous marginal costs (c) that produce intermediate varieties and compete under monopolistic competition. There are two types of downstream markets who sell to consumers with CES preferences. One set of markets are perfectly competitive and another set have one superstar monopolist in each.

3. The wholesale sector is defined as those with the 2-digit NACE 45 and 46. We exclude wholesaler exporters in our baseline superstar definition as they are unlikely to generate spillovers. Nevertheless, we show that our results are robust to adding wholesalers back in.

Each superstar firm seeks a preferred upstream supplier with whom she will form a long-term relational contract. A key benefit of this relationship is that the supplier will receive a transfer of know-how that will reduce the marginal cost of the supplier, so that a supplier with original cost c will have lower costs γc, after starting to supply the superstar firm ($0 < \gamma < 1$). We think of this as the spillover which could involve the learning and training effects discussed in the case study literature. Formally, we model the determination of the superstar contract as a first-price auction, where the superstar wants to receive a supply quantity and upstream firms bid to supply the superstar at a fixed price. In addition to the usual benefits of supply, the upstream firm knows that they will receive this productivity spillover, that will reduce their marginal costs enabling them to sell more to the competitive firms. Hence, they will bid more aggressively in order to win the superstar contract compared to the prices they charge competitive downstream firms.

The structure of the economy is that in the first stage, firms enter and take their productivity draw. In the second stage they bid in the superstar firm's procurement auction and the winner is determined. In the final stage, all firms produce, sell to downstream firms and take profits.

The model has several implications. First and most obviously, the firm forming a relationship with a superstar should enjoy productivity improvements. Lower costs will mean increased sales overall and in particular to non-superstar firms on the intensive (output) and extensive (number of buyers) margins. The increased output will also require more inputs (e.g. intermediate purchases and labor). Our main results focus on these channels (particularly the productivity and "other sales" channels), probing the causality of these superstar spillovers.

A second set of implications are over profitability. Since an upstream firm has to bid a lower price in order to win the superstar contract, the overall price-cost margin should fall after a superstar relationship forms. Overall profits should (weakly) *rise* as these losses are made up by selling more output to other firms. The superstar firm does not, in general, extract all the profits from the supplier because we assume a finite set of upstream firms ($I < N$) who bid in the auction. Formally, we model this as a random draw of the N possible firms, but in reality the set of firms will be those who are closer to the location of the superstar geographically and/or in the bundle of goods the superstar purchases. This will motivate the IV strategy we implement in subsection 7.2.

A third set of predictions relates to the identity of the winning bidder. In our model, *ex ante* more productive firms will bid more aggressively for the superstar contract as they receive more aggregate profits from the unit cost reduction as they sell more to the non-superstars even in the absence of the relational contract (low cost firms charge less and sell more).

We find that all of these three sets of predictions are confirmed in our data.

We also extend the model in several ways to probe the mechanisms underlying our results. Rather than assuming a common superstar spillover, it is likely that the more technologically intensive superstars - for example, the ones who are doing more research and development (R&D) or using more digital technologies - will confer greater spillovers. Second, there is likely to be greater scope for learning for firms who are younger than those who are older. We show that these extensions all have purchase in the data.

Finally, we also consider two other superstar spillover mechanisms that are outside our model of productivity enhancements. Bernard et al. (2022) detail a model where firms may be very large for two reasons. They may have higher TFP as in our model (which is standard). But they may also have a second dimension of "relationship capability" that makes them superior at reaching more customers (for example, through better marketing ability). Bernard et al. (2022)find this second dimension to be very important in explaining firm size,so we consider whether this relationship capability of superstar firms also spills over to their suppliers. We do find some evidence for this, even though this channel cannot explain our main effects on productivity. We then introduce a new "dating agency" channel to the literature, a mechanism whereby a superstar firm can enhance the number of buyers for a supplier by boosting their profile within the superstar's network of buyers. We document evidence for the importance of this mechanism over and above relationship capability and TFP spillovers, as we find that the growth of new buyers is particularly strong within the superstar firm's network.

4 Empirical Strategy

Our main empirical strategy is to use an event study difference-in-difference design to estimate the spillovers from selling to a superstar firm. We define three different treatment type K superstars as (i) multinational firms, with at least ten percent share of inward or outward FDI; (ii) non-wholesale exporters with at least ten percent export share; and (iii) large firms in terms of the top 0.1 percentile of total sales. All of these measures are based on the average over the sample period. We classify a firm i as a treated firm if it starts to sell to firm j of treatment type K for the first time and the amount sold to at least one of the treatment type K firms constitutes at least ten percent of its total sales in that period.[4] Having a sales share cut-off to define a "serious" relationship is motivated by the need to distinguish between small sales vs. those that are indicative of a longer-term relationship contract. Appendix Table A5 shows that our cutoff succeeds in making this distinction. For example, a firm forming an multinational relationship of more than ten percent of sales in 2004 was 56% more likely to survive until 2014 than one with less than ten percent of sales (see the discussion in Appendix 4 for more detail).

In another restriction we drop any firm i that starts selling to a treatment firm j of type K if its sales share is less than ten percent. To ensure that we have enough pre- and post- periods around our event windows, we drop any firm that forms a new relationship in the first two years or the last two years of the sample. Consequently, the control group comprises firms that never sell to the treatment type K, but also includes firms that sell to other treatment type K firms. We also drop from the control group any firm i that is a superstar firm, for example if we define a superstar firm to be a multinational, we drop any firm i that is a multinational. In extensive robustness tests, we show that

4. The ten percent threshold is consistent with US SEC regulations for publicly listed corporations who have to report their major buyers if this constitutes ten percent (or more) of their sales (e.g. Barrot and Sauvagnat (2016)). We show in the robustness section that our results are qualitatively unchanged to flexing the exact threshold (see Table D15).

none of the results are sensitive to alternative definitions of the exact thresholds or choices of sample.[5]

Our main interest is in identifying whether selling to a superstar firm generates productivity spillovers to firm i. We estimate the following equation separately for each treatment type K for each outcome y:

$$y_{i,t} = \sum_{\ell=M}^{L} \beta_{l+1} I_{i,t}^{\ell} + \delta_i + \gamma_{s,t} + \epsilon_{i,t}. \tag{1}$$

We define $I_{i,t}^{\ell} = \mathbf{1}(t - E_i = \ell) \forall \ell \in (M, L)$ where E_i is the year that a firm i first starts a new serious selling relationship with at least one firm type K and $\mathbf{1}(.)$ is an indicator function. We have defined things so that β_1 is the year of the treatment event, and (as is conventional) we normalize relative to the year prior to treatment setting $\beta_0 = 0$. Our baseline estimates set $M = -6$ and $L = 4$, so that we have a ten year window around the event. We estimate a separate coefficient for each period before and after the event, all relative to the year before the event, which we denote as $t = 0$. All the specifications include firm fixed effects (δ_i) and industry-year fixed effects ($\gamma_{s,t}$) at the NACE 4-digit level, comprising 648 industries spanning across all sectors of the economy. The error term $\epsilon_{i,t}$ is clustered by firm to allow for serial correlation. We look at a variety of outcomes, y, with a focus on TFP, which is estimated in an initial stage using a variety of methods with the baseline method as the Wooldridge (2009) GMM approach. Additionally, we examine firm sales, intermediate inputs and the wage bill (a measure of labor inputs). Since there is a mechanical increase in sales and the number of total buyers when forming a relationship with a new firm, we also look at the number of buyers and the amount of sales to firms *other* than the superstar firm ("number of other buyers" and "other sales"). We also examine a large number of other outcomes such as capital, employment, survival and the value and number of varieties of exports and imports (on the extensive and intensive margins).

A major empirical concern is whether firms would have also had better performance even in the absence of the superstar relationship. By estimating β_{-1} to β_{-5}, we can examine pre-trends to check whether firm i was already on a positive productivity trend prior to forming a relationship. We will show an absence of pre-trends, suggesting no strong relationship with productivity trends and superstar relationships (treated firm i's do have a higher level of productivity, but this is controlled for in the δ_i). The inclusion of the four-digit NACE industry by year interaction fixed effects, $\gamma_{s,t}$, control non-parametrically for superstar spillover effects to firms who do not form direct relationships. These absorb the industry spillover effects in the extant literature (e.g Javorcik (2004)). Of course, there is still the concern of an unobserved *contemporaneous* shock to firm i causing it to start supplying a superstar and do better in the future. We assess this first, by looking at placebo tests of firms who form relationships with non-superstar firms and show that we do not see any of the performance

5. Our focus is on estimating spillovers from starting to sell to a superstar firm i.e. via backward linkages. Our identification strategy is not suited for estimating spillovers from a new purchasing relationship with a superstar firm i.e. forward linkages because most firms in our sample are already buying from a superstar firm in the first year they appear in the sample. For purchases from multinationals, we found that 98 percent of the observations would have to be dropped: 80 percent were already purchasing from a multinational in the first year they appeared in the sample; and another 18 percent did not have either a pre or post period.

benefits arising after superstar relationships. Second, Section 7 considers designs focusing on shocks to superstar firms independent of those to firm i in order to identify the causal impacts of superstar firms.

5 Baseline Results

5.1 Gains from Selling to Superstar Firms: multinationals and exporters

Our first set of results considers selling to to a multinational firm, so treatment firm type $K =$ *multinational*. Our baseline results are presented graphically in Figure 1 with estimates of year by year treatment coefficients reported in Appendix Table D1. The first panel of Figure 1 plots the regression coefficients from equation (1), with log TFP as the dependent variable. We see a significant rise in TFP of just under three percent in the year of treatment, which increases to about eight percent three years after treatment and remains around this level by the end of our event window (i.e. four or more years after the serious relationship began).[6]

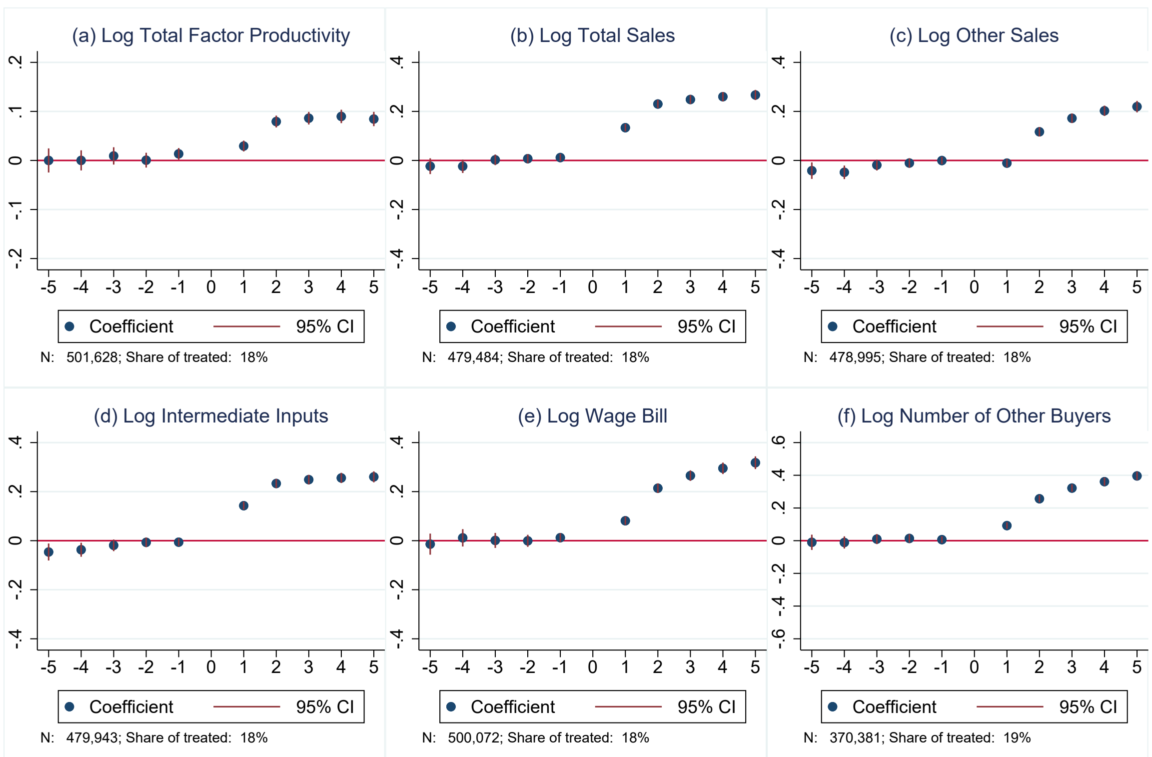
We also consider the effect of starting a new relationship with a multinational on a number of other outcome variables in the subsequent panels (b)-(f), again plotting the coefficients in equation (1), but replacing the dependent variable for firm i for output, inputs and the number of buyers. First, if there is a genuine increase in TFP this should mean that a firm subsequently grows in scale (its greater efficiency will mean it can reduce prices and so increase demand). Panel (b) of Figure 1 looks at total sales where we also see some increase in the year of the relationship forming, growing to 26.7 log points (31 percent) four years later. Since mean sales are €1.07 million (see Table A1), the estimates imply about a €332,000 increase in sales. Of course, there is a mechanical increase in sales because by definition of the event, a new relationship has begun (this mechanical effect is not true of the productivity result in panel (a)). However, panel (c) shows that even if we net off sales to the multinational, sales to other firms ("Other Sales"), also significantly increases by about 22 log points in the long-run. Notice that there is even a small negative effect on "other sales" in the first year of the relationship, which is consistent with some diversion away from existing customers in order to meet the demands of the superstar firm. This is consistent with the "venting out" model of Almunia et al. (2021) where short-run marginal costs are rising in output (as also found in Alfaro-Ureña, Manelici, and Vasquez (2022)).

Since there is an increase in scale, more inputs will likely be needed. Panel (d) of Figure 1 shows that total intermediate inputs rise and panel (e) shows that labor services (proxied by the wage bill) also rise, following a similar dynamic pattern to TFP and output in the first three panels.[7] Finally,

6. Our baseline measure of TFP is from an industry specific value-added production function using the Wooldridge (2009) (WR) approach. We show that the results are robust to a wide variety of alternative approaches to measuring productivity in Appendix Table D4.

7. The fact that inputs rise is reassuring as if the superstar shock simply caused the firm to raise prices, we would not expect to see such a large increase in input usage. The wage bill is a good summary of labor services as it implicitly weights the raw number of workers by their wage thus accounting for differential skill mix and part-time work. One might be concerned that this exaggerates labor inputs if FDI causes hourly wages to substantially rise as in Setzler and Tintelnot (2021), but Table D6 shows that employment increases by around 20 log points.

Figure 1: Gains from selling to multinationals



Notes: The horizontal axis indicates the year firm i starts selling to a multinational (MNE), defined as a firm located in Belgium with at least 10% inward or outward foreign ownership, with $t = 1$ indicating the treatment year. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The outcome in panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of sales to MNE treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is the log of number of buyers net of MNE treatment firms. “N” is the number of observations. All regression results are in Table D1.

in panel (f) we show that an extensive margin - the total number of buyers other than multinational, also significantly increases.

Taken together, the results in Figure 1 suggest that firms who start a relationship with a multinational experience significant long-run increases in TFP, output, inputs, and sales to other buyers on the intensive and extensive margins. These results are consistent with a large literature that has documented spillovers from FDI firms, but has never (to our knowledge) looked at whether this also operates directly through buyer-seller relations in a developed country. Moreover, we find that these spillovers are not specific to firms with inward FDI, which has been the main focus of the prior literature. Instead, we find that spillovers of similar magnitude are generated by superstar firms more generally, where superstar firms include firms that engage in outward FDI, or exporting, or are just very large domestic firms (see below).

In order to estimate whether links to exporting firms also yield spillovers, we adopt the same strategy as with multinational links, but instead define a superstar firm as one that exports at least ten percent of its sales. We plot the results from estimating equation (1) in Figure 2 and report the full set of coefficients in Table D2. We find that selling to an exporter yields similar sized gains to a firm i as selling to a multinational. In panel (a), a firm that starts selling to an exporter has a small increase in TFP of 1.9 percent in the first year of treatment, which rises to about seven percent by four years after the event: these are only slightly smaller than the treatment effects from selling to multinationals. Panels (b) through (f) replicate the outcomes in Figure 1 examining total sales, sales to firms other than the superstar, intermediate inputs, labor services and the number of other buyers. We find significant positive long-run effects in all panels, with similar magnitudes and dynamic patterns to those for multinational linkages.

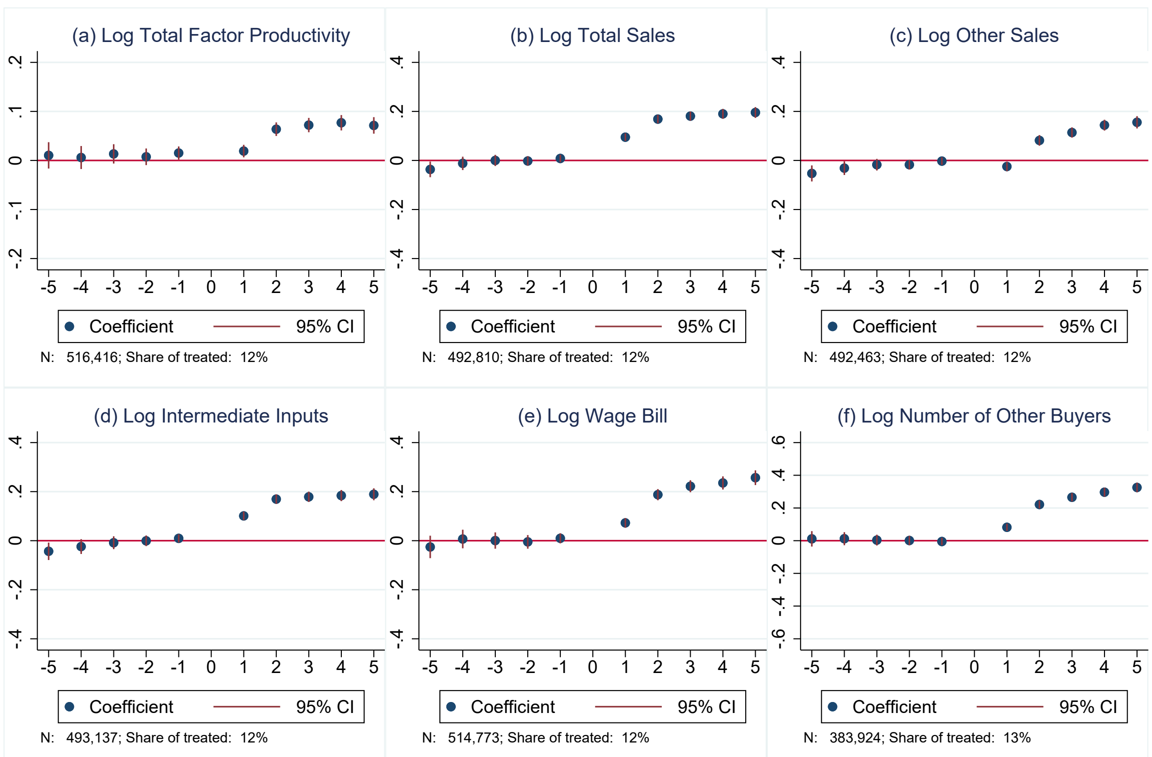
5.2 Gains from Selling to Domestic Large Superstar Firms

We next consider whether there are gains to selling to a large firm, where "large" is defined as a firm in the top 0.1 percentile of the total sales distribution in our sample, and present the results in Figure 3 and Appendix Table D3. Interestingly, we see a similar pattern to multinationals and exporters: forming a relationship with a large firm raises TFP by around eight percent after four years as well as significantly increasing outputs, inputs and the number of customers.

Although we have shown evidence of significant gains from forming a relationship with a large firm of a similar magnitude to that of forming a relationship with a multinational, one may be concerned that large firms are also basically all multinationals. Indeed, we see from the summary statistics in Table A4 describing our superstar firms, that 74 percent of the large firms are "global", either through inward FDI, outward FDI, or exporting.[8] In order to investigate whether being a multinational (or an

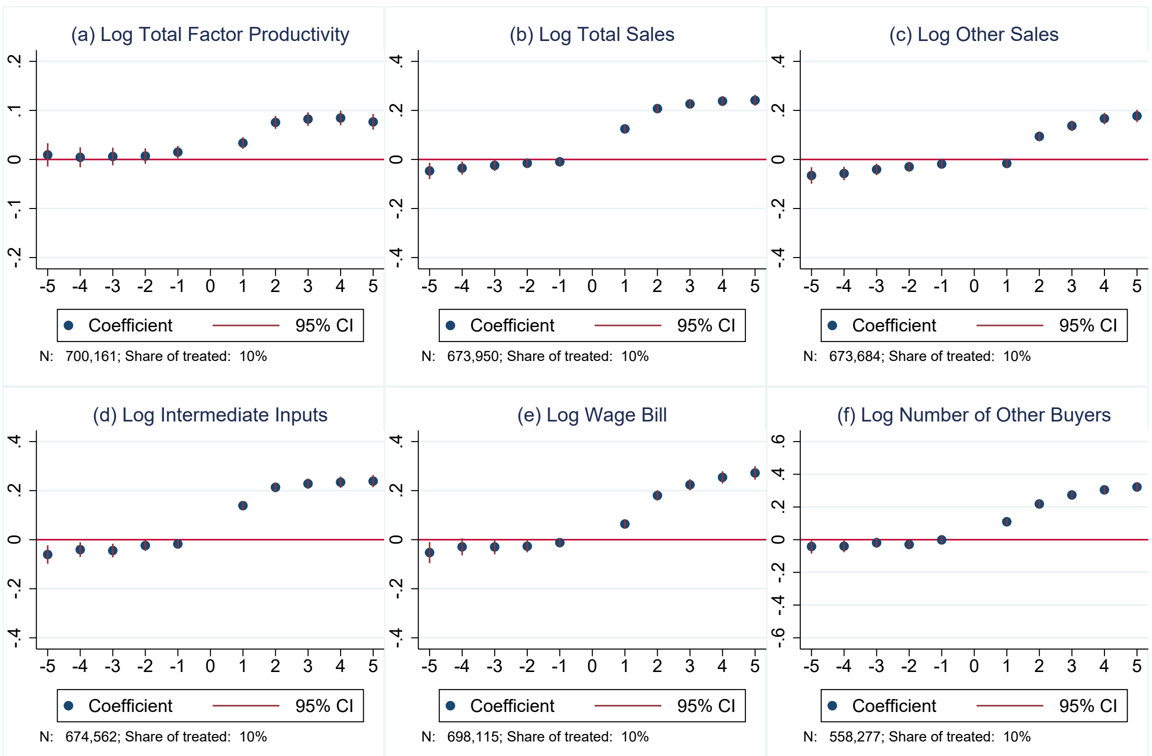
8. Some examples of large Belgian firms who are not multinationals nor major exporters (based on publicly available company accounts and a search through websites of the largest companies) include Comfort Energy (https://www.comfortenergy.be) one of the largest distributors of heating oil to households; Corelio (http://corelio.be), the largest newspaper group in Belgium; Belorta (https://belorta.be/) the largest fruit and vegetable auction in Belgium; Febelco (https://www.febelco.be/) a distributor and supplier of pharmaceutical products to local pharmacists; Hubo (https://www.hubo.be/nl.html) a chain of 150 hardware stores headquartered in Wommelgem and founded in 1992 (note

Figure 2: Gains from selling to Exporting Firms



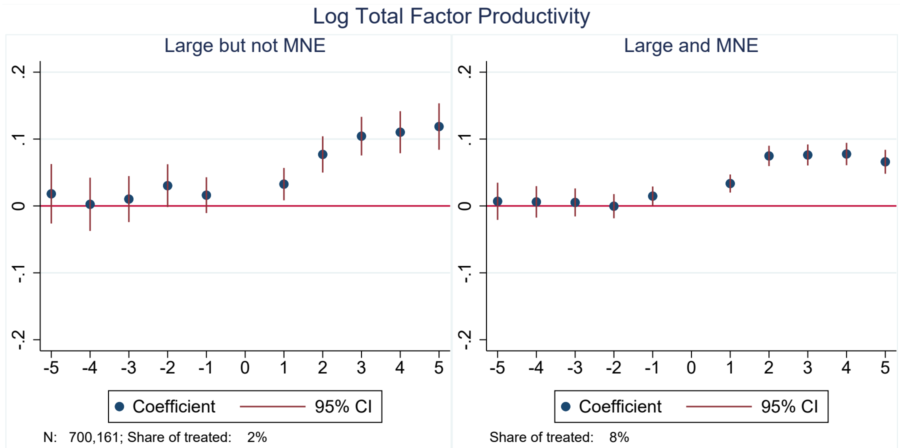
Notes: The horizontal axis indicates the year firm i starts selling to an exporting firm, where exporter is defined as a firm located in Belgium, not in the wholesale industry, that exports at least 10% of its sales, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The outcome in panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of exporter treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is log number of buyers net of exporter treatment firms. "N" is the number of observations. All regression results are in Table D2.

Figure 3: Gains from selling to Large Firms



Notes: The horizontal axis indicates the year firm i starts selling to a large firm, where large is defined as the top 0.1 percentile according to total sales, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The outcome in panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of large treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is the log of number of buyers net of large treatment firms. "N" is the number of observations. All regression results are in Table D3.

Figure 4: TFP gains from selling to Large Firms vs. Multinational Firms



Notes: The dependent variable is the log TFP estimated using the Wooldridge (2009) methodology. The two panels are part of the same regression, where treatment is defined at least 10 percent sales to a a large firm, with the coefficients on the left depicting treatment to a large firm that is not an MNE and the right panel treatment to a large firm that is also an MNE. Large is defined as the top 0.1 percentile according to total sales. The horizontal axis indicates the year firm i starts selling to a superstar firm, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. The regression includes 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level.

exporter) is necessary for generating spillovers, we re-estimate equation (1) for the large firm links, but split the large firm treatment into two bins – those that are large *domestic*, and those that are large *and* multinational firms. We plot the results in Figure 4. The coefficients on the left panel correspond to the treatment effect of selling to a large domestic firm whereas the right panel is the treatment effect from selling to a firm that is both large and a multinational (as well firms that sell to both types of treatment firms in the same year).[9] What is clear from the graphs is that there are significant gains to selling to a large domestic firm that is not multinational. The coefficients are very similar for both types of firms.

Up to this point, our results on the impact of multinational relationships are qualitatively and quantitatively consistent with the Alfaro-Ureña, Manelici, and Vasquez (2022) work on Costa Rica. One point of departure, however, is that they find no effects of forming a superstar relationship with large domestic firms whereas we do in Figure 4. We probe the reasons for this in Appendix D.4 and Table D5, showing that it is not due to some obvious differences in the definition of what it means to be a domestic superstar (e.g. dropping exporters and those with indirect FDI).[10] The most likely explanation is that in Costa Rica there are hardly any very large purely domestic firms, so there is

there is a Dutch firm named Hubo, but it is a completely separate entity).

9. The categorization of the last group (which is small in number) is arbitrary, but makes little difference to the results.

10. In the last column of Table D5, we further split the domestic large category by isolating the effect on large firms that are state-owned. There are only 29 of these firms, and netting them out of the domestic large group hardly effects the magnitude of the coefficient. However, what might at first appear surprising is that large government firms also yield spillovers of similar magnitude. Looking more closely at these large government firms, we found that they are in fact intensive in R&D expenditure, and thus are likely to be able to transfer knowledge spillovers in the same way as other superstar firms.

little quasi-experimental variation to contrast with multinational effects. From a policy perspective, access to highly productive superstars for smaller emerging economies is probably only possible through allowing multinational entry. Our results suggest that for richer countries, domestic superstars are also a possible source of such spillovers, so there is no obvious policy reason for favoring multinationals over large domestic firms on productivity spillover grounds.[11]

5.3 Placebo: Productivity or sales spillovers from supplying to non-Superstar Firms?

We have argued that there are positive causal effects on productivity from forming a relationship with a superstar firm. However, we have not explicitly examined whether forming a relationship with a non-superstar also brings benefits. If we found that productivity increased by a similar amount when forming a serious new relationship with a non-superstar, this would cast doubt on our interpretation of the treatment effects as representing productivity spillovers. For example, it might be that forming a serious new supplier relationship creates significant additional demand which generates scale economies and other efficiencies. Of course, *ex ante* such "demand shocks" have ambiguous effects. In Almunia et al. (2021), for example, firms have upward sloping marginal cost curves, so increasing demand increases costs which will reduce productivity and sales to other firms as own prices rise. Indeed, this is our interpretation of the initial drop in post-event "other sales" in panel (c) of Figures 1 - 3.

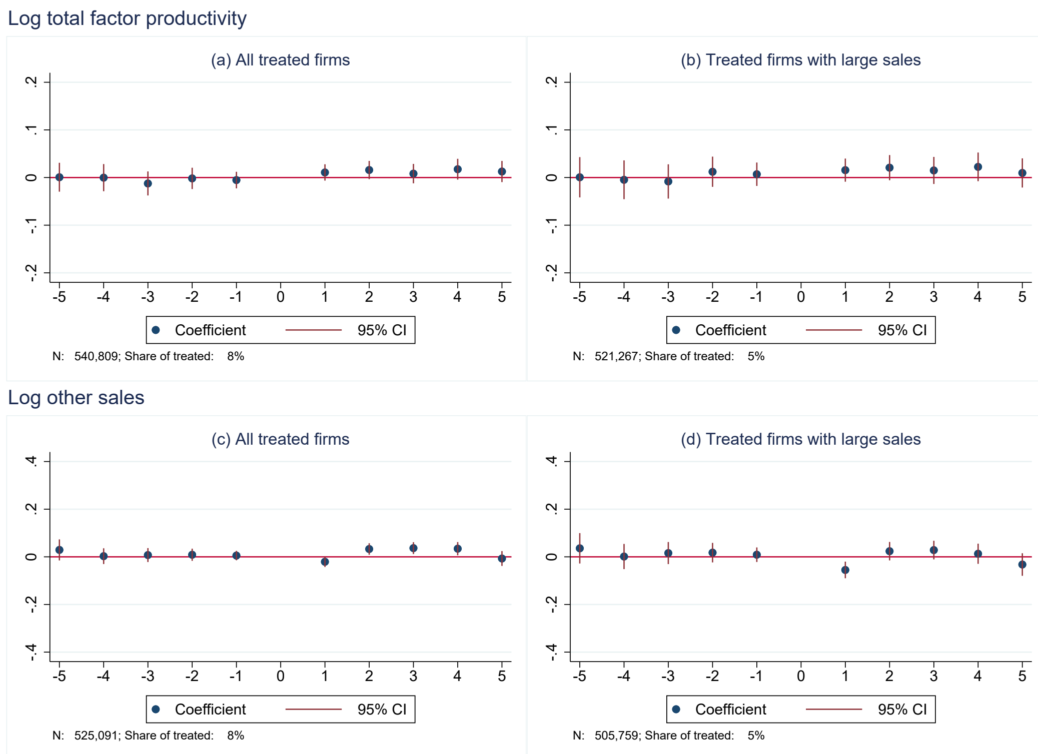
To investigate this issue, we run a placebo experiment, focusing on treatments with non-superstar firms (e.g. smaller firms) and re-estimating equation (1). We consider whether there are spillovers generated to a firm i from starting a new serious relationship with a "small" firm, which we define in various ways. In parallel with our baseline strategy, we drop any firm i that starts selling to a small firm j at the beginning or the end of the sample (to give us a large enough pre- and post-event window), as well as firms that sell less than ten percent to a small firm.[12] In panel (a) of Figure 5 we look at these treatment effects from starting a relationship with a firm in the bottom quintile of the sales distribution.[13] The results indicate that there are no significant TFP spillovers from relationships with a small firm, with all of the post-event coefficients close to zero. Since the average treatment sales in this placebo are much smaller than the treatment sales to large superstar firms in our baseline exercise, we further limit the treatment firms in panel (b) to sales of at least €3,000 to a small firm. With this restriction, the average amount of sales in euros to the new customer firm is similar to the mean new sales to Large Superstar firms in Figure 3. Again, we estimate a rather precise zero effect of selling large amounts to non-superstar firms. Panels (c) and (d) repeat the exercise of the previous

11. In a parallel exercise, we check whether the spillovers generated by global firms are not purely due to the treatment firms being large. We found significant coefficients of similar magnitudes for multinational and exporter firms even if suppliers were small.

12. One issue with this type of test in our setting is that a firm i can start new relationships with both a small firm j and a superstar firm j at the same time. To ensure that these "dual status" firms do not contaminate our placebo test, we classify firm i to be treated if it starts a new serious relationship with a small firm j but did not sell to a superstar firm. For the set of dual status firm i that started a new serious relationship with a small firm and a new relationship with a superstar, we drop them from the sample. Note that putting these dual status firms into the control group produces similar results.

13. Using the within four-digit NACE industry bottom quintile (or other lower quantiles) produces very similar results.

Figure 5: Placebo: No Gains from selling to Smaller Firms



Notes: The dependent variable in panels (a) and (b) is the log TFP estimated using the Wooldridge (2009) methodology. The dependent variable in panels (c) and (d) is the log of total sales net of sales to the treatment firms. Rather than the event being starting to supply to a superstar firms, placebo event here is starting to supply to "smaller" firms, defined as those in the bottom quintile of the sales distribution. The treated firms in panels (a) and (c) include all firms that sell at least ten percent of their sales to the small firms, while the treated firms in panels (b) and (d) are restricted to those with sales greater than or equal to 3,000 euros to the small firm (this cut-off ensures the mean sales to these firms is close to the mean sales to the superstars). The median sales value of a treated firm to a small firm in panels (b) and (d) thus closely matches the median sales value of a treated firm to a large firm in the baseline Figure 3 panels (a) and (c). All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level.

panels, but use sales to other firms as the outcome rather than TFP. Once again, there is essentially zero effect.

These results strongly suggest that it is selling to a superstar firm that really matters for productivity spillovers. Forming a new serious relationship *per se* with another firm is not associated with economically or statistically significant gains.

5.4 Other Firm Performance Outcomes

The richness of our data also allows us to examine the effect of starting a relationship with a superstar firm on many other outcomes (see Appendix Table D5). In Table D6, we show the probability of survival is higher for treated firms (the dependent variable is defined as equal to one if the firm has positive sales, and zero in the year it exits and all subsequent years). Forming a superstar relationship increases survival chances by 5 to 6 percentage points, over a mean of 88.6 percent. So our main results, which implicitly condition on having a firm survive at least one period after forming a superstar relationship, actually underestimate the spillover benefits of superstars. We also show positive and significant treatment effects on jobs, tangible capital (as measured by fixed assets) and intangible capital.

Table D7 shows positive effects for many aspects of trade. The total value of exports and imports increases whether measured by their value or by the number of varieties (defined as the number of HS8 by country locations). Moreover we show this operates on the extensive margin of exporting and importing as well as the intensive margin. These are all consistent with the idea that the transferal of know-how increases productivity and enables a performance improvement on a number of dimensions.

Table D8 show that there are effects on the *quality* as well as the quantity of new buyers. We look across all a firm's customers (excluding the superstar firm) and calculate measures such as the average number of suppliers these customers have, their average employment, their average sales and their average number of buyers. We find positive treatment effects on all these outcomes. In addition, when we split the count of buyers into superstar and non-superstar buyers, we find that forming a relationship with a superstar firm makes it significantly more likely a firm forms a relationship with *another* superstar firm in the future.

Summary of Core Results In summary, we find strong effects on firm performance after forming a serious relationship with a superstar firm. The existing literature focuses on FDI spillovers and we confirm that these exist and extend the literature in developed countries by showing that these operate through an explicit buyer-seller linkage. Moreover, we show these spillovers also exist for forming a relationship with an exporting firm. However, our results show near identical benefits from forming a relationship with a very large, but purely domestic firm. This suggests the fundamental factor is high productivity, and such firms are more likely to be multinationals (as well as being very large and/or exporting). In the next section, we explore the precise mechanisms of where these spillovers might come from.

6 Exploring the Mechanisms

Having established a robust positive performance effect of forming a relationship with a superstar firm, we now investigate some possible mechanisms behind the spillover effects. We first explore some of the predictions from the formal model of Appendix C (sketched in Section 3). We then consider two complementary models focusing on relationship capability and a new "dating agency" effect.

6.1 Further Implications of the Superstar Spillover Model

6.1.1 Price-Cost Margins and Profitability

In addition to the performance measures we have considered thus far, our modelhas some further predictions regarding firm profitability. A firm who starts selling to a superstar firm will face a tougher contract, as the superstar firm will extract some of the surplus from the productivity spillover conferred on the supplier. Although our data allows us to distinguish sales, we cannot separately identify markups to superstars as we do not know how prices and costs are allocated between superstar vs. non-superstar customers. Nevertheless, we would expect a fall in the firm's aggregate markup following the formation of a superstar relationship (since in our model, the markup is the same across all non-superstar buyers, so the firm forming a superstar relationship unambiguously will have a lower average markup).

We calculate price-cost margins in two ways. First, we follow the econometric approach of De Loecker and Warzynski (2012) and exploit our estimation of industry-specific production functions to calculate the output elasticities with respect to intermediate inputs. We then divide this by the (measurement error corrected) share of intermediate inputs costs in total revenues. This generates an estimate of the price-cost mark-up in a wide class of models. Second, we take the simpler "accounting" approach of Antràs, Fort, and Tintelnot (2017) and simply divide sales by material inputs.[14] The results are shown in columns (5) and (6) of Appendix Table D6. For all three definitions of superstar firms across both measures of the markup we see significantly negative treatment effects (of between 1 to 2 percent) on the markup of forming a relationship with a superstar firm, consistent with the predictions of our model.[15]

These results are also important in dealing with a related statistical concern. We do not have firm-specific prices for our firms, so the TFP measures we have used so far are revenue based measures ("TFPR") which potentially include not only efficiency gains, but also an element of the markup. Thus, the positive TFP effects we observe could have potentially just reflected higher mark-ups of supplier firms.[16] The fact that, empirically, we see *falling* markups rules out this alternative interpretation.

Our model predicts that despite falling overall markups, firms forming relationships with superstars should generally earn higher total profits. This is because although they might lose some margin on the superstar contract (it could even be negative), they will gain on net from the fact that they have lower costs from superstar spillovers, and can therefore sell more to non-superstar firms. To investigate this implication, we also estimate the impact on gross profit as measured by Earnings Before Interest, Tax and Amortization (EBITA). The last column of Appendix Table D6 shows that total profits rise following a superstar relationship, consistent with the model's predictions.

14. We used intermediate inputs to estimate the output elasticity for obtaining De Loecker-Warzynski markups. Intermediate inputs comprise material inputs and service inputs. De Loecker, Eeckhout, and Unger (2020) suggest that service inputs should be interpreted as fixed. Thus in the "accounting" approach we therefore just use material inputs.

15. The model also predicts that the magnitude of the negative margin effect should be growing in the share of the supplier's sales going to the multinational. We confirmed this in the data by interacting the treatment effect with the fraction of firm i's sales going to the multinational at the start of the contract (the post-event share may be endogenous). The coefficient on this interaction was negative for all three superstar definitions, and significantly so for multinational and very large superstars. Of course, negative margins can arise in other models. For example, the superstar may have monopsony buying power over the supplier and/or be offering greater security of demand. However, these models cannot explain the positive effects on the supplier's performance in terms of TFP and sales to other buyers that we have already documented.

16. Some models do predict such positive effects on supplier margins. Macchiavello (2022) for example, surveys studies from developing countries where domestic suppliers to foreign multinationals do often earn *higher* markups. He argues that one reason for this is through a relational contract that incentivizes the local supplier to continue supplying quality products when the temptation to renege on the contract is higher. Since we are examining Belgium, a high income country where formal contracts are stronger and monitoring is easier, this effect may not be so important.

Table 1: Spillover Mechanisms - Heterogeneity of treatment effects depending on characteristics of the Superstar firm

Dependent variable:	Log TFP				Log Other Buyers			
	Indicator Variable				Indicator Variable			
	R&D (1)	ICT (2)	Skill labor (3)	RC (4)	R&D (5)	ICT (6)	Skill labor (7)	RC (8)
MNE								
1 or more years after event	0.068***	0.065***	0.062***	0.070***	0.287***	0.276***	0.277***	0.260***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.011)	(0.012)	(0.011)	(0.014)
x indicator variable	0.043***	0.032***	0.050***	0.008	0.133***	0.106***	0.132***	0.075***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.023)	(0.017)	(0.019)	(0.016)
Observations	532,790	532,790	532,790	532,790	397,129	397,129	397,129	397,129
Adjusted R^2	0.645	0.645	0.645	0.645	0.834	0.834	0.834	0.834
Exporters								
1 or more years after event	0.056***	0.056***	0.060***	0.056***	0.242***	0.247***	0.228***	0.228***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.012)	(0.013)	(0.014)	(0.014)
x indicator variable	0.022*	0.010	-0.001	0.006	0.137***	0.045**	0.073***	0.068***
	(0.013)	(0.010)	(0.010)	(0.010)	(0.027)	(0.019)	(0.018)	(0.018)
Observations	537,247	537,247	537,247	537,247	401,859	401,859	401,859	401,859
Adjusted R^2	0.644	0.644	0.644	0.644	0.805	0.805	0.805	0.805
Large								
1 or more years after event	0.060***	0.062***	0.059***	0.075***	0.260***	0.261***	0.250***	0.249***
	(0.006)	(0.007)	(0.006)	(0.008)	(0.012)	(0.014)	(0.013)	(0.015)
x indicator variable	0.065***	0.019**	0.042***	-0.010	0.147***	0.052***	0.131***	0.055***
	(0.012)	(0.009)	(0.011)	(0.009)	(0.028)	(0.019)	(0.023)	(0.018)
Observations	723,803	723,803	723,803	723,803	579,068	579,068	579,068	579,068
Adjusted R^2	0.648	0.648	0.648	0.648	0.850	0.850	0.850	0.850

Notes: Columns (1) to (4) regress our baseline measure of TFP on the post-treatment indicators (as in column (1) of Table D4) and also this variable interacted with a dummy to indicate if the superstar firm is in the higher quantiles of the distribution of different indicators of technology, etc. (of all superstar firms of type K with K =MNE, Exporter, Large). The dummy indicator variable in each column is as follows: (1) **"R&D"** equals 1 (and zero otherwise) if the superstar firm is in the top decile of research and development expenditure. (2) **"ICT"** equals 1 (and zero otherwise) if the superstar firm is in the top quartile of spending on information and communication technology as a share of total purchases (where total purchases includes purchases from all Belgium firms plus imports); (3) **"Skill labor"** equals 1 (and zero otherwise) if the superstar firm is in the top quartile of the skill share distribution, defined as the share of full-time-equivalent workers with a college degree; (4) **"RC"** equals 1 (and zero otherwise) if superstar firm is in the top quartile of Relationship Capability as measured by number of buyers. Columns (5) to (8) report the parallel regressions replacing the dependent variable with log other buyers. All regressions include the year of event dummy but coefficients not reported to save space. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% , **5%, * 10% levels.

6.1.2 Larger Spillovers *from* High Know-how Superstar Firms

The most common mechanism posited in the literature (and our model) is that a superstar firm has superior technological or managerial know-how. Starting a relationship with such a firm means a potential transfer of this know-how to the supplier firm. In order to investigate this, Table 1 uses proxies of the technological intensity of the superstar firm. In particular, we look at whether the superstar firm is in the top decile of the R&D to sales ratio ("R&D" in column (1)), the top quartile of spending on Information and Communication Technology as a share of total purchases ("ICT" in column (2)) and/or the top quartile of human capital, defined as the share of full-time equivalent workers with a college degree or higher ("Skills" in column (3)). Using our baseline TFP regressions we interact the treatment effect with a dummy for whether the superstar firm is particularly intensive in the relevant dimension. Eight of the nine interactions are positive and seven of these eight are significant at the 10% level or greater. For example, a large firm that is R&D intensive generates a spillover that is twice as big as a large firm that is non-R&D intensive (12.5% vs. 6%). In columns (5)-(7) we replace TFP with "other buyers" as the dependent variable. All nine interactions are positive and significant (this is also true when we use "other sales" as an outcome - see Appendix Table D10). These results strongly suggest that the technology transfer mechanism is likely to be at play.

6.1.3 Larger Spillovers *to* Young Firms

The previous subsection showed heterogeneity of the treatment effect with respect to superstar characteristics, focusing on the larger effects from firms who have "much to teach". We would expect certain types of firms to have greater benefits from technological spillovers. In particular, we would expect firms who have "much to learn" to enjoy larger effects. We proxy this by age: younger firms are likely to be more amenable to learning new techniques than older firms who are likely more resistant to change. To investigate this treatment heterogeneity with respect to firm i characteristics, we interact the treatment effects with whether or not a firm was five years old or younger at the time the superstar relationship began. Looking across all the standard outcomes, Table D11 shows that the treatment effects are significantly larger for young firms in all eighteen regressions. For example, for large firm superstars, the TFP effect is three log points for old firms and 16 log points (over five times higher) for young firms.

6.1.4 What type of firms supply superstars?

We noted a third set of predictions from the model regard the *type* of firms that should win auctions to supply superstar firms. The prediction was that larger and more productive firms should bid more aggressively because they gain the most from a cost reduction. Table A2 examines this by splitting the treated firms before and after the event to enable a comparison of the characteristics of treated firms pre-treated with the controls. It can be seen immediately that the predictions are confirmed. Firms forming a superstar relationship are larger in terms of inputs and outputs. For example, in the pre-treatment period, firms eventually supplying large superstars have twice as many sales as control firms (1.34 vs 0.77 million Euros) and 5.2% higher TFP. Consistent with the greater effects on young firms, we also find that they are about two years younger.

Summary on predictions of superstar spillover model The simple model we outlined in Section 3 had three broad sets of predictions. The first set was over positive causal effects of supplying a superstar firm on productivity and therefore on outputs, numbers of buyers and inputs and was the focus of the previous section. In this subsection we have shown that the other two sets of predictions on profitability and the types of firms forming relationships with superstars are also confirmed in the data. Treatment effect heterogeneity (from superstar and treated firm characteristics) also seems broadly in line with the model.

6.2 Non-productivity Superstar Spillover

Our emphasis on productivity spillovers should not be taken to mean that we are ruling out other mechanisms through which superstar relationships have positive effects on suppliers. We turn now to two alternative mechanisms outside of our formal model. We label these "relationship capabilities" and "dating agency" effects.

6.2.1 Relationship Capability

In an important contribution, Bernard et al. (2022) argue that the high sales of many superstar firms is not related to their productivity, but rather a quite separate capability to sell to a large number of customers. They develop a model where firms have two draws: of productivity and of relationship capability ("RC") and find that these are negatively correlated (but are both strongly related to size). This motivates our idea that some of this relationship capability might also spill over to supplier firms and help explain some of our results. To investigate this, we follow Bernard et al. (2022) and measure RC by a firm's number of buyers. In particular, we count the number of customers for each superstar, and define a high RC superstar as one in the top quartile of this distribution. Column (4) of Table 1 interacts high RC with the treatment dummy and shows an insignificant effect on TFP. However, when we look at the number of other buyers as an outcome in column (8), we do see a positive and significant interaction. For the multinational superstars, for example, a high RC superstar adds an additional 7.5 log points extra buyers on top of the baseline effect of 26 log points. Appendix Table D10 shows that this is also true for "other sales".[17]

These results suggest that RC does play an independent role in addition to the transfer of technological know-how to firms forming relationships with superstar firms. It does not, however, appear to be able to account for the increase in productivity that we have documented in Section 5.

17. The Table also shows that when we include all four interactions of Table 1 together in one regression, none of the conclusions change. The last three columns of Appendix Table D10 show this for TFP, other buyers and other sales. Of the 12 interactions, all are positive and ten are significant at the five percent level. In particular, the RC interactions on other buyers and other sales is robust to the inclusion of all the high-tech indicators.

Table 2: Dating Agency Mechanism

Superstar Treatment:	MNE		Exporters		Large	
Number of other buyers:	In network (1)	Out of network (2)	In network (3)	Out of network (4)	In network (5)	Out of network (6)
Mean of dependent variable	0.937	11.3	0.199	9.0	0.739	15.2
Year of event	0.496**	-0.459*	0.010	-0.345**	1.627**	0.296
	(0.214)	(0.236)	(0.034)	(0.162)	(0.643)	(0.362)
1 or more years after event	1.231***	3.646***	0.352***	2.654***	2.213***	4.740***
	(0.211)	(0.371)	(0.066)	(0.191)	(0.593)	(0.639)
Observations	397,129	397,129	401,859	401,859	579,068	579,068
Adjusted R^2	0.927	0.829	0.820	0.861	0.807	0.877
Expected number of buyers in network	0.248		0.085		0.649	
Odds of actual number compared to expected number	4.96:1		4.16:1		3.39:1	

Notes: The dependent variable in columns (1), (3), and (5) is the number of other buyers that firm i sells to that are in the superstar firm's network; and in columns (2), (4), and (6), it is the number of other buyers outside the superstar's network. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%. The "expected number of buyers" are new buyers in-network that could happen by random chance given the treatment effects on total number of other buyers and the "odds of actual number" is the ratio of the actual in-network treatment effect (in the odd columns) to this expected number. See text and Appendix D.7 for details on these calculations.

6.2.2 Dating Agency Effects

Our discussion of relationship capability suggests that there is some transferal of a general skill of customer acquisition from the superstar firm. But a more direct route might be that selling to a superstar helps a supplier access a new network of potential customers. We call this a "dating agency" effect to reflect the matchmaking role of the superstar firm. This could be through just reducing the search costs of suitable buyers or also that the signal of dealing with the superstar firm causes other firms to update their beliefs over the quality of firm i and these signaling effects are particularly strong in-network. To investigate this mechanism, we look again at the effect on the number of other buyers, but now distinguish between buyers inside and outside of the superstar's network. We define a variable which is the number of buyers in the network of superstar firm j that firm i sells to: if there is a dating agency effect we should expect to see impacts here. Columns (1), (3) and (5) of Table 2 shows that there is indeed a positive and significant effect of treatment on this outcome for all superstar types. We look at the complement of this - buyers outside the superstar's network in columns (2), (4), and (6). We also find positive effects here, which suggests that the channel is not solely through the dating agency effect, but also operates through an increase in productivity. The coefficient for the superstar's network is smaller in magnitude, but this underestimates the importance of dating agency effects as the mean of the dependent variable is much smaller for in-network buyers vs. out of network buyers. For example, the ratio of the coefficients of in-network vs. out of network in columns (1) and (2) is three (3.646 vs. 1.231), but the average firm has eleven times (11.3 vs. 0.94 in the header of the table) more out-of-network buyers than in-network buyers. To calculate the odds of a larger in-network increase in buyer numbers from random chance requires some more calculations, however, because in-network firms are larger we have seen that there is also a treatment effect on the quality of buyers. Appendix D.7 details our calculations, with the odds ratio given in the final row of Table 2. For all firms, the odds of obtaining such large coefficients on in-network buyers is small. For example, there is only a one in five chance that the magnitude of the effect from multinationals on increasing in-network buyers could have arisen by chance.

6.2.3 Summary on non-productivity superstar spillovers

Overall, these results suggest that in addition to our core model of spillovers (a transfer of production know-how), there is an additional effect through the transfer of relationship capability as well as through a dating agency effect, allowing a firm to further expand its supply network.

7 Potential Endogeneity of Superstar Links

Our event studies establish that a firm i that starts a serious relationship with a superstar firm seems to gain higher productivity in subsequent years. Forming a relationship is not randomly assigned, however, so a concern is that the firm would have had better outcomes even in the absence of such a relationship.

To formalize this concern, consider TFP as an outcome, simplify the model of equation (1) to assume there is just a contemporaneous effect and no sector dummies and difference out the firm fixed effect:

$$\triangle a_{i,t} = \beta \triangle I_{i,t} + \triangle \epsilon_{i,t} \tag{2}$$

where $a_{i,t}$ is log TFP. Decompose the error into a truly idiosyncratic shock, $\triangle e_{i,t}$, and a correlated shock, $\triangle c_{i,t}$, so $E[\triangle I_{ijt} \triangle e_{i,t}] = 0$ and $E[\triangle I_{ijt} \triangle c_{i,t}] \neq 0$. Hence,

$$\triangle a_{i,t} = \beta \triangle I_{i,t} + \triangle c_{i,t} + \triangle e_{i,t} \tag{3}$$

If firms experiencing a productivity shock are more likely to form a new match with a superstar firm $E[\triangle I_{ijt} \triangle c_{i,t}] > 0$, our estimate of β will be biased upwards.

We have tackled this issue in several ways. Our baseline approach has been to choose treatment and control groups such that we can plausibly difference out the unobserved correlated shock $\triangle c_{i,t}$ across the two groups. So, denoting T as the treatment group indicator:

$$\hat{\beta} = E(\triangle a_{i,t} | \triangle I_{i,t} = 1, T_i = 1) - E(\triangle a_{i,t} | \triangle I_{i,t} = 0, T_i = 0), \tag{4}$$

which will be an unbiased estimate of β if $\{E(\triangle c_{i,t} | \triangle I_{i,t} = 1, T_i = 1) - E(\triangle c_{i,t} | \triangle I_{i,t} = 0, T_i = 0)\} = 0$

The event studies in our baseline estimation showed that we do not observe pre-trends, which is reassuring as it rules out the idea that firms on a positive productivity trend are both more likely to have higher future productivity and to form serious relationships with a superstar firm, confounding our main effects. However, there remains a concern that there is a contemporaneous unobservable positive

TFP shock to firm i which makes it more likely to be picked as a suitable partner by a superstar firm. For example, the appointment of a new dynamic CEO or the discovery of a new technology. This would not be captured by the pre-trends. Note that the dynamics of the event studies are also helpful. The full effect does not come in the first period, but builds up over time which implies that the contemporaneous shock cannot fully account for what we observe.

Moreover, the placebo tests in subsection 5.3 are also reassuring, as an unobserved contemporaneous productivity shock should also generate new relationships with non-superstars, yet an examination of these events in Figure 5 revealed no performance changes after forming such a relationship. Nevertheless, it could be argued that the putative unobserved shock has to be large to generate a superstar relationship, so the placebo of a non-superstar relationship is not picking up such large correlated firm i TFP shocks.

To assess these concerns we consider three main empirical designs. First, we use an approach from Amiti and Weinstein (2018) exploiting the entire buyer-seller network to explicitly condition on the shocks in a control function approach.[18] Second, we consider shocks to only superstar firm j to identify the treatment effect. In particular, we construct instruments based on shocks to firm j to account for the potential endogeneity of the match between firm i and superstar firm j. A third (and related) approach is to look at new entry of superstars, e.g. multinational entrants who are looking for new suppliers. Although each method has issues, taken together we believe they strongly suggest superstar spillovers.

7.1 Control Function approach

We construct a time-varying firm indicator to reflect firm i's overall growth due to factors related to the firm, and condition out this potential bias through a control function approach. To this end, we use the methodology in Amiti and Weinstein (2018) for identifying idiosyncratic demand and supply shocks. Consider a class of empirical models in which we can decompose the sales ($Y_{i,j,t}$) growth in the population dataset from firm i to firm j in time t as:

$$(\triangle Y_{i,j,t}/Y_{i,j,t-1}) = \mu_{it} + \pi_{jt} + u_{ijt} \tag{5}$$

where π_{jt} are firm j year specific shocks, μ_{it} are firm i year specific shocks and u_{ijt} is a match specific shock. The endogenous part we are concerned about is μ_{it}, shocks specific to firm i ($\triangle c_{i,j,t}$ in equation (3)) that violate the orthogonality assumption. If we can form consistent estimates of μ_{it}, we can include functions of this proxy variable $f(\hat{\mu}_{it})$ in equation (2) and obtain a consistent estimate of β. Note that this method allows for endogenous matching based on match-specific levels of productivity between i and j, year specific shocks to firm i and to firm j but rules out endogenous matching due to match-specific shocks (u_{ijt}). Hence, the identification conditions in Abowd, Kramarz, and Margolis

18. Effectively, we control for the idiosyncratic sales shocks to firm i (that may cause endogeneity bias) as revealed by all the other trading relationships firm i has with every firm j in the population (including firms which it already had pre-existing relationships with).

Table 3: Superstar TFP spillovers with control for shocks to firm i

Dep. var.: Log TFP	MNE			Exporters			Large		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
t1: Year of event	0.022***	0.022***	0.011	0.010	0.007	0.001	0.025***	0.014*	-0.001
	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)
1 or more years after event	0.075***	0.055***	0.040***	0.059***	0.055***	0.043***	0.069***	0.051***	0.035***
	(0.005)	(0.007)	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
Control_{it}			0.042***			0.042***			0.045***
			(0.001)			(0.001)			(0.001)
Observations	532,790	305,499	305,499	537,247	305,789	305,789	723,803	454,968	454,968
Adjusted R^2	0.645	0.669	0.673	0.644	0.668	0.672	0.648	0.670	0.674

Notes: TFP is estimated using the Wooldridge (2009) methodology. The time-varying firm i control function is calculated as equation ((6)) with time-varying firm level shocks estimated as in Amiti and Weinstein (2018). All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

(1999) two-way fixed effect models would be sufficient to guarantee this, but are not necessary as the model allows for (some) time varying shocks to determine matching.[19]

Direct estimation of equation (5) using OLS with fixed effects for firm i by year t and firm j by year t, would generate potentially biased coefficients because the equation is only defined for relationships that exist in t and $t-1$, so excludes relationships that begin or end in these two periods. Appendix B.3 describes how we recover μ_{it} incorporating these new relationships. As μ_{it} is relative to some arbitrary firm, we re-normalize it relative to the median firm each year. We convert this to predicted sales levels as:

$$Control_{it} = \hat{\mu}_{it} Y_{it-1} \tag{6}$$

This is the predicted level of sales in t based on firm i-specific shocks, which we include as a control function in equation (1).

Although our methodology allows for new bilateral relationships, the firm must be in the sample in $t-1$, which means that $Control_{it}$ is not defined for all observations. Therefore, to see how the inclusion of the control function effects β we first compare the baseline estimates in column (1) of Table 3 to the subsample with non-missing $Control_{it}$, in column (2). This point estimate of 0.075 drops to 0.055 in in column (2). When we additionally include the control function in column (3), we see that its coefficient is positive and significant but it only reduces the spillover coefficient from selling to multinationals by about a quarter, from 0.055 to 0.040. Although we use a first-order approximation for the control function, $f(\hat{\mu}_{it})$, adding in higher order polynomials did not change the result. For firms selling to exporters, the coefficient only falls from 0.055 in column (5) to 0.043 in column (6). For the links to large firms, the reduction is from 0.051 to 0.035 comparing columns (8) and (9).

These results show that even after conditioning on the firm-level time-varying growth of sales arising from factors only related to the firm, we still find positive and significant spillover affects, which are

19. This method is essentially identifying the matches to superstar firms through pure random variation and shocks to the superstar firm itself (i.e. a sub-set of the π_{jt}'s). For example, a superstar firm may innovate and need to grow, so it adds new suppliers from the area it has located in (or indeed, locates in a new area).

only modestly smaller than our baseline results. We should consider these as lower bounds, because some of the genuine treatment effect may be taken out by controlling for the shock in this way. In other words, if some (or all) of the μ_{it} shock is due to the superstar relationship, we are removing part of the genuine treatment effect.

7.2 Instrumental Variables

An alternative strategy is to construct instrumental variables for a firm starting a new relationship with a superstar firm. We consider a new approach that uses shocks to superstar firm j, interacted with pre-shock measures of closeness between firm j and all potential firm i's. Consider a superstar which has a large exogenous demand shock (e.g. it develops a new product) and wants to expand. If its existing suppliers cannot produce enough to meet all this new demand, the superstar will seek out new suppliers. Which new suppliers will it form a relationship with? It will be much more likely to start forming relationships with buyers who are in the industries it also purchases from ("product purchase overlap") and/or geographical areas it is already purchasing from ("place purchase overlap"). In the context of the model in Section (3), the subset of firms I who bid in an auction for a superstar firm contract are drawn from the subset of all firms N who are in closer proximity to the product-place location of the superstar.

To formalize this idea we use sales changes to firm j interacted with measures of proximity (defined in an early pre-shock period) between all firms i's and the superstar j. We start with the firm j-year-specific log(sales) changes, $\Delta log Y_{jt}$. We weight the shocks using time-invariant weights for each firm i-firm j pair, adopting the "exposure" measure of firm overlap as in Bloom, Schankerman, and Van Reenen (2013), thus constructing the instrument as

$$\triangle Z_{it} = \sum_{j \in J} EXPOSURE_{ij} \Delta log Y_{jt}. \tag{7}$$

We use the well-known Jaffe (1986) cosine similarity measure of firm overlap, $EXPOSURE_{ij} = \frac{F_i F_j'}{(F_i F_i')^{1/2}(F_j F_j')^{1/2}}$, to measure the overlap of firm i sales to and firm j purchases from the set of 4-digit NACE industries, or, in a separate instrument, the overlap of firm i sales to and firm j purchases from the set of Belgian provinces. That is, the $1 \times P$ vector $F_i = (F_{i1}, ..., F_{iP})$, where P is the set of 4-digit NACE industries (provinces) and F_{ip} is the share of firm i sales to industry (province) p in the first two years that firm i is in the sample, and similarly the $1 \times P$ vector $F_j = (F_{j1}, ..., F_{jP})$, where F_{jp} is the share of firm j purchases from industry (province) p in the first two years that firm j is in the sample. $EXPOSURE_{ij}$ lies between one if the overlap is perfect (e.g. all firm j's purchases are in car parts and firm i only sells car parts), and zero (e.g. all firm j's purchases are in car parts and firm i sells no car parts).

Since the instrument is intrinsically in differences we set this up as a long-differenced regression. The event studies show that the treatment effect takes about three years to peak, so we estimate:

$$y_{it} - y_{it-3} = \alpha \triangle D_{it-2} + \gamma_j + \eta_a + \tau_t + \nu_{it}, \tag{8}$$

where $\triangle D_{it-2}$ is a dummy variable equal to 1 if firm i starts supplying a superstar firm between period $t-2$ and $t-3$ and zero otherwise and γ_j, η_a, τ_t are industry, province and year dummies respectively. The instrument for $\triangle D_{it-2}$ is $\triangle Z_{it-2}$.[20] The control firms are as usual all firms who never form relationships with superstars. We drop all observations for treated firms for the periods after three years that they have formed a superstar relationship (but keep all years prior to forming this relationship that do not overlap with the treatment period).

The results of the instrumental variables regressions are shown in Table 4. In the first two columns, we begin with the baseline TFP regressions in changes using OLS, with a full set of industry, province and year dummies. Despite the change in specification, the results are very similar to our baseline results. For example, the multinational superstar treatment effect is 0.073 compared to 0.075 in column (1) of Table 3. The first stages are strong with F-statistics for the joint significance of the excluded instrument (shown in the lower rows of the upper panel) of over 54 and both individualinstruments have high t-values as shown in the last two rows of the lower panel of the Table. Column (2) has the IV results, showing a strong positive and significant effect which is an order of magnitude higher than the OLS results. Columns (3) and (4) repeat the exercise for export superstars and columns (5) and (6) do this for large firm superstars - all with qualitatively similar results. The IV effects are large, positive and significant.

Why are the IV results so much larger than the OLS? We think it is unlikely that attenuation bias and omitted variables can fully explain the large changes. The most likely explanation is a LATE interpretation - the compliers from the IV are those firms forming relationships with a superstar who are closely linked in product space and/or geographical area, and therefore are likely to be the suppliers best able to absorb technological know-how from the superstar firm. In other words, they are more likely to be "appropriate" technologies transferred for firm i than those from a more random relationship. One piece of evidence in line with this view is that if we examine the treatment effects in our baseline model, they are generally larger for firms where $EXPOSURE_{ij}$ is higher.[21]

7.3 Superstar Entry

A related strategy to that of the last subsection is to focus on spillovers from the entry of superstar firms. This empirical design again aims to identify a new relationship being formed because of a shock to firm j rather than to firm i. An example of this would be a foreign multinational who takes over a

20. For example, for a superstar relationship which forms in 2008, we examine growth between 2007 and 2010, using the superstar sales shock between 2007-8 (interacted with proximity to firm i) as an instrument. We also experimented with longer dated lags (e.g. 2006-7 superstar shocks) as instruments, and found similar results.

21. Formally, we estimate the specifications in column (1), (4) and (7) of Table 3, but also include an extra interaction between the treatment dummy and $EXPOSURE_{ij}$. For multinational and large firm superstars the coefficient (standard error) on the geographical interaction is 0.054 (0.020) and 0.043(0.023) respectively, i.e. is positive and significant (the interaction for exporters is insignificant). For the product overlap all three interactions are positive, but are only significant for exporters: a coefficient (standard error) of 0.109(0.047).

Table 4: IV Regressions

Dependent variable: Three-year change in log Total Factor Productivity	MNE		FX		FLS	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
t1: Year of event	0.073***	0.851***	0.065***	0.636**	0.071***	0.539**
	(0.007)	(0.275)	(0.007)	(0.309)	(0.007)	(0.213)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	230,629	230,629	251,181	251,181	357,864	357,864
Kleibergen-Paap F-stat.		54.440		62.763		146.624
Hansen J-stat.		0.355		0.050		6.602
Hansen J-stat. p-val.		0.551		0.823		0.010
First stage						
	Dependent variable: t1: Year of event					
$Z_{it}^{industry}$		0.097***		0.068***		0.374***
		(0.013)		(0.008)		(0.038)
$Z_{it}^{province}$		0.020***		0.012***		0.071***
		(0.003)		(0.002)		(0.005)

Notes: The dependent variable is the three year change in log TFP, from t0 to t3. TFP is estimated using the Wooldridge (2009) methodology. The instruments are constructed as in equation (7), where $\Delta logY_{jt}$ is the one period change in a superstar's log sales, winsorized at the 1st and 99th percentiles. For $Z_{it}^{industry}$, the $EXPOSURE_{ij}$ is defined over the set of 4-digit NACE industries. For $Z_{it}^{province}$, the it is defined over the set of Belgian provinces. $Z_{it}^{industry}$ and $Z_{it}^{province}$ are winsorized at the 5th and 95th percentiles. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

domestic firm and then expands by seeking out new suppliers. Whereas the previous IV strategy used the intensive margin of shocks to superstar firm j, this approach uses only shocks that are large enough to change the extensive margin such that we observe the entry of a superstar firm.[22] In the top panel of Appendix Table D12, we present the results for multinationals across all six of our main outcome variables (the middle panel has it just for inward FDI and the last panel for exporters). Although the share of treated firms is smaller now, all treatment effects are positive and significant with similar magnitudes to our baseline estimates.

Summary on Endogeneity issues We have presented several alternative strategies to deal with omitted productivity shocks to firm i that could confound the causal estimation of superstar spillovers. Each design has pros and cons, and the interpretation of the treatment effect is different in each approach. Nevertheless, the finding of a positive, significant and non-trivial superstar spillover across all three designs does suggest a causal superstar spillover interpretation.

22. Note that the superstar firm existed in the previous period, but it was not classified as a superstar. In the FDI example, the firm was a domestic firm who switched status when it became owned by a foreign multinational. We also considered an even purer sub-group of multinational entrants who set up entirely new greenfield affiliates in Belgium. Unfortunately, there were too few of these over the sample period to construct a meaningful design.

8 Robustness

In this section, we show our results are robust to a number of potential concerns (see also Appendix D).

Ending Superstar Relationships Our main design is to examine event studies around the start of superstar relationships. One can also examine what happens after the ending of such a relationship. Appendix Table D13 shows that, as expected, there is a significant loss of performance after such an event. For example, forming a relationship with a multinational superstar generates a 10.6% increase in productivity for an unbroken relationship, but this falls to 5.7% if the relationship subsequently dissolves. This appears to be consistent with our learning effects mechanism, as some part of the TFP benefit remains even following the end of the relationship.

Heterogeneous Treatment Effects: cohort-specific estimators A recent literature has emphasized problems of interpreting estimates of equation (1) in the presence of heterogeneous treatment effects. Even when OLS estimation of equation (1) generates consistent estimates of the causal effects in a homogeneous treatment effect model, the $\hat{\beta}$ may not correspond to a convex weighted average of the cohort-specific treatment effects.[23] Some of the weights can be negative, for example. Many estimators have been proposed to deal with this issue, and here we focus on Sun and Abraham (2021) whose design is close to ours - a binary, staggered, absorbing state treatment with no covariates and a large group of never treated.[24] They suggest estimating the cohort-specific lags non-parametrically and then re-weighting these based on the sample size of the different cohorts. We implement their approach for all the specifications and find very similar results to our baseline approach (see Appendix Figures D1, D2, and D3 for the results).

A related concern is that we use the full range of firms in the control group, many of whom are highly unlikely to have relationships with superstar firms, so this may give a misleading impression of the magnitude of the effects (only 13 to 23 percent of our sample are treated). In Appendix Table D14, we show that using a nearest neighbor matching methodology produces results of very similar magnitudes to our baseline. For example, the multinational spillover effect on TFP is 0.071, compared to 0.075 in our baseline.

Benefits from reduced sales volatility? Could one of the benefits of having a major supplier such as a superstar firm be lower sales volatility which encourages suppliers to make greater investments in managerial and technological know-how? This would still be a real benefit, but would not come

23. A "cohort" is a treatment in a particular calendar year, e.g. if a firm starts selling to a superstar in 2004 it is part of the 2004 cohort. In our paper we have nine cohorts between 2004 to 2012.

24. As pointed out *inter alia* by de Chaisemartin and D'Haultfoeuille (2022), the Sun and Abraham (2021) approach generates the same estimates as the method proposed by Callaway and Sant'Anna (2021) when using the never-treated as a control group. Sun and Abraham (2021) have the advantage of using analytical standard errors, while Callaway and Sant'Anna (2021) use the bootstrap. Borusyak, Jaravel, and Spiess (2021) propose alternative estimators that are more efficient under more stringent assumptions, one of which is that there is no serial correlation. We are using a panel of firms, so there is likely to be serial correlation over time, so their imputation estimator is less attractive in our context.

from the transferal of knowledge. Subsection 5.3 showed that it was not simply an increase in the first moment (sales demand) causing our spillover effects because an equivalent growth in sales with from a new non-superstar relationship had no spillover benefits. But what about the second moment (i.e. sales variance)? We calculated the change in the variance of log sales for firms post-event vs. pre-event. Across all three outcomes, there was actually a (small) *increase* in sales volatility in the years after forming a superstar relationship compared to the years before supplying a superstar. For example, for very large superstars the increase in the variance was 0.02 (from 1.75 in the three pre-event years to 1.77 in the three post-event years). Hence, this does not seem to be the likely reason for the effects we identify.

Alternative Treatment Definitions of Superstar Firms Another potential concern is that many of our choices of thresholds are somewhat arbitrary and that our results could hinge on them. This is not the case as we show in Appendix Table D15. First, we chose to define a "serious relationship" if 10% or more of firm i's sales went to superstar firm j. This was in order to avoid firms who sold trivial amounts to the new firm. We looked at various other thresholds (up to fifty percent). As one might expect, there was a tendency for impacts to become slightly larger as we increase the importance of the new relationship,[25] but things generally stabilized after a five percent threshold.. However, if we do not impose any threshold (i.e. include any new relationship with a superstar firm), we detect significant pre-trends. Although these were smaller in magnitude than the post-event effect (e.g. -1% vs. 6% for multinationals), it suggested that firms on an upwards productivity trajectory may be more likely to sell more to a wide range of firms including superstars. Hence, it is important to use some initial screen, in order to be able to focus on serious relationships as we have done throughout the paper (see also the analysis of relationship duration in Appendix subsection (A.4)).

Next, we varied the definition of an multinational in Table D16. First, we considered links to inward FDI and outward FDI separately and found essentially the same results (0.077) as in the baseline where these are combined (0.075). Second, instead of the 10% ownership threshold to define a multinational, we considered alternative such as 50% or more, which generated similar results (0.076).[26] Third, we include links to Belgium firms with indirect inward or outward FDI. Finally, we split the baseline multinational treatment by source and destination country, where we allow effects to differ for multinationals in the EU, US, other developed, and less developed countries. We find the largest treatment effects come from American multinationals and the smallest are from multinationals whose origin is inless developed countries, like India or China.

We change the definition of exporters and large superstar firms in analogous ways in Table D17, again with similar results. We show robustness to including wholesale exporters; adjusting the cutoff for the fraction of sales exported from our 10% baseline (i.e>0%, 20%, and 50%) andallow for different

25. For example, for large firm spillovers, insisting on having the initial sales threshold at 50% generated treatment effect of 8%, compared to only 5% if we included any new sales to a superstar.

26. Appendix Figure (A1) shows why this is the case by plotting the kernel density of multinational ownership within a firm. Once crossing a lower threshold of 10 percent, most multinationals seek to own 90 percent or more of a firm's equity to ensure full control.

treatment effects depending on the superstar exporters primary destination.. We alter the definition of a large firm from the top 0.1% of sales distribution to other thresholds such as the top 0.2% of sales or even the TFP distribution. All of these experiments produce very similar results to our baseline.

Alternative Samples We experimented with different samples in Table D18. Rather than include all firms, we dropped firms with low full-time equivalent (FTE) employment(e.g. less than 10, 5 or one). Rather than our baseline approach of dropping firms who formed non-serious relationships (i.e. under 10 percent of sales) with superstars, we include them in the control group. We also look at requiring firms to only have a minimum of one pre- and post-event year of data (instead of the two years in the baseline). None of these had a material effect on the results. One robustness test that did cause a change in the treatment effect was conditioning on the balanced panel, where we estimate on the subsample where a firm has to be alive throughout the 2002-2014 period. We still identify significant treatment effects in all cases, but these fell somewhat in magnitude (e.g. from 7% to 5% for multinational superstars). This is consistent with the larger treatment effects we found for young firms in subsection 6.1.3. The balanced panel drops all the young firms - exactly those who have most to learn from superstars.

Business Stealing Effects? A final concern is that some of the positive effects we identify in this paper could be over-estimated because there may be negative effects on rivals from a supplier winning a superstar contract (violating the Single Unit Treatment Value Assumption).The direction of such a bias is not obvious, however, as other firms may also *benefit* from the proximity of the superstar even if they are not in a supply relationship with the superstar, or indeed if they are connected to the supplier who is enjoying the productivity spillovers. One possible negative effect on the control group may be through business stealing as rival firms lose out as the superstar's new supplier expand (this is not a concern for the TFP estimates, but may be for the other outcomes such as sales). Such rivalry effects seem unlikely in our context because the typical treated firm is very small. Table A2 shows that it has only four or five workers on average, and such firms are unlikely to be in much strategic rivalry with others.

Nevertheless, we examine one test of the business stealing hypothesis in Table D19 by replacing the industry by year dummies with just linear year dummies (the linear industry fixed effects are absorbed by the firm fixed effects). In our baseline specifications of equation (1), the presence of industry by year dummies means we are effectively comparing treated firms to control firms within an industry-year cell. In Table D19, we are comparing treated firms to the control firm in the economy as a whole (for a particular year). If there were significant business stealing effects, there should be much smaller treatment effects in Table D19 than in our baseline estimates as the coefficients are not biased upwards by so much (rivalry effects are much stronger within an industry than for the economy as a whole). In fact, the results do not change much in the new table. They are near identical for TFP and are actually, if anything, larger for "other sales" as an outcome. This suggests that upwards biases from business stealing are not a major concern in our context.

9 Conclusions

Despite concerns over the increasing dominance of superstar firms, governments spend many billions of dollars trying to attract foreign investment in the hopes of creating positive spillovers to local firms. The literature remains inconclusive, however, and even when positive effects are discovered the mechanisms underlying any effects remain opaque. This paper addresses this issue using very rich firm-to-firm transactions panel data. We use an event study approach, examining what happens when a firm begins supplying a foreign multinational for the first time. This has, to our knowledge, never been done before in a developed country due to data constraints. We uncover a sharp increase in productivity (which rises by about 8% after three years) and other performance measures (e.g. sales to firms other than the new multinational partner). The fraction of aggregate value accounted for by multinationals declined by about ten percentage points in Belgium in our sample period (2002 and 2014), which would suggest a strong headwind against productivity growth. However, in a novel result we are also able to document that when we look at similar events of starting a serious relationship with other "superstar firms" - defined as those who are in the top thousandth of the size distribution and/or export intensively - we find very similar performance impacts. Moreover, we show that these performance effects exist even if a large firm is not a multinational or an exporter. We also provide placebo tests showing no performance effects on suppliers who start selling to smaller firms.

We interpret these results through the lens of a simple model where there are productivity spillovers from superstar firms who auction (long-term) contracts with potential suppliers. This model has auxiliary predictions on the impacts on markups (negative for supplier), treatment effect heterogeneity (e.g. larger for technology intensive superstars) and the type of suppliers who form superstar relationships (e.g. they have higher TFP), all of which are consistent with the data. Over and above our model, we also document two more novel spillover channels through "relationship capability" (Bernard et al. (2022)) and a "dating agency" effect whereby new suppliers access the superstar's network more easily.

In terms of policy, our results imply that there are benefits to "anchor firms" in value chains as many proponents of industrial policy have argued (e.g. Rodrik and Sabel (2019)). However, it is not obvious such firms are more valuable if they are foreign or domestic. Indeed, the fact that large domestic firms create similar spillovers whilst having more local linkages (see Alfaro-Ureña et al. (2023)), suggests moving away from targeting subsidies towards multinationals and having a more level playing field. Finally, although there may be costs associated with the dominance of large firms in the modern economy (e.g. concerns over market power and political influence) our work shows some advantages to allowing superstar firms to grow and form relationships with less successful firms. Inappropriate policies to limit their growth may have negative consequences (e.g. Garicano, Lelarge, and Van Reenen (2016) on regulatory barriers).

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Appendix

A Data Construction

A.1 Data Sources

We draw on five main datasets for our baseline results, for the period 2002 to 2014, which are all easily merged with a unique VAT number at the firm level.

(i) Business-to-Business (B2B) data The B2B data reports all domestic transactions over €250 between Belgium firms, annually. These data are used to identify the first year a firm i starts selling to a firm j of treatment type K, as well as the share of sales sold to these superstar firms and the number of buyers each firm has. We drop two very large firms that have unusually large jumps in the number of buyers and suppliers from year to year, and we drop any firm i and any firm j that are not in the company accounts data (see below). This mostly drops firms that are self-employed.

(ii) Company accounts data from the NBB Central Balance Sheet Office These cover all incorporated firms in Belgium, which includes annual data necessary to estimate production functions - value added, sales, labor, intermediate inputs and capital. Small companies are only required to submit a shortened version of their annual accounts, while large companies must submit a full, more detailed, version. The size thresholds are determined by an EU directive.[27] A firm is classified as "large" if at least two of the following three criteria are exceeded: (i) 50 full-time equivalent employees, (ii) sales of €9 million, (iii) total balance sheet of €4.5 million. Otherwise, the firm is classified as "small", which means they are not required to report information on sales and intermediate inputs, but they are required to report value added, capital and employment. Around 90% of the firms in the Company Accounts data fall in this small category.

(iii) VAT declarations Comprehensive data on sales and inputs for large and small firms are provided by the NBB, taken from the quarterly VAT declarations, which the NBB annualized and made consistent with the reporting period of the annual accounts. The sales from the quarterly VAT declarations also include sales to final consumers and exports, as in the accounts data, and the intermediate inputs include material goods, raw materials and service inputs as well as imported inputs.

(iv) FDI survey The FDI survey is collected within the framework of the NBB annual survey on foreign direct investment, which it has to organize to comply with Belgium's statistical obligations to the international bodies of which it is a member (the IMF, the OECD, the European Commission, EUROSTAT, and the ECB). The survey is comprehensive, covering all incorporated firms in Belgium

27. EU directive 2013/34/EU, https://www.nbb.be/en/central-balance-sheet-office/drawing/size-criteria/size-criteria-companies

in which a non-resident holds at least 10% of the ordinary shares or voting rights, to identify inward foreign direct investment. The data include information on the country of origin of the parent firm that is investing and the direct and indirect participation in the Belgian firm.

The data also include information on outward FDI, by destination country, covering firms in Belgium with at least 10% of the ordinary shares or voting rights of an enterprise established outside of Belgium. In certain specific cases the ownership criterion of 10% of the ordinary shares or voting rights may be replaced by the possession of a significant influence over the management of the enterprise in the capacity of direct investor.

(v) International Trade data The international trade data are provided by the National Bank of Belgium and comprise transactions on intra-EU trade data collected by the Intrastat Inquiry, which is a compulsory survey firms are required to fill out. The extra-EU transactions data are provided by Customs. For the intra-EU trade, all transactions above €1 million for intra-EU exports and €0.4 million for intra-EU imports are reported. In the Customs data, all extra-EU transactions greater than €1,000 or whose weights are more than 1,000 kilograms are included. Since these thresholds were reduced in 2006, we keep to the pre-2006 thresholds throughout. The data report values and quantities at the level of the firm, by destination or source country, and by product classified at 8-digit CN.

A.2 Sample

Our baseline results are for the sample of firms in the accounts data that report non-missing full-time equivalent workers at the beginning of the sample period. About one percent of the firms are dropped due to missing employment data. Observations that report zero full-time equivalent employment (i.e. the self-employed) are not included because we cannot estimate TFP for those observations, accounting for 55 percent of the firms. These firms had average annual sales of 0.26 million euros. We also drop any firm that does not appear as a seller (firm i) in the B2B data, as our objective is to understand whether selling to superstar firms generates spillovers. That drops 5.2 percent of the sample, most of which are very small firms accounting for only 3.7 percent of total employment, as shown in the top panel of Table A1. For our event study analysis, we include industry by year fixed effects, so we require each firm's main industry in order to be included in the sample. Finally, since our main interest is in estimating TFP spillovers, we drop any firm for which we cannot calculate their TFP. We lose 5.2% of firms because of missing TFP, which is mostly due to zero employment but also some additional ones due to zeros or missing values on capital or value added. After all this cleaning, we end up with an average of 120.2 thousand firms per year.

Each firm's main 5-digit NACE industry is recorded in the NBB, however, this varies by time due to changes in NACE revisions and changes in the firm's "main" industry. We assign a time-invariant 4-digit NACE revision 2 industry code based on the firm's most recent year in the sample. Using this approach, there were 4.6% firm's that were missing an industry code, which we were able to fill using the NBB's conversion from revision 1 codes (this reduces the missings to 2.6%) and then from Orbis.

This fills in the missing 4-digit NACE codes for all of the firms in our sample with non-missing initial employment.

Thee upper part of Table A1 shows the implications of the cleaning. Although the number of firms drops quite substantially from 364,500 employer firms to 132,690 firms in the analysis sub-sample (i.e. those from which we can obtain a TFP estimate), we cover 82.3% of all jobs (i.e. we lose only 17.7% of jobs). The lower part of the Table reports the summary statistics on this analysis sample which covers about 812,000 observations.The average firm has 4.4 FTE workers and has sales of 1.1 euros at the mean (and 1.8 and 350,000 euros at the median). TFP growth is about 2% per annum.

A.3 Variables

Total Factor Productivity (TFP) To estimate a value-added production function, we take the reported value added from the company accounts, defined as operating revenue minus intermediate inputs, which all firms report. Operating revenue includes sales, change in work and contracts in progress, capitalized own construction and other operating income. We also experimented with computing value added as sales minus intermediate inputs, using the data from the VAT declarations, which yielded very similar results.

The factors of production comprise full-time equivalent employment for labor and total tangible fixed assets for capital, both taken from the company accounts. Total intermediate inputs, which is used as the proxy variable in the control function approach to estimate TFP, are from the VAT declarations and are defined as purchases of services, of raw and auxiliary materials and of goods for resale. The wage bill, which is used as an alternative proxy for labor as a robustness is taken from the company accounts and refers to the total expenses a firm incurs for a worker, which includes direct costs, mainly gross wages, as well as various benefits, such as in-kind benefits, profit sharing and participation schemes.[28] For robustness, investment is used as a proxy variable in the control function instead of intermediate inputs to estimate TFP. Investment is obtained from the VAT declarations and refers to purchases of investment goods, such as machines, vehicles, and structures/buildings.

Another robustness we explore is to estimate TFP from an output-based production function, using total sales data reported in the VAT declarations, instead of the value-added production functions.

The TFP measures are estimated for each specific 2-digit NACE industry, as described below, and normalized relative to the mean firm within each 2-digit industry by year. We trim the TFP measures on the top and bottom percentiles.

Number of buyers (and "other buyers") The number of buyers for each firm i is calculated from the B2B data. From these data, we also calculate the number of superstar firms it starts to sell to at the time of treatment. This number is usually just one, but there are cases where a firm i starts to sell to more than one superstar firm in the same year. The number of other buyers is then just equal to the number of total buyers less the number of superstar buyers. To calculate the number of buyers

28. The indirect cost is mostly employer social security contributions, but also includes transport costs paid to the workers and training costs.

in the superstar's network, we use the B2B data to identify all of the superstar's buyers in the years before firm i is treated.

Total Sales (and "other sales") Total sales, from the VAT declarations, includes the sales in euros to other Belgium firms, final consumers located in Belgium, as well as exports. To calculate "other sales", we need to net out sales to treatment superstar firms. This is calculated using the B2B data, where we identify the first year the firm starts selling to a superstar firm and then calculate the sales to the superstar firm each year. This is subtracted from total sales to get the sales net of those sales to the superstar firm, which we use as an outcome in many specifications. As with the number of buyers, in the exceptional circumstance when a firm starts selling to more than one superstar for the first time, we define "other sales" as net of all sales to the superstar firm.

Research and Development expenditure (R&D) R&D expenditures are from ECOOM (KU Leuven)[29], collected through a bi-annual survey covering all firms which are known to have R&D projects. These are identified by a number of different approaches, including firms which have reported R&D costs in their annual company accounts, firms which have applied for patents, firms which have received tax credits for R&D expenditures, firms which received R&D subsidies, a list of R&D-active firms provided by technology employer federations, and a search in the general media. In addition, a stratified random sample of the general population of firms is included to detect potential other R&D-active firms. We include R&D expenditures as a share of total sales.

Information and Communication Technology expenditure (ICT) Firm level ICT spending is from Dhyne, Konings, et al. (2021). They construct ICT spending from the B2B VAT transactions data as follows. First, all firms that produce or sell ICT-related products or services are identified using their main four digit NACE sector code, as listed in Table A3. Second, using the B2B data, all of a firm $i's$ customers j are identified. The total ICT spending by each firm j is computed by taking the sum of all of firm j's purchases from all firm i's that are active in any of the ICT sectors. While the B2B VAT transaction data set provides information on domestic ICT spending for all Belgian firms, it does not include ICT imports. Thus, import data at the product-firm level (8-digit CN) are used to capture ICT purchases from abroad. The CN8 product code is used to identify ICT imports. We scale total spending on ICT by total purchases, which includes purchases from Belgium firms and foreign firms (i.e. imports).

Skilled Labor The number of employees, by level of education (university, higher education, secondary education, primary education), are sourced from the NBB social accounts data (a supplement to the annual financial accounts). We define the fraction of skilled workers as the number of employees with college education or higher as a share of the total reported employees (full-time equivalent). These data are only available from 2008 onwards, so we average these over 2008 to 2012.

29. https://www.ecoom.be/nodes/rd/en

Relationship Capability (RC) This is measured as simply the number of customers a firm has (following Bernard et al. (2022)).

Firm Age The firm's age is computed using the date of incorporation of the firm reported in ORBIS (BvD).[30] The age of the firm is then the year the firm is observed in the data minus the date of incorporation. We define a young firm as a firm which is less than or equal to five years old. For 32 firms a negative age is computed, which were checked (and corrected) using the Official Gazette of Belgium that provides the business registration details and deed of incorporation. These were typically older firms that changed either their legal status (e.g. into limited liability) or that changed their address.

Intangibles We compute intangible assets for each firm, from the B2B data, by tracing the purchases of each firm from firms in sectors that produce intangible assets. We follow Corrado et al. (2013) in classifying sectors that produce intangible assets. The capital stock for intangibles is built from a perpetual inventory method using a 30% depreciation rate (see Corrado et al. (2013) for a discussion). For the robustness tests on production function with intangibles (Appendix subsection D.3) we adjust the intermediate inputs variable used in the proxy variable in the control function by netting out purchases of intangible assets and we also adjust value added accordingly.

A.4 Persistency of serious and non-serious relationships

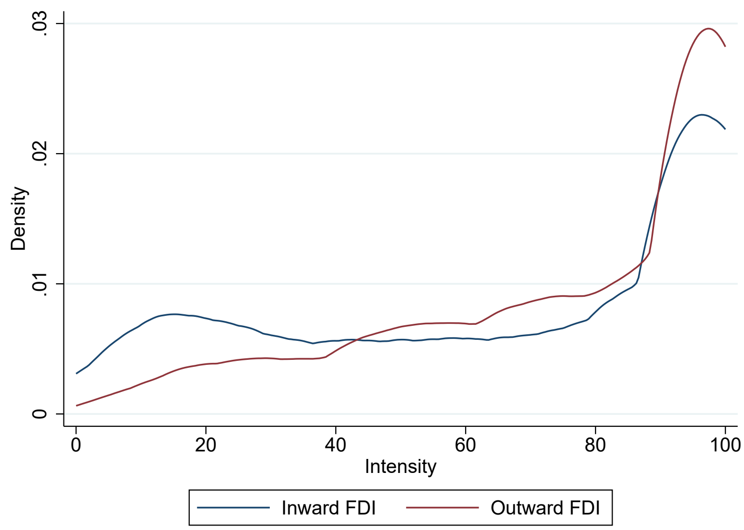
Our event study considers the impact of starting a serious relationship with a superstar firm, i.e. either an MNE, an exporter or a large firm. Recall that we defined a "serious" relationship as a firm that starts selling at least 10% of its total sales to a superstar firm. We focus on these serious relationships as the case study evidence suggests that spillovers are more likely to materialize when there is a long-term relationship. Thus we expect that such a serious relationship will survive longer as well and hence it should be more persistent over time than a non-serious relationship.

In Table A5a, we show the fraction of all new serious relationships which were formed with an MNE in a particular year t and that still exist in year $t + s$ (t = 2004,.., 2012; s = 1,2,...). In a few cases, a firm may form a new serious relationship with more than one MNE; we focus only on the relationship that has the largest sales with a particular MNE. We do the same in Table A5b for non-serious relationships. In this case, we define a non-serious relationship as a firm starting to sell to an MNE, but which does not exceed more than 10% of its total sales. If a firm starts selling to more than one MNE we keep the relationship with the lowest fraction of sales.

The cells in the table give the survival rates, i.e. the fraction of relationships that survive from year t to year $t+s$, as a fraction of all relationships formed in year t. For example, of the firms starting a serious relationship with a MNE in 2004, 57 percent of them still continue selling to this MNE t in 2005, 43 percent in 2006, etc.

30. https://www.bvdinfo.com/en-gb/

Figure A1: Kernel Density of MNE intensity



Notes: Inward FDI intensity is the equity capital share of inward FDI for all Belgium firms with nonzero foreign ownership. Outward FDI intensity is the capital share of outward FDI averaged over all foreign countries for all Belgium firms with nonzero ownership in foreign countries.

A comparison of the first row of these two tables for the 2004 cohort shows that the one-year survival rate is 57 percent for serious relationships (see column labeled "2005"), while it is only 40 percent for non-serious relationships, which is consistent with our priors. This is a very large difference of 17 percentage points, or 30% in relative terms (=17/57). By 2014, 9% of the 2004 cohort continue to supply this MNE for serious relations vs. 4% for non-serious relationships. This is only a five percentage point difference, but at 56% (=5/9) this is even larger than the initial 2005 persistency rate in relative terms. Our survival rate implies an average duration of 2.3 years of a new relationship formed at any time, which is comparable to the 2.7 years reported by Alfaro-Ureña, Manelici, and Vasquez (2022) for Costa Rica. Similar remarks could be made of the later cohorts.

We find very similar survival rates for relationships formed with exporters and large firms.

One issue with this analysis is that this could be due solely to the greater survival rates of firms who form serious relationships with an MNE compared to those who do not. Of course, this is part of the spillover benefits so we do not want to ignore it. However, as an exercise we conditioned in Tables A5c and A5d on firms that did not exit the economy after forming a MNE relationship. The persistence of serious relationships was found to be even higher among these firms. For example, of the firms starting a serious relationship with a MNE in 2004, 63 percent of them still continue to sell in 2005 and 17 percent still do so in 2014. In Table A5d we show the survival rate of non-serious relationship conditioning on firm survival. If we take the cohort of 2004, 43 percent of the sales relationship with a MNE persist one year later, while only 7 percent continue by 2014. This disparity in persistence rates between serious and non-serious relationships when conditioned on firm survival again confirms our priors that the threshold of 10 percent sales is a good indicator of the duration of a relationship.

Table A1: Summary Statistics–Sample and Cleaning

Sample cleaning

Sample	Average annual: N firms (thousands)	Average annual: Employment (millions)	Share of sample dropped: N firms	Share of sample dropped: Employment
Full sample NBB	368.19	1.90		
Sample after drop due to:				
firms missing initial emp	364.50	1.90	1.0	
observations with zero emp	160.35	1.90	55.4	
firms not in B2B	139.33	1.83	5.7	3.7
observations missing TFP	120.21	1.50	5.2	17.4

Summary statistics

Variable	P50	Mean	SD
$ln(TFP_{WR})$	-0.37	-0.40	0.67
$\Delta ln(TFP_{WR})$	0.03	0.02	0.44
Sales (millions euros)	0.35	1.07	17.71
Intermediate inputs (millions euros)	0.20	0.87	57.16
Wage bill (millions euros)	0.05	0.18	1.27
# buyers (hundreds)	0.05	0.16	0.60
Employment (FTE)	1.80	4.36	16.42
Total fixed assets (millions euros)	0.06	0.41	5.61
Export value (millions euros)	0.00	0.08	1.63
Export dummy	0.00	0.05	0.22
Export varieties	0.00	1.15	28.65
Import value (millions euros)	0.00	0.09	1.56
Import dummy	0.00	0.09	0.28
Import varieties	0.00	2.06	16.77
Firm survival	1.00	0.64	0.48
Intangible assets (millions euros)	0.00	0.05	2.23
Purchases (millions euros)	0.15	0.62	5.11
Operating profit (thousands euros)	13.95	40.39	113.25
Markup (accounting estimate): ratio of sales to materials	1.59	2.12	1.89
Markup (de Loecker and Warzynski (2012))	1.18	1.24	0.39

Notes: These descriptive statistics are based on our main analysis sample of firms with non-missing TFP (132,690 firms). The average number of observations is 811,645.

Table A2: Summary Statistics of Treated Firms pre- and post- treatment year vs. control Firms

	MNE			Exporters			Large		
Variable	Pre	Post	Control	Pre	Post	Control	Pre	Post	Control
$ln(TFP_{WR})$	-0.444	-0.266	-0.477	-0.449	-0.264	-0.436	-0.382	-0.219	-0.434
	(0.673)	(0.670)	(0.678)	(0.646)	(0.650)	(0.677)	(0.673)	(0.671)	(0.669)
Sales (millions euros)	0.832	1.854	0.610	0.820	1.328	0.678	1.345	2.337	0.766
	(4.048)	(50.774)	(3.023)	(9.163)	(10.134)	(6.562)	(5.640)	(9.776)	(2.845)
Intermediate inputs (millions euros)	0.637	1.335	0.492	0.617	1.843	0.510	1.052	1.853	0.590
	(3.355)	(9.759)	(30.743)	(8.834)	(201.429)	(29.473)	(4.688)	(9.142)	(24.879)
Wage bill (millions euros)	0.148	0.266	0.103	0.135	0.243	0.145	0.238	0.392	0.134
	(1.127)	(1.182)	(0.312)	(0.853)	(1.222)	(1.367)	(1.595)	(2.235)	(0.445)
# buyers (thousands)	0.006	0.020	0.011	0.005	0.014	0.009	0.009	0.027	0.015
	(0.010)	(0.091)	(0.023)	(0.007)	(0.033)	(0.019)	(0.016)	(0.157)	(0.031)
Total fixed assets (millions euros)	0.383	0.577	0.298	0.292	0.525	0.405	0.527	0.966	0.303
	(3.533)	(6.259)	(3.026)	(2.565)	(5.427)	(4.700)	(4.838)	(15.388)	(2.797)
Employment	4.144	6.021	2.920	3.782	5.519	3.596	5.934	8.051	3.553
	(23.264)	(19.950)	(7.775)	(17.852)	(19.532)	(14.130)	(30.556)	(32.189)	(9.503)
Age of firm	10.630	11.920	12.419	10.873	12.546	12.336	11.252	12.820	12.991
	(10.089)	(9.944)	(10.444)	(9.379)	(9.813)	(10.606)	(10.210)	(10.382)	(10.751)
Average N	33,038	86,306	405,277	24,616	56,015	447,709	29,060	63,666	623,069

Notes: The Pre columns report the value of each variable for treated firms for all years before treatment and the Post columns for the years of treatment i.e. $t1$ to $t5$. The Control column reports the average of the variables over the sample period for untreated firms. The standard deviations are reported in parentheses. The average N is the average number of observations across the different variables.

Table A3: ICT-Producing Industries

ICT type	NACE Rev 2 code	Description
IT goods	2620	Manufacture of computers and peripheral equipment
	4651	Wholesale of computers, computer peripheral equipment and software
	4741	Retail sale of computers, peripheral units and software in specialized stores
	5829	Other software publishing
IT services	6200	Computer programming, consultancy and related activities
	6201	Computer programming activities
	6202	Computer consultancy activities
	6203	Computer facilities management activities
	6209	Other information technology and computer service activities
	6311	Data processing, hosting and related activities
	6312	Web portals
Communication goods	2630	Manufacture of communication equipment
	4652	Wholesale of electronic and telecommunications equipment and parts
	4742	Retail sale of telecommunications equipment in specialized stores
Communication services	6110	Wired telecommunications activities
	6120	Wireless telecommunications activities
	6130	Satellite telecommunications activities
	6190	Other telecommunications activities

Notes: From Dhyne, Konings, et al. (2021). We use these industry definitions in the calculation of ICT purchases.

Table A4: Summary Statistics by Treatment Type

Total N	491,155		
Treatment type K:	MNE	Exporters (FX)	Large
N	3,928	4,260	491
Share of firms	0.80	0.87	0.10
Share of employment	33.01	17.70	21.44
Average employment	182	90	944
MNE intensity	77.37		
Export intensity (average)		45.51	
Out of treatment type K, share of:			
MNE		18.80	71.69
Large	8.96	3.71	
Exporter	20.39		32.18
MNE or Exporter			74.13
Large or Exporter	25.64		
Large or MNE		19.08	
High TFP (1 percentile)	13.72	4.20	46.03
Technology			
R&D top-10 percentile cutoff	0.328	1.394	0.924
ICT top-25 percentile cutoff	2.099	1.203	2.196
Skill labor top-25 percentile cutoff	66.667	26.376	68.205
Networks			
Median number of buyers	27	37	132
Mean number of buyers	441	115	1,588
Mean number in network as share of all potential buyers	0.019	0.008	0.139
Median sales (million euros)	0.109	0.042	0.384
Mean sales (million euros)	1.021	0.277	3.438
Relationship capital top-25 percentile cutoff	112.625	100.397	701.769

Notes: These are summary statistics broken down by the three types of "superstar firm" treatments we consider. "FX" denotes firms in non-wholesale sector that export at least 10% of their total sales.

Table A5: The Persistency of a Relationship with a MNE

(a) Serious Relationship with a MNE

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2004	1.00	0.57	0.43	0.35	0.29	0.23	0.20	0.17	0.14	0.12	0.09
2005		1.00	0.57	0.43	0.34	0.28	0.23	0.19	0.16	0.13	0.11
2006			1.00	0.56	0.41	0.32	0.26	0.22	0.18	0.16	0.12
2007				1.00	0.56	0.41	0.32	0.26	0.21	0.17	0.13
2008					1.00	0.58	0.43	0.34	0.28	0.22	0.18
2009						1.00	0.57	0.43	0.34	0.27	0.21
2010							1.00	0.57	0.42	0.32	0.23
2011								1.00	0.56	0.40	0.28
2012									1.00	0.52	0.36

(b) Non-Serious Relationship with a MNE

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2004	1.00	0.40	0.30	0.23	0.18	0.15	0.13	0.10	0.08	0.07	0.05
2005		1.00	0.40	0.29	0.22	0.18	0.14	0.12	0.10	0.07	0.06
2006			1.00	0.38	0.27	0.21	0.17	0.14	0.11	0.09	0.06
2007				1.00	0.39	0.28	0.22	0.18	0.14	0.11	0.08
2008					1.00	0.38	0.28	0.23	0.17	0.13	0.09
2009						1.00	0.37	0.26	0.20	0.15	0.10
2010							1.00	0.39	0.28	0.19	0.13
2011								1.00	0.36	0.23	0.15
2012									1.00	0.36	0.22

(c) Serious Relationship with a MNE, conditional on firm survival

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2004	1.00	0.63	0.50	0.43	0.38	0.32	0.28	0.25	0.23	0.20	0.17
2005		1.00	0.64	0.51	0.43	0.37	0.32	0.28	0.24	0.21	0.18
2006			1.00	0.61	0.49	0.40	0.35	0.31	0.27	0.24	0.20
2007				1.00	0.62	0.49	0.40	0.34	0.30	0.25	0.21
2008					1.00	0.65	0.52	0.43	0.37	0.32	0.27
2009						1.00	0.64	0.51	0.43	0.36	0.30
2010							1.00	0.63	0.50	0.41	0.32
2011								1.00	0.63	0.48	0.37
2012									1.00	0.61	0.46

(d) Non-Serious Relationship with a MNE, conditional on firm survival

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2004	1.00	0.43	0.33	0.27	0.22	0.19	0.16	0.14	0.11	0.09	0.07
2005		1.00	0.42	0.31	0.26	0.21	0.18	0.15	0.13	0.10	0.08
2006			1.00	0.40	0.31	0.25	0.21	0.17	0.14	0.11	0.08
2007				1.00	0.43	0.32	0.26	0.22	0.18	0.14	0.10
2008					1.00	0.42	0.32	0.26	0.20	0.16	0.12
2009						1.00	0.39	0.29	0.23	0.18	0.13
2010							1.00	0.41	0.30	0.22	0.16
2011								1.00	0.37	0.25	0.17
2012									1.00	0.38	0.24

Notes: The cells in the table give the survival rate of relationships formed with superstar firms, calculated as the number of relationships that survive from year t to year $t + s$ as a fraction of all relationships formed in year t.

B Econometric Details

B.1 TFP Estimation

Our baseline results focus on the effect of forming a new supplier-buyer relationship on the supplier's total factor productivity (TFP). To obtain TFP for firm i in year t, we start from a standard Cobb-Douglas production function:

$$Q_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} \tag{9}$$

where Q_{it} represents output, L_{it} and K_{it} are inputs, labor and capital, respectively, and A_{it} captures productivity in firm i and year t. Taking natural logarithms and using lower case letters to denote this (e.g. $q = logQ$) we obtain the following log-linear production function:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \varepsilon_{it} \tag{10}$$

$$ln(A_{it}) = a_{it} = \alpha_0 + \varepsilon_{it} \tag{11}$$

While α_0 is the mean efficiency level across firms and over time, ε_{it} is the time and firm specific deviation from that mean, which can be further decomposed into an observable and unobservable part, as follows:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + v_{it} + e_{it}, \tag{12}$$

with $\omega_{it} = \alpha_0 + v_{it}$ representing firm level productivity, and e_{it} is a white noise error term. The productivity term, ω_{it}, can be estimated by a control function using investment (i_{it}) as a proxy as in Olley and Pakes (1996) or intermediate inputs, (m_{it}), as in Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015). This function is specified as a third-order polynomial of the state variables, capital and productivity (k_{it} and ω_{it}). We also include indicator variables to indicate whether the firm is a multinational (MNE), its export (FX) and import status (FM), as follows:

$$m_{it} = f_t(\omega_{it}, k_{it}, FX, FM, MNE). \tag{13}$$

By inverting (13), productivity, ω_{it}, can be written in terms of observables. Our baseline estimates are obtained using the General Method of Moments (GMM) procedure proposed by Wooldridge (2009). We estimate production functions separately for each two-digit NACE industry (72 sectors). In our baseline approach, output is given by value added, capital is measured by tangible fixed assets and labor by the number of full-time-equivalent jobs in the firm. All specifications include year fixed effects, which capture unobserved price effects common to all firms in the same sector.

As robustness tests we also estimate productivity using various other approaches, in particular, Olley and Pakes (1996), Ackerberg, Caves, and Frazer (2015), and Collard-Wexler and De Loecker (2020) and using a translog specification. Following Hsieh and Klenow (2009), we also experimented with using the wage bill as a proxy for labor instead of the number of full-time-equivalent jobs, which captures skill heterogeneity as higher skilled workers tend to get paid higher wages.

Finally, we also estimated a gross output production function instead of a value-added production function following Gandhi, Navarro, and Rivers (2020). They show that when using proxy variable methods for estimating a gross output production function additional sources of variation in the demand for flexible inputs are required. They develop a new non-parametric identification strategy which regresses the flexible's input revenue share on all inputs (labor, capital and intermediate inputs) to identify the flexible input elasticity. The latter is used to identify the part of the production function that depends on the flexible input. A standard proxy variable approach as in Ackerberg, Caves, and Frazer (2015) is then used to identify the remaining coefficients on the other inputs.

B.2 Markup Estimation

We follow De Loecker and Warzynski (2012) to estimate firm level markups. The markup is given by the ratio of the output elasticity with respect to the flexible input in a production function and its (corrected) expenditure share. These are obtained from estimating the production function. To this end we use a gross output Cobb-Douglas type production function:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_l k_{it} + v_{it} + \epsilon_{it} \tag{14}$$

with $w_{it} = \alpha_0 + v_{it}$ representing firm level log productivity, and ϵ_{it} is a white noise error termWe estimate the productivity term, w_{it}, using a control function with investment as a proxy Olley and Pakes (1996). We use a third order polynomial of the state variables capital, labor and productivity and also add controls for the multinational, export and import status of the firm or

$$i_{it} = f_t(w_{it}, k_{it}, l_{it}, FX, FM, MNE). \tag{15}$$

Inverting (15) allows us to substitute out productivity w_{it} in (14) and we obtain:

$$q_{it} = \alpha_m m_{it} + \theta(i_{it}, k_{it}, l_{it}, FX, FM, MNE) + \epsilon_{it}. \tag{16}$$

Equation (16) can be estimated with OLS to obtain an estimate of α_m.To obtain the markup we need to divide $\hat{\alpha_m}$ by its expenditure share. However, as argued by De Loecker and Warzynski (2012), we do not observe the correct expenditure share, since we only observe $\tilde{q}_{it}$,which is given by $q_{it}e\hat{x}p(\epsilon_{it})$. By estimating (14) we obtain an estimate of ϵ_{it}. Thus the corrected expenditure share is given by

$$\hat{\beta}_{it} = \frac{m_{it}}{y_{it}e\hat{x}p(\epsilon_{it})}$$

.

The markup is then given by $\frac{\hat{\alpha_m}}{\hat{\beta_{it}}}$.

B.3 Control Function Approach: conditioning on shocks to firm i using Amiti and Weinstein (2018)

To construct the control variable in Table 3, we need an estimate of μ_{it} in equation (5), where the dependent variable is the percentage change in sales from firm i to firm j at time t. The right-hand side variables are firm i-year fixed effects and firm j-year fixed effects. In order to identify these coefficients, there must be a connected set of seller and buyer transactions, and the error term must satisfy $E[u_{ijt}] = 0$. The problem with using standard fixed effects regressions to estimate the coefficients is that the dependent variable is undefined for new trading relationships, i.e., a firm $i - j$ pair that trade in t but not in $t-1$, and the bias in the coefficients is increasing in the share of new trading relationships.

The Amiti and Weinstein (2018) methodology overcomes this problem by incorporating new trade relationships, estimating supply and demand shocks that exactly match the percentage change in aggregate sales. If there were no new relationships, the methodology collapses to weighted least squares estimation, with lagged sales weights (see Amiti and Weinstein (2018) Appendix A for proof). To provide some intuition for how the methodology works, it is useful to write the percentage change in a firm i's total sales to firm j, D_{it}, by summing equation (5) across all firm j;'s (that firm i sells to); and the percentage change in a firm j's total purchases, D_{jt}, can be obtained by summing equation (5) across all firm i to give us the following moment conditions:

$$D_{it} \equiv \frac{\displaystyle\sum_j Y_{ijt} - \sum_j Y_{ij,t-1}}{\displaystyle\sum_j Y_{ij,t-1}} = \mu_{it} + \sum_j \phi_{ij,t-1}\pi_{jt}, \text{with } \phi_{ij,t-1} \equiv \frac{Y_{ij,t-1}}{\sum_j Y_{ij,t-1}};$$

and

$$D_{jt} \equiv \frac{\displaystyle\sum_i Y_{ijt} - \sum_i Y_{ij,t-1}}{\displaystyle\sum_i Y_{ij,t-1}} = \pi_{jt} + \sum_i \theta_{ij,t-1}\mu_{it}, \text{with } \theta_{ij,t-1} \equiv \frac{Y_{ij,t-1}}{\sum_i Y_{ij,t-1}}.$$

These are $I + J$ equations in $I + J$ unknowns, which will produce unique μ_{it} and π_{jt} up to a numeraire. These adding-up constraints ensure that sales equal purchases, and the predicted values will exactly match aggregate sales at the seller level, buyer level, and year level. Note that the denominator in the first equation is firm $i's$ total sales, since it is summed across purchases from all the firm j that bought from that seller at time $t-1$; so new relationships that form between these firms at time t will still be included provided there was a sale from firm i to at least one firm j in $t-1$.

C A model of superstar spillovers

We consider a simple network model of superstar firms. The model endogenizes who forms relationships with superstar firms and examines the implications of productivity spillovers transferred to suppliers. We derive some empirical predictions in subsection C.5 and consider extensions in subsection C.6.

C.1 Set Up

There is a downstream sector where firms sell final goods to consumers and an upstream sector selling intermediate goods to this downstream sector. The upstream market operates under monopolistic competition. We partition the downstream sector into two groups of markets. There are K_1 markets where there is only a single monopolist k in each market (a "superstar" firm) and another K_2 markets which are all perfectly competitive. We assume that there are sufficiently large sunk costs of entering the superstar markets, such that only one (high productivity) firm can be supported in equilibrium. For example, a market might be dominated by a single large retailer and firm i 's are manufacturers (as in the WalMex model of Iacovone et al. (2015)). Or the superstar might be a multinational which has an effective monopoly in its home (foreign) market. Rather than endogenize this market structure we simply take this as given at Stage 0.[31]

The upstream market has N firms indexed $i = 1, ..., N$, where we assume that N is sufficiently large that we can abstract away from strategic oligopolistic interactions. each of whom produces a single variety. Firms have heterogeneous TFPQ, A, with the high TFPQ firms having lower marginal costs and therefore lower prices and higher output. Output Q is produced with a production function $Q = AL^{\alpha}$ where L are competitively supplied labor services[32] and $\alpha \leq 1$.

In Stage 1, upstream firms enter the economy and draw A from a known i.i.d. distribution, $\bar{F}(A)$. At Stage 2 there is an allocation over who will be the preferred suppliers of the downstream superstar firms. Apart from higher sales, the advantage of supplying a superstar is that firm i receives a productivity increase of γ, such that a firm with marginal cost c before forming a relationship with a superstar firm will have a marginal cost of γc afterwards, $\gamma < 1$. We think of this as the superstar working with the supplier to improve its productivity, but collapse this to an immediate benefit for simplicity. In the empirical work we study the dynamics of this process more explicitly. One could consider the downstream superstar firm as forming a relationship contract with suppliers (e.g. Gibbons and Henderson (2012)), whereas the competitive downstream markets are spot transactions.

We model the Stage 2 auction protocol as follows. Each superstar runs an auction with I firms, which are a (random) finite subset of all N upstream firms. For simplicity, we assume that firm i can only supply at most one superstar, and a superstar obtains all its intermediates from just one firm i supplier. The superstar firm offers a procurement contract where firm i must supply a quantity $\bar{Q}_k^{SS}$. We model this as the superstar having an auction for the right to supply.[33] Firms with superstar contracts supply both the superstar and the competitive markets, firms without superstar contracts just supply the competitive market.

31. It would be simple to endogenize this set up where the superstar markets have a high sunk cost and the competitive markets have zero sunk costs. Firms draw from a productivity distribution identical to the structure of the problem in the upstream market.

32. See Kroft et al. (2022) and Bernard et al. (2022) for ways of allowing for imperfect competition in the supply of labor and intermediates respectively.

33. We assume that the formal price per unit to the superstar is the same as is set to the non-superstar market, but that the auction determines the transfer the winning firm pays to the superstar for the right to supply. We think of this as the "revenue"(Z) a firm gets from the contract - see below.

To summarize, the structure of the game is as follows:

0. The number and identity of downstream superstar and competitive firms is determined

1. Upstream firms enter and draw costs

2. Firms bid to supply superstar firms in an auction process. The winners are determined and supply the superstars.

3. Upstream firms produce and supply the competitive downstream firms

As usual we solve Stage 3 first and work backwards.

C.2 Output market

Competitive firms price at marginal cost (which is the price charged by upstream firms for intermediate varieties plus a labor cost). Because of monopolistic competition with CES preferences, the elasticity of derived demand (and markups) facing the upstream firms will be constant. When the absolute elasticity of demand is $\eta > 1$, the upstream price cost margin is:

$$\frac{p_i - c_i}{p_i} = \frac{1}{\eta}, \tag{17}$$

where p is the upstream firms' product price. Profits are:

$$\pi_i = \widetilde{\eta} \left(\frac{1}{c_i} \right)^{\eta - 1}, \tag{18}$$

where $\widetilde{\eta} = \eta^{-\eta} (\eta - 1)^{\eta - 1} > 0$. Although margins are the same for all firms, low cost (higher TFP) upstream firms have higher profits because their sales are higher (although prices are lower quantities are higher).

C.3 Relationship Contracts with Superstar Firms

We model each supply contract to the superstar firm as a first price sealed bid auction. Firms choose bids considering their opportunity costs. The opportunity costs is the profit difference in the future spot market of *not* having a superstar relationship (π_{0i}^{SS}) compared to having one (π_{1i}^{SS}). Denote this opportunity cost $\sigma(\phi_i) = \pi_{0i}^{SS} - \pi_{1i}^{SS}$ where the subscripts emphasize that this difference will depend on TFP.

In the procurement auction, bidders observe common information about the size of the superstar contract, $\bar{Q}^{SS}$, the number of bidders, I and the distribution of TFP, A. As noted above, TFP is distributed $\bar{F}(.)$ and is i.i.d. which induces an i.i.d. distribution of opportunity costs $\sigma_i \sim F(.)$. Revenue from winning the auction is Z_i. The difference between the benefit and opportunity cost of winning the auction with bid Z is thus $Z_i - \sigma_i$. A firm with productivity A_i will choose the optimal bid to solve:

$$\max_{Z_i} (Z_i - \sigma_i) Pr(D_i = 1 | Z_i) \tag{19}$$

The first term is the payoff to winning the auction, which is increasing in Z, and the second term is the probability of winning the auction, which is decreasing in Z. Thus the firm faces the usual trade-off between profits if one wins and the probability of winning. The firm's optimal bidding strategy in the auction is (Milgrom and Weber (1982) and Maskin and Riley (1984)):

$$s_i = \sigma_i \delta_i;\ where\ \delta_i = 1 + \frac{\int_{\sigma_i}^{\bar{\sigma}} [1 - F(\bar{\sigma})]^{I-1} d\bar{\sigma}}{\sigma_i [1 - F(\sigma_i)]^{I-1}} \tag{20}$$

We can interpret $\delta_i \geq 1$ as the bid markup relative to the opportunity cost. When $\delta_i = 1$, each firms' optimal bid equals its opportunity cost, so each firm makes zero economic profit from receiving a contract. As the number of auction participants I declines, δ_i rises, so firms that receive contracts extract greater profits when there is less competition. We might think the superstar can easily extract all the profits, but there are a finite number of local firms who can supply the specific input in the time frame that the superstar wants (and it might be a very trivial amount of the superstar's overall profit, so the procurement manager may not be incentivized to get a very large number of firms to participate). Since Z_i exceeds σ_i due to finite bidders I, and the bidding strategy is strictly increasing in the opportunity cost, equation (20) defines the unique symmetric equilibrium. The winner of the auction is determined as:

$$D_i = 1\{s(\phi_i) < s(\phi_{i'})\}, \forall i' \neq i\ such\ that\ i, i' \in \mathcal{H}$$

where $\mathcal{H}$ is the set of firms participating in the auction.

C.4 Some results

There are two benefits from contracting with a superstar firm in this model. First, the relationship will result in a TFP increase which will increase profits on all the non-superstar contracts (the opportunity cost, σ_i). Second, supplying the superstar firm itself generates revenue (this is what we have denoted Z_i).[34] Focusing on the first element, we know from equation (18) this is:

$$\widetilde{\eta} \left\{ \gamma^{1-\eta} \left(\frac{1}{c_i} \right)^{\eta-1} - \left(\frac{1}{c_i} \right)^{\eta-1} \right\} = \left(\frac{1}{c_i} \right)^{\eta-1} \widetilde{\eta}(\gamma^{1-\eta} - 1) \tag{21}$$

This expression is decreasing in marginal cost, c, as $(1-\eta)\widetilde{\eta}(\gamma^{1-\eta} - 1) < 0$.[35] In other words, high TFP firms will get a greater benefit from a superstar contract.[36]

In terms of our model, this enters into the opportunity cost and delivers the implication that low cost firms will be the ones who form contracts with a superstar. We would expect the suppliers of superstar firm to be higher TFP and larger even before they form contracts. If all firms could bid,

34. Since there is a reduction in marginal cost for the winner, this will also make it cheaper to supply the SS firm. This would give a further advantage to the low-cost firm, but we abstract from this for simplicity.

35. Note that $\frac{\partial \left(\widetilde{\eta}(\gamma^{1-\eta}-1)\left(\frac{1}{c_i}\right)^{\eta-1} \right)}{\partial c} = (1-\eta)\widetilde{\eta}(\gamma^{1-\eta} - 1)c_i^{-\eta}$. $\widetilde{\eta} > 0$ and $(1-\eta) < 0$ because $\eta > 1$.$\gamma^{1-\eta} > 1$ because $\gamma < 1$, so $(\gamma^{1-\eta} - 1) > 0$

36. This follows from the convexity of the profit function in marginal costs from equation (18): a small fall in marginal costs benefits a low-cost firm by more as their sales are higher so they get more total profits.

our model implies that the lowest cost firm will win. However, the set of bidders I is finite. If we model this as a random draw of I firms from all firms being invited to bid, the lowest cost firm in the participating set will win the auction.

C.5 Empirical Implications

Proposition 1. *Forming a relationship with a Superstar firm results in increases in (i) TFP, (ii) outputs (total sales, total sales to firms other than the multinational, more buyers), and (iii) inputs (intermediates, labor and capital).* The increase in TFP follows directly by assumption and leads to lower (firm specific) prices, which generates higher demand. To meet the higher output the firm must also use more inputs.

Proposition 2. *The firms who form superstar relationships will experience (i) a fall in price-cost markups and (ii) increasing profits.* Part (i) on margins follows from from the fact that price-cost markups are constant to non-superstars (equation 17), whereas they will be lower to the superstar firm due bidding more aggressively in the auction due to the spillover benefits (see equation (20)). Thus, the total margin (a weighted sum of both margins for the winning firms) will be strictly less than the margins of non-winners. Part (ii) on total profits is because a winning firm benefits from a higher number of sales to non-Superstar downstream firms (selling at the standard markup) which compensates for the lower markups on the Superstar contract (equation (18)). Profits for winners are strictly positive so long as the number number of bidders (I) is finite.

Proposition 3. *The firms who form relationships with a Superstar (i) have higher TFP; and (ii) are larger (as they have higher TFP).* This follows from equation (21).

The evidence for Proposition 1 was established in the main results section 5. The evidence for Proposition 2 is in subsection 6.1.1. The analysis of subsection 6.1.4 also confirms Proposition 3: firms who form serious superstar relationships also had higher TFP and were relatively larger prior to forming these relationships.

C.6 Extensions to the Basic Model

C.6.1 Technological know-how of Superstar Firms ("more to teach")

We consider several extensions to the basic model. First, we can relax the assumption that the productivity spillover γ is homogeneous across superstar firms. It is likely that the size of the spillover depends on the size of the know-how possessed by the superstar, so we consider $\gamma(T)$, where T is the technological know-how of the superstar firm. The magnitude of all the impacts in Propositions 1 and 2 will be larger the bigger is T. It is hard to accurately measure T, not least because we do not observe all the activities of superstars. However, we can use some proxies that are indicators of high technological intensity such as R&D, ICT and the use of high human capital employees. Table 1 shows that we see exactly this kind of heterogeneity in the data

C.6.2 Benefits from Learning from Superstar firms ("more to learn")

Under our argument that suppliers obtain technological know-how from superstars, we would expect this effect to be greatest from those firms who have most to learn. If the firm has higher intrinsic capability (i.e. high TFP), one would expect younger firms will be more amenable to learning compared to more established firms ("you can't teach old dogs new tricks"). This implies that young suppliers are likely to experience larger productivity spillovers than older firms. We confirm this in the paper looking at treatment effect heterogeneity with respect to firm i age (see Table D11).

C.6.3 Relationship Capability

Our model focuses on the benefits of productivity spillovers. As noted in the text, a recent literature stresses that superstar firms may have higher capability related to marketing and the acquisition/retention of customers. Bernard et al. (2022) refer to this as "relationship capability" (RC). An extension of their idea is that this RC may also spillover to suppliers. Following Bernard et al. (2022), using the number of customers a superstar has as a proxy for RC, subsection 6.2.1 shows that forming a link with a high RC superstar does have an especially strong effect on increasing other buyers and other sales (but does not, as we might expect) have an effect on productivity.

C.6.4 Dating Agency Effects

In addition to reducing suppliers' marginal costs through spillovers, superstar firms could provide other benefits. Since superstars have extensive networks, they might help reduce the cost of customer acquisition for suppliers by introducing them to other firms within the superstar's network. If this was the case, we would expect to see a particularly strong increase of "other buyers" within the superstar firm's network compared to potential customers outside the network. We detail how to calculate the odds of this by chance in Appendix subsection D.7 below. Subsection 6.2.2 shows that there is evidence for these dating agency effects in our data.

D Additional Results

This Appendix has some further results, many of which are referenced in the discussion in the main text.

D.1 Full Event Studies

Tables D1-D3 have the coefficients and standard errors on all the leads and lags that are visually illustrated in the event study Diff-In-Diffs in the main text in Figures 1-3.

D.2 Cohort-Specific Diff-In-Diff designs

Figures D1-D3 show the event studies using the Sun and Abraham (2021) approach for all our main outcomes for the three definitions of superstars.

D.3 Alternative Productivity Measures

Column (1) of Table D4 has our baseline results which we simplify to an effect in the year of the event and a dummy for all subsequent post-event years, as this captures the dynamic pattern reasonably well. The other columns replicate this specification but use alternative methods of calculating productivity. Column (2) measures labor input by the wage bill following Hsieh and Klenow (2009) (measuring workers in efficiency units based on their wage), instead of full-time equivalents as in the baseline of column (1). In column (3) we use the two-step method of Ackerberg, Caves, and Frazer (2015) (ACF) instead of our baseline Cobb-Douglas GMM approach and show the ACF translog version of this in column (4). In column (5) we use estimates from a gross output production function instead of a value-added function following the Gandhi, Navarro, and Rivers (2020) (GNR) method. In column (6) we use investment as the proxy control instead of intermediates as in Olley and Pakes (1996) (OP) and in column (7) deal with measurement error in the capital stock following Collard-Wexler and De Loecker (2020) (CWDL). Column (8) uses a simple levels OLS estimate of the production function to calculate TFP. Finally, in column (9), we re-estimate TFP using the Wooldridge approach as in column (1), but with an adjustment to the capital stock to also include intangible assets alongside tangible assets. Given our finding in Table D6, that firms purchase a lot more intangible assets after forming a relationship with a superstar firm, we check whether our baseline TFP results could be driven by the increase in intangibles.[37]

We continue to find positive and significant long-run effects across all 27 specifications. The exact magnitudes differ as we would expect, with the largest effects coming from the more general translog specifications (18 percent for MNE) and the smallest ones coming from the methods which do not control for endogeneity (e.g. OLS generates a 3.4 percent effect in column (8) for multinational superstars).

D.4 Further refinements to the definition of large domestic superstars

Table D5 probes the definition of large domestic superstars. We showed in the main text (Figure 4) that dropping multinationals from the set of very large firms did not alter the fact that we still observe spillovers. This is illustrated again in column (1) where we allow separate treatment effects for large domestics vs. large global superstars. The impact of a large domestic superstar is not smaller than a large multinational (if anything, it is somewhat larger: 9 percent vs. 6 percent). Since some of the non-MNE domestic firms are intensive exporting superstars, it could be that our results are driven by these type of firms. Column (2) removes these from the large domestic definition and includes them in the "large global" definition alongside multinationals. Note that this reduces the fraction of domestically treated firms from 2.8% in the first column to 2.7%. Nonetheless, the results are almost unchanged. Some domestic superstars may do indirect FDI, i.e. they do not have serious foreign

37. As noted in Appendix A above, we compute intangible assets for each firm, from the B2B data, by tracing the purchases of each firm from firms in sectors that produce intangible assets following Corrado et al. (2013). We adjust the intermediate inputs variable used in the proxy variable in the control function by netting out purchases of intangible assets and we also adjust value added accordingly.

ownership or overseas affiliates directly, but they are owned by a domestic firm which does have such an ownership structure. Column (3) further refines things by switching this group from domestic into global making the fraction domestic is only 1.7%. Again, the results remain robust with a significant effect of such narrowly defined domestic superstars. Some of these residual domestic firms are partially publicly owned. One could consider these to be non-superstars, so we also remove them and make them another category. The final column shows that the purely domestic, non-government superstars still create significant spillovers.[38]

D.5 Other Performance Outcomes

Tables D6 and D7 has a variety of other performance outcomes. Note that the positive effect on survival effects in column (1) of Table D6 implies that we are underestimating the full benefits of superstars because the event studies on productivity, etc. are conditional on being alive. We positive and significant effects on employment, tangible assets, intangible assets and total profits. Columns (5) and (6) show negative and significant effects on alternative measure of the price-cost margin, which is what our Appendix C model predicts (see the discussion in subsection 6.1.1).

D.6 Quality of Average Buyers

Table D8 shows that the average quality of buyers increases after forming a relationship with a superstar. We proxy for quality of buyers with the average number of suppliers that buyers have, average employment, sales, and buyers of the buyers in columns (1) to (4). In the last two columns we see a positive effect on the count of the number of other superstar buyers of the same type in column (5) and of all superstar types in column (6) that firm $i's$ buyers have. In other words, selling to a superstar firm increases the chances of selling to another superstar firm in the future.

D.7 Odds Ratio: Calculating the Probability of obtaining an in-network customer by random chance

In Table 2, we showed that the effect of treatment on the number of other buyers, split into number of buyers in the superstar firm's network and those not in the network. We interpreted this as a dating agency effect in subsection 6.2.2. In order to confirm that these results do suggest a disproportionately high chance of forming an in-network match, we have to calculate the odds that our treatment effects could occur random chance. The treatment effect on number of buyers in-network appears to be large relative to the number of firms in the superstar's network. For example, for multinationals in Table 2, the treatment effect is 1.2 vs. 0.94 (the mean number of in-network firms) compared to 3.6 vs.

38. An interesting finding is that this publicly owned group also create spillovers. It turns out that the bulk of this group are owned locally and are subject to strict rules over competitive tendering. Hence, they are likely to be under pressure to maintain high levels of efficiency (like other superstars they tend to have high levels of technology and skills). So it is plausible that they are able to transfer this know-how to suppliers. See footnote 8 for examples of large domestic private firms. An example of a large publicly owned firm is Aquafin (www.aquafin.be), which deals with waste water treatment/sewage, purifying household and industrial water a water distribution. They are engaged in various innovation projects.

11.3 (the mean number of out-network firms). However, this comparison underestimates the odds of forming an in-network relationship for two reasons. First, firms in the superstar's network tend to be larger and therefore seek more suppliers. Second (more subtly), we also identified a treatment effect on the quality of buyers as indicated, for example, by the average number of suppliers a firm has (see column (1) of Table D8). Both of these effects make the odds of getting supplying a firm in the superstar's network by random chance higher.

To explicitly calculate the odds ratio, consider an economy where there is a set $\mathscr{I}$ of J buyers denoted by $j = 1, ..., J$. Divide the set $\mathscr{I}$ into two groups, those in a superstar firm k network (i.e. the superstar k firm sells to firm j) and those who are not. There are $J_{SS=k}$ firms in the superstar firm's network and $J - J_{SS=k}$ who are out of the network. Denote the firms who supply these buyers in set $\mathscr{I}$ as S, and those who supply to firms in the network of SS firm k as $S_{SS=k}$. The number of suppliers per network firm is therefore $\frac{S_{SS=k}}{J_{SS=k}}$. Note that this is netting out the overlap supplier firms (i.e. if a firm supplies two different buyers in the network).

What is the probability that a buyer (we are thinking of a treated firm i) will be randomly matched with one of the $J_{SS=k}$ firms in the superstar firm's network (denote this $Pr(k)$)? If firms in the superstar network were identical to those outside, the probability would simply be $\frac{J_{SS=k}}{J}$. But as noted, in-network firms tend to have more suppliers. Hence, the probability of random match is this ratio multiplied by a weight reflecting the fact that in-network firms have more suppliers ($\frac{S_{SS=k}}{J_{SS=k}}$), or:

$$Pr(k) = \frac{J_{SS=k}}{J}(\frac{S_{SS=k}}{J_{SS=k}}) = \frac{S_{SS=k}}{J} \tag{22}$$

For example, if a firm gets five new buyers, the expected number of new buyers in a superstar k network is $5 \times Pr(k)$.

Now we come to the second consideration. Since the quality of in-network firms is higher than out-network firms, this further increases the chances of firm i supplying to an in-network after an exogenous increase in the number of other buyers. Denote the causal impact on the average quality of a new buyer as β_x and the differential quality of in-network vs. out-network firms as x. The calculations for $Pr(k)$ above need to uprated by $1 + \beta_x$ to reflect this. Denote this quality adjusted probability as $Pr(k')$:

$$Pr(k') = Pr(k)(1 + \beta_x x) = \frac{S_{SS=k}}{J}(1 + \hat{\beta}_x x) \tag{23}$$

To calculate the expected number of in-network buyers that could arise by random chance ($E(B^{in})$), we take the estimated treatment effect on the total number of buyers ($\hat{B}$) and multiply this by $Pr(k')$, i.e.

$$E(B^{in}) = \hat{B}Pr(k') = \hat{B}\frac{S_{SS=k}}{J}(1 + \hat{\beta}_x x) \tag{24}$$

The odds ratio is the treatment effect on the increase in the number of in-network buyers ($\hat{B}^{in}$) divided by the expected number of in-network buyers through random chance:

$$ODDS = \frac{\hat{B}^{in}}{E(B^{in})} = \frac{\hat{B}^{in}}{\hat{B}\frac{S_{SS=k}}{J}(1+\hat{\beta}_x x)} \tag{25}$$

To be concrete, take the example of superstar multinationals. The treatment effect on the increase in the number of in-network buyers ($\hat{B}^{in}$) is 1.231 from column (1) of Table 2 and reproduced in the third from bottom row of Table D9. The expected number from random chance from equation (24) is $\hat{B}\frac{S_{SS=k}}{J}(1+\hat{\beta}_x x)$ = 4.877*(13,662/319,369)*(1 + (0.252*0.75)) = 0.248 (given in second to last row of Table D9). All these numbers are given on different rows of column (1) in Table D9 which are taken either directly from the data or our econometric estimates (i.e. $\hat{\beta}_x$ comes from column (1) of Table D8; $\hat{B}^{in}$ and $\hat{B}^{out}$ are from columns (1) and (2) of Table 2 and $\hat{B} = \hat{B}^{in} + \hat{B}^{out}$). The Odds ratio of equation (25) is $\frac{\hat{B}^{in}}{E(B^{in})}$ = 1.231/0.248 = 4.96, which is given in the final row of Table D9 and in the last row of Table 2 in the main text. These imply that we would expect to see on average 0.25 new buyers from a superstar firm's network, whereas in reality we observe five times as many (1.2).

The other superstar treatments are calculated in the same way in Table D9 and also suggest substantially larger effects on obtaining more in-network than out-network buyers as discussed in subsection 6.2.5.

D.8 Superstar Entry

Table D12 holds the results for the superstar entry design used in subsection 7.3. Here we use only connections to firms who become superstars in the previous period to identify the spillover effects.

D.9 Matched Control Group

In our baseline approach, the control group includes all other firms which did not form a new relationship with a superstar firm. As another robustness check we use an alternative control group of non-treated firms, by applying a matching approach. In particular, we use nearest neighbor matching procedure, which selects the closest possible control firm to be paired with each treated firm.[39] We use the multi-variate Mahalanobis distance[40] to find close matches on the basis of the pre-treated average values of employment, tangible fixed assets and average wages. We use exact matching, that is each treated firm is matched to exactly one control firm. Since the treatment period varies per treated firm, we implement this procedure separately for each treatment period and firm. We also require that matches take place between firms operating within the same NACE two-digit sector. We experimented also with matching on other variables, such as TFP, as well with non-exact matching, yielding very similar results. As noted in the main text, Table D14 contains the results, which are remarkably similar to the main results even though the sample is much smaller than the baseline sample.

39. For an overview of different evaluation methods and matching procedures including nearest neighbor see Imbens and Wooldridge (2009).

40. This is a multivariate distance measure, which computes how many standard deviations an observation (vector of characteristics) is away from another observation.

D.10 Alternative Thresholds for what counts as a "serious relationship"

There are a variety of assumptions we have had to make to define a superstar relationship, so it is reasonable to want to make sure that our results do not hinge on any arbitrary choices. Our main results define a serious relationship if a firm starts selling at least 10% of its sales to a superstar. We wanted to have an ex-ante definition to screen out the smaller transactions that are unlikely to confer any of the benefits of a longer relationship and 10% is the cut-off used by the US SEC in defining a market-relevant supplier that must be disclosed.

Table D15 shows various alternative thresholds to 10% from anything at all (">0") to greater than 1%, 5%, 15%, 20% and 50%.

The results are robust across all specifications, showing significant and positive treatment effects of similar magnitudes regardless of exact cut-off. Two remarks can be made, however. First, there is a tendency of the magnitudes of the treatment effects to increase as the "seriousness" of the relationship increases as indicated by the sales share. For example, for very large superstars the treatment effect on TFP is 8 percent for a sales share of at least 50% (column (1)) compared to five percent for any sales to a superstar (column (6)). Secondly, we also check for pre-trends evidence. There is evidence for significant negative coefficients on the pre-trend indicator in column (1) when we consider any sales to a superstar (in all three panels), whereas there is no systematic evidence of pre-trends for the higher thresholds. This indicates that for the most liberal definition, we have evidence that firms who were on positive TFP trajectories were more likely to start selling to a superstar. This makes sense: firms who are doing well may well start selling more to all types of firms including superstars. Being able to form a serious relationship with a superstar is a much rarer and more difficult event, and be likely to be driven by shocks to the superstar j, rather than the local firm i. This is the formal IV strategy we pursue in subsection 7.2, but Table D15 suggests that our 10% threshold helps screen out these more endogenous relationships, and effectively balance the pre-trend between treatment and control.

D.11 Multinational Definition and country of origin

Table D16 explores some alternative definitions of multinational superstar. Recall that in our baseline results we define a MNE if it has inward (i.e. foreign owned) or outward (i.e. domestically owned but with overseas affiliates) FDI. Column (1) considers only inward FDI and column (2) only outward FDI. We see essentially identical sets of results to the pooled definition. Next, recall that we used a 10% ownership threshold for inward and outward FDI. This is conventional in accounting and academic work, but is somewhat ad hoc. Figure A1 shows that nothing much is likely to hinge on this as the kernel density of ownership has a large mass near 100%. Nevertheless, column (3) uses a 50% cut-off instead of 10% and shows near-identical results, as expected. Column (4) includes inward FDI with little change. In the final column we break down the country of ownership. We do this for four large blocks: the US, EU, other developed countries and less developed. American multinationals confer the largest benefits (9.4%) and less developed countries the least (5.2%). EU and other developed are in between with 7% and 8%. This makes intuitive sense: US superstar firms have more know-how that can be transferred than those from poorer countries, so should confer larger benefits, which is what we see (in line with Bloom, Sadun, and Van Reenen (2012)).

D.12 Other thresholds for non-multinational superstars

Table D17 explores alternative thresholds for non-multinational superstars. Column (1) includes wholesalers in the definition of exporting superstars. We dropped these from the baseline results, as it is not clear we should treat wholesalers as superstar exporters. There are not that many of them, so the results do not change much. As with multinationals we defined an intensive exporter as one who had 10% or more of its sales sold overseas. Columns (2)-(4) flex this from any exporting to over 50% exporting and finds robust results. Column (5) examines whether there is heterogeneity in the effects of exporting superstars based on where the firm is exporting to. We do not find much systematic effects here. Column (6) changes the definition of a very large superstar to be in the top 0.2% of the sales distribution instead of our baseline 0.1% with little change to the basic results. The final column uses firms in the top 0.2% of the TFP distribution to define superstars (so productivity instead of size). Unsurprisingly, since these are highly correlated, the results are similar to baseline.

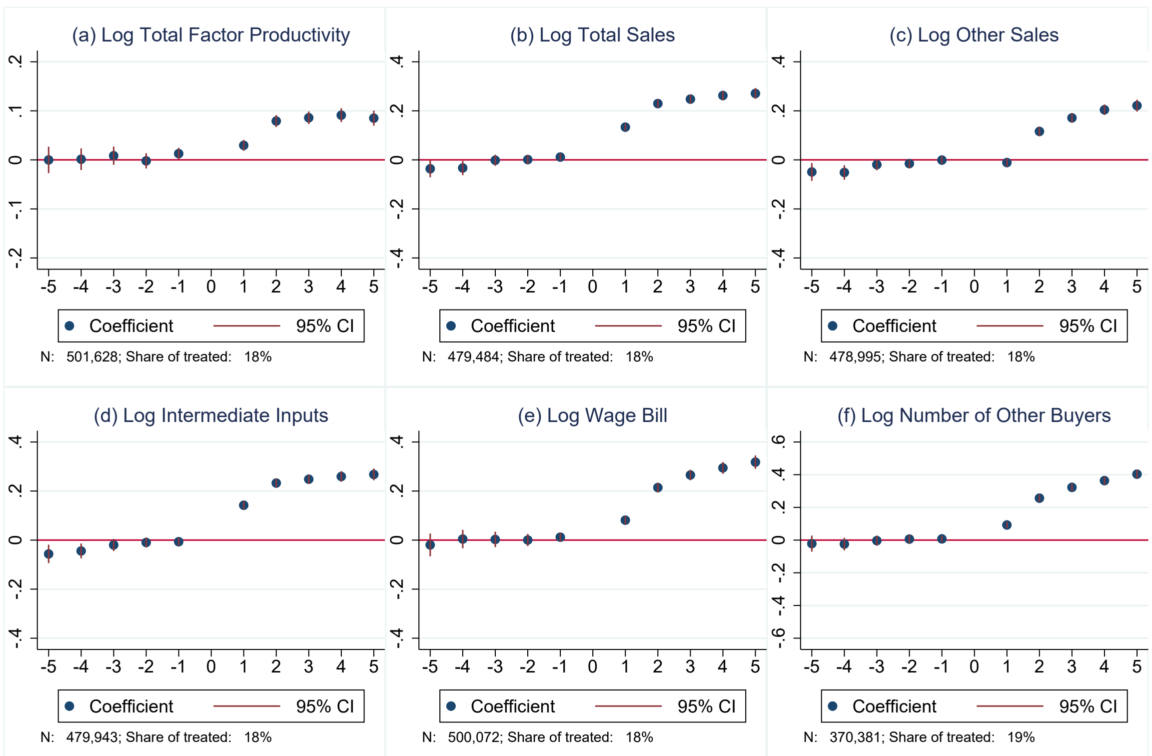
D.13 Samples

Table D18 examines a variety of alternative sampling assumptions. We show robustness to dropping firms with low levels of initial employment (columns (1)-(3)). Our baseline approach drops firms who formed non-serious relationships (i.e. under 10 percent of sales) with superstars, so instead column (4) includes them in the control group. We also look at requiring firms to only have a minimum of one pre- and post-event year of data (instead of the two years pre and post as in the baseline) in column (5). The baseline approach drops firms who are not in the B2B data. Column (6) adds these back into the control group. We dropped wholesalers in our baseline sample and column (7) adds these back in. None of these had a material effect on the results. One robustness test that did cause a change in the treatment effect was conditioning on the balanced panel, where we estimate on the subsample where a firm has to be alive throughout the 2002-2014 period in column (8). We still identify significant treatment effects in all cases, but these fell somewhat in magnitude (e.g. from 7% to 5% for multinational superstars). This is consistent with the larger treatment effects we found for young firms in subsection 6.1.3. The balanced panel drops all the young firms - exactly those who have most to learn from superstars.

D.14 Business Stealing

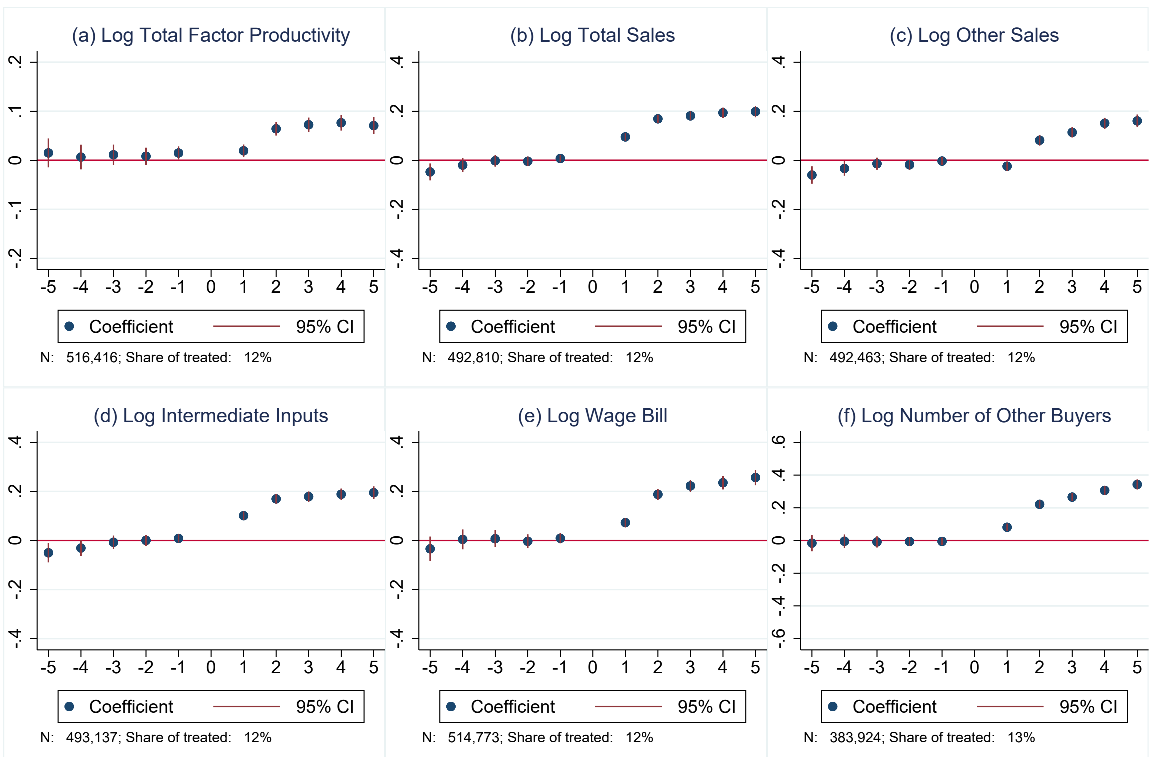
Table D19 simplifies the basic specification. Instead of including a full set of industry by year fixed effects, we instead just include linear industry and linear year fixed effects. The results do not change much from the baseline specifications

Figure D1: Gains from selling to MNE's, Robustness using Sun and Abraham (2021) approach



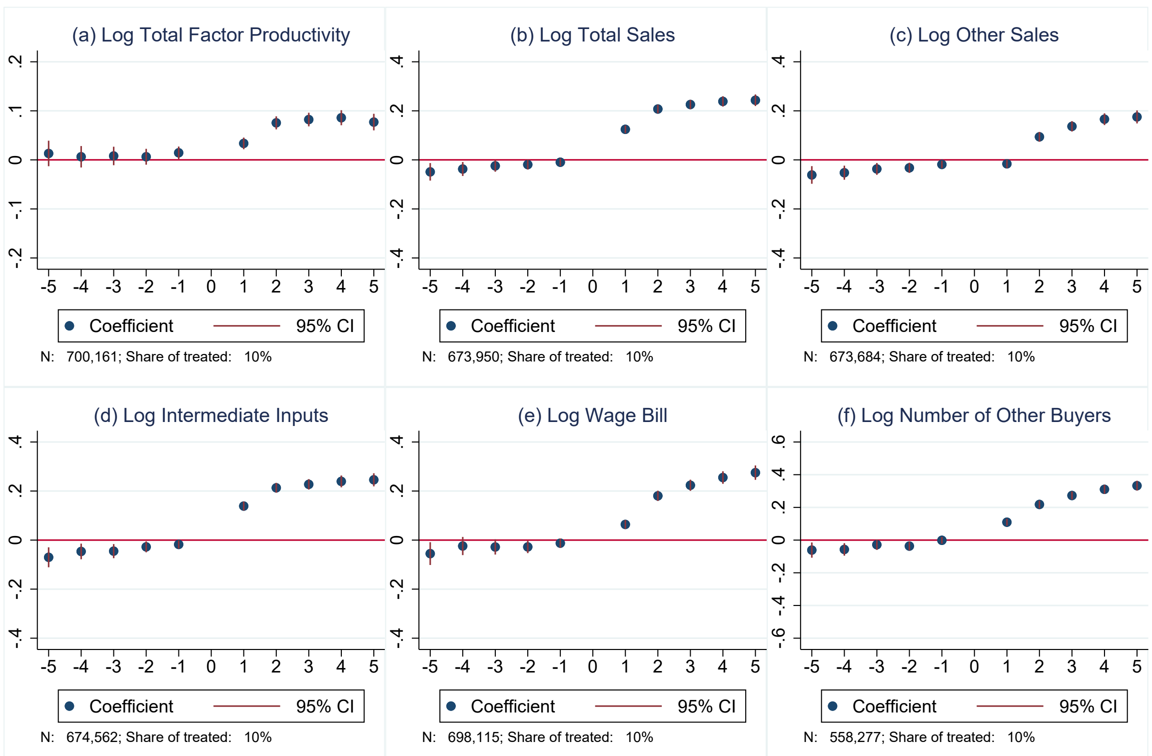
Notes: Regressions are specified as in the baseline Figure 1 but using the robust difference-in-differences estimator from Sun and Abraham (2021). The horizontal axis indicates the year firm i starts selling to an MNE, defined as a firm located in Belgium with at least 10% inward or outward foreign ownership, with $t = 1$ indicating the treatment year. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. Panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of MNE treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is the log of number of buyers net of MNE treatment firms.

Figure D2: Gains from selling to Exporting Firms, Robustness using Sun and Abraham (2021) approach



Notes: Regressions are specified as in the baseline Figure 2 but using the robust difference-in-differences estimator from Sun and Abraham (2021). The horizontal axis indicates the year firm i starts selling to an exporting firm, where exporter is defined as a firm located in Belgium, not in the wholesale industry, that exports at least 10% of its sales, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. Panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of exporter treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is log number of buyers net of exporter treatment firms.

Figure D3: Gains from selling to Large Firms, Robustness using Sun and Abraham (2021) approach



Notes: Regressions are specified as in the baseline Figure 3 but using the robust difference-in-differences estimator from Sun and Abraham (2021). The horizontal axis indicates the year firm i starts selling to a large firm, where large is defined as the top 0.1 percentile according to total sales, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative to the untreated, with the 95% confidence interval. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. Panel (a) is the log of TFP estimated using Wooldridge (2009) methodology, (b) is the log of total sales, (c) is the log of total sales net of large treatment firms, (d) is the log of intermediate inputs, (e) is the log of wage bill, and (f) is the log of number of buyers net of large treatment firms.

Table D1: Links to Multinationals (MNE's) - Full regression results

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
t-5: 6 years before event	0.000	-0.023	-0.041**	-0.046***	-0.014	-0.010
	(0.013)	(0.016)	(0.017)	(0.018)	(0.022)	(0.024)
t-4: 5 years before event	0.000	-0.024*	-0.048***	-0.037**	0.012	-0.011
	(0.010)	(0.014)	(0.014)	(0.015)	(0.018)	(0.019)
t-3: 4 years before event	0.009	0.003	-0.019*	-0.019	0.001	0.010
	(0.009)	(0.011)	(0.011)	(0.012)	(0.016)	(0.016)
t-2: 3 years before event	0.001	0.007	-0.010	-0.007	-0.000	0.014
	(0.008)	(0.009)	(0.010)	(0.010)	(0.013)	(0.013)
t-1: 2 years before event	0.013**	0.012	-0.000	-0.006	0.012	0.006
	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)
t1: Year of event	0.029***	0.134***	-0.011	0.143***	0.081***	0.092***
	(0.006)	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)
t2: 1 year after event	0.079***	0.230***	0.117***	0.233***	0.214***	0.256***
	(0.006)	(0.008)	(0.010)	(0.009)	(0.010)	(0.011)
t3: 2 years after event	0.086***	0.249***	0.172***	0.249***	0.265***	0.322***
	(0.007)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)
t4: 3 years after event	0.090***	0.260***	0.202***	0.256***	0.295***	0.361***
	(0.007)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)
t5: 4 years after event	0.085***	0.267***	0.219***	0.260***	0.318***	0.396***
	(0.007)	(0.011)	(0.012)	(0.011)	(0.013)	(0.013)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	501,628	479,484	478,995	479,943	500,072	370,381
Adjusted R^2	0.645	0.849	0.838	0.869	0.802	0.835

Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%. These are the full set of regression results underlying Figure 1.

Table D2: Links to Exporting Firms

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
t-5: 6 years before event	0.010	-0.036**	-0.053***	-0.043**	-0.025	0.011
	(0.014)	(0.016)	(0.017)	(0.018)	(0.023)	(0.024)
t-4: 5 years before event	0.006	-0.012	-0.031**	-0.024	0.007	0.012
	(0.012)	(0.014)	(0.014)	(0.015)	(0.019)	(0.020)
t-3: 4 years before event	0.013	0.000	-0.017	-0.008	0.001	0.004
	(0.010)	(0.012)	(0.012)	(0.013)	(0.017)	(0.017)
t-2: 3 years before event	0.007	-0.002	-0.017*	-0.000	-0.005	0.001
	(0.009)	(0.010)	(0.010)	(0.011)	(0.014)	(0.014)
t-1: 2 years before event	0.015**	0.008	-0.002	0.009	0.010	-0.005
	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.012)
t1: Year of event	0.019***	0.095***	-0.025**	0.101***	0.073***	0.082***
	(0.006)	(0.008)	(0.010)	(0.009)	(0.010)	(0.012)
t2: 1 year after event	0.064***	0.169***	0.082***	0.170***	0.188***	0.221***
	(0.007)	(0.009)	(0.011)	(0.010)	(0.012)	(0.012)
t3: 2 years after event	0.072***	0.181***	0.114***	0.179***	0.222***	0.266***
	(0.007)	(0.009)	(0.011)	(0.011)	(0.012)	(0.013)
t4: 3 years after event	0.077***	0.190***	0.144***	0.184***	0.235***	0.297***
	(0.008)	(0.010)	(0.011)	(0.012)	(0.014)	(0.014)
t5: 4 years after event	0.071***	0.196***	0.156***	0.189***	0.257***	0.326***
	(0.009)	(0.011)	(0.013)	(0.012)	(0.015)	(0.015)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	516,416	492,810	492,463	493,137	514,773	383,924
Adjusted R^2	0.645	0.843	0.837	0.865	0.808	0.805

Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The mean of the Number of other buyers variable is 9.205. *** indicates significance at the 1% level, **5%, * 10%. These are the full set of regression results underlying Figure 2.

Table D3: Links to Large-Sales Firms

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
t-5: 6 years before event	0.009	-0.047***	-0.065***	-0.060***	-0.052**	-0.042*
	(0.012)	(0.017)	(0.017)	(0.019)	(0.022)	(0.022)
t-4: 5 years before event	0.004	-0.035**	-0.057***	-0.040***	-0.029	-0.040**
	(0.010)	(0.014)	(0.014)	(0.015)	(0.018)	(0.019)
t-3: 4 years before event	0.006	-0.024**	-0.041***	-0.044***	-0.030*	-0.019
	(0.009)	(0.012)	(0.012)	(0.014)	(0.015)	(0.016)
t-2: 3 years before event	0.007	-0.015	-0.030***	-0.024**	-0.027**	-0.029**
	(0.008)	(0.010)	(0.010)	(0.011)	(0.013)	(0.013)
t-1: 2 years before event	0.015**	-0.009	-0.018**	-0.017**	-0.012	-0.001
	(0.006)	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
t1: Year of event	0.034***	0.125***	-0.016*	0.139***	0.064***	0.110***
	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)
t2: 1 year after event	0.076***	0.208***	0.094***	0.213***	0.180***	0.219***
	(0.007)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)
t3: 2 years after event	0.082***	0.226***	0.137***	0.228***	0.224***	0.274***
	(0.007)	(0.009)	(0.011)	(0.011)	(0.012)	(0.013)
t4: 3 years after event	0.085***	0.238***	0.167***	0.234***	0.254***	0.305***
	(0.008)	(0.010)	(0.012)	(0.012)	(0.013)	(0.014)
t5: 4 years after event	0.077***	0.241***	0.177***	0.239***	0.272***	0.322***
	(0.008)	(0.011)	(0.013)	(0.013)	(0.014)	(0.014)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	700,161	673,950	673,684	674,562	698,115	558,277
Adjusted R^2	0.648	0.860	0.854	0.877	0.813	0.852

Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The mean of the Number of other buyers variable is 15.978. *** indicates significance at the 1% level, **5%, * 10%. These are the full set of regression results underlying Figure 3.

Table D4: Robustness of TFP to Alternative Ways of Estimating Production Functions

	WR (1)	WR with wagebill (2)	ACF (3)	ACF with translog (4)	GNR (5)	OP (6)	CWDL (7)	OLS (8)	WR with intangibles (9)
MNE									
t1: Year of event	0.022***	0.034***	0.007	0.062***	0.033***	0.014***	0.008	0.001	0.031***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)
1 or more years after event	0.075***	0.098***	0.041***	0.182***	0.054***	0.057***	0.061***	0.034***	0.069***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	532,790	532,786	532,790	532,790	508,177	532,790	532,646	532,790	519,251
Adjusted R^2	0.646	0.674	0.609	0.812	0.777	0.612	0.622	0.553	0.655
Exporters									
t1: Year of event	0.009	0.014**	-0.005	0.044***	0.020***	0.002	-0.005	-0.010	0.014**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)
1 or more years after event	0.059***	0.073***	0.031***	0.147***	0.039***	0.043***	0.045***	0.024***	0.054***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.004)	(0.006)	(0.007)	(0.006)	(0.006)
Observations	537,247	537,244	537,247	537,247	511,548	537,247	537,155	537,247	523,279
Adjusted R^2	0.645	0.679	0.606	0.819	0.718	0.607	0.618	0.542	0.656
Large									
t1: Year of event	0.026***	0.036***	0.011*	0.066***	0.040***	0.018***	0.009	0.005	0.033***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
1 or more years after event	0.069***	0.089***	0.038***	0.165***	0.057***	0.053***	0.053***	0.031***	0.059***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	723,803	723,794	723,803	723,803	695,295	723,803	723,596	723,803	707,682
Adjusted R^2	0.649	0.681	0.609	0.819	0.774	0.613	0.625	0.554	0.659

Notes: Column (1) is our baseline method using TFP estimated from the Wooldridge (2009) methodology in panel (a) in figures 1, 2, and 3, with the only difference being that we pool all periods after the first year into one coefficient, and we do not include pre-treatment indicators. The subsequent columns are all the same as this, but replace the baseline TFP with alternative measures: (2) Wooldridge with the wage-bill instead of employment; (3) Ackerberg, Caves, and Frazer (2015) (ACF) with Cobb-Douglas; (4) ACF with translog; (5) Gandhi, Navarro, and Rivers (2020) (GNR); (6) Olley-Pakes (OP); (7) Collard-Wexler and De Loecker (2020) CWDL; (8) OLS; (9) Wooldridge with intangible assets included in the capital stock. All these measures are in logs. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D5: TFP gains from selling to Large Domestic Firms

	Exclude the following firms from large domestic definition:			
Dependent Variable: Log Total Factor Productivity	MNE (1)	& exporters (2)	& indirect MNE (3)	& govt. (4)
Large domestic, t1: Year of event	0.021* (0.012)	0.021* (0.012)	0.026* (0.016)	-0.034 (0.027)
Large domestic, 1 or more years after event	0.092*** (0.012)	0.092*** (0.012)	0.097*** (0.015)	0.081*** (0.025)
Large global, t1: Year of event	0.026*** (0.007)	0.026*** (0.007)	0.024*** (0.006)	0.024*** (0.006)
Large global, 1 or more years after event	0.062*** (0.006)	0.063*** (0.006)	0.065*** (0.006)	0.065*** (0.006)
Large govt., t1: Year of event				0.062*** (0.019)
Large govt., 1 or more years after event				0.105*** (0.019)
Firm FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Percentage of treated large domestic	2.79	2.73	1.68	0.66
Observations	723,803	723,803	723,803	723,803
Adjusted R^2	0.648	0.648	0.648	0.648

Notes: These specifications are the same as in Figure 4, panel (a) with alternative definitions of large, domestic firms. Column (1) defines large, domestic firms as those large firms that are non-MNE, as in Figure 4. Column (2) defines large, domestic firms as those large firms that are non-MNE and non-exporting. Column (3) defines large, domestic firms as those large firms that are non-MNE, non-exporting, and non-indirect-MNE. Column (4) defines large, domestic firms as those large firms that are non-MNE, non-exporting, non-indirect-MNE, and non-government. TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D6: Gains from selling to Superstars on other Performance Outcomes

	Firm survival	Log employment	Log tangible fixed assets	Log intangible assets	Log markup	Log sales / to materials	Profits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MNE							
t1: Year of event	0.049***	0.071***	0.119***	0.305***	-0.011***	-0.036***	0.523
	(0.002)	(0.008)	(0.012)	(0.030)	(0.001)	(0.008)	(0.827)
1 or more years after event	0.053***	0.207***	0.200***	0.345***	-0.015***	-0.031***	7.813***
	(0.002)	(0.009)	(0.015)	(0.031)	(0.001)	(0.008)	(0.885)
Observations	999,051	527,874	531,492	523,019	402,843	415,681	532,790
Adjusted R^2	0.548	0.794	0.804	0.603	0.814	0.799	0.634
Exporters							
t1: Year of event	0.048***	0.055***	0.120***	0.225***	-0.006***	-0.035***	-1.291
	(0.002)	(0.010)	(0.014)	(0.036)	(0.001)	(0.009)	(0.915)
1 or more years after event	0.061***	0.162***	0.175***	0.265***	-0.010***	-0.017*	6.491***
	(0.003)	(0.011)	(0.017)	(0.036)	(0.002)	(0.009)	(0.936)
Observations	995,190	532,138	536,034	526,845	409,354	413,660	537,247
Adjusted R^2	0.550	0.801	0.805	0.613	0.815	0.798	0.635
Large							
t1: Year of event	0.046***	0.071***	0.131***	0.281***	-0.011***	-0.051***	0.514
	(0.002)	(0.009)	(0.013)	(0.032)	(0.001)	(0.009)	(1.160)
1 or more years after event	0.051***	0.190***	0.197***	0.299***	-0.013***	-0.038***	8.532***
	(0.003)	(0.010)	(0.016)	(0.033)	(0.001)	(0.009)	(1.205)
Observations	1,315,233	717,452	722,150	712,544	560,041	576,211	723,803
Adjusted R^2	0.549	0.806	0.803	0.610	0.813	0.800	0.634

Notes: These specifications are the same as in Table D4 except with a different outcome variable as the dependent variable. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. In column (1), the firm survival variable is defined as equal to one for all years the firm is in the sample and zero for all subsequent years. The mean of the firm survival variable is around 0.886. We add 1 before logging in column (4). In column (5), markups are calculated following De Loecker and Warzynski 2012 (see text). In column (6), markups are the accounting method of Antràs, Fort, and Tintelnot 2017, wherein sales comprise all sales, both domestic and foreign. In column (7), profits are in thousands of euros. The variables in columns (5) to (7) have been winsorized at the 1st and 99th percentiles.

Table D7: Gains from selling to Superstars: International Trade Outcomes

	Export value (1)	Export dummy (2)	Export varieties (3)	Import value (4)	Import dummy (5)	Import varieties (6)
MNE						
t1: Year of event	-0.001	0.004**	0.097	-0.015	0.009***	-0.045
	(0.006)	(0.002)	(0.076)	(0.014)	(0.002)	(0.123)
1 or more years after event	0.049***	0.012***	0.277***	0.040***	0.022***	0.306**
	(0.009)	(0.002)	(0.088)	(0.011)	(0.002)	(0.154)
Observations	532,790	532,790	532,790	532,790	532,790	532,790
Adjusted R^2	0.907	0.668	0.851	0.803	0.630	0.748
Exporters						
t1: Year of event	-0.001	0.001	-0.141	0.002	0.004*	0.156
	(0.001)	(0.002)	(0.201)	(0.005)	(0.002)	(0.115)
1 or more years after event	0.005	0.005***	-0.442	0.016**	0.013***	0.334***
	(0.004)	(0.002)	(0.580)	(0.006)	(0.002)	(0.122)
Observations	537,247	537,247	537,247	537,247	537,247	537,247
Adjusted R^2	0.627	0.515	0.319	0.729	0.536	0.738
Large						
t1: Year of event	0.041**	0.007***	0.245**	0.032*	0.011***	0.131
	(0.016)	(0.002)	(0.119)	(0.016)	(0.003)	(0.125)
1 or more years after event	0.117***	0.014***	0.464**	0.118***	0.024***	0.678***
	(0.022)	(0.002)	(0.191)	(0.023)	(0.003)	(0.171)
Observations	723,803	723,803	723,803	723,803	723,803	723,803
Adjusted R^2	0.826	0.684	0.752	0.784	0.663	0.767

Notes: These specifications are the same as in Table D4 except with a different outcome variable as the dependent variable. The dependent variable in column (1) is export value in million of euros; in column (2) a dummy equal to 1 if the firm is an exporter in period t; and in column (3) the number of varieties exported, defined at the country-HS8 level. Columns (4) to (6) report the parallel regressions for imports. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D8: Effects on Average Buyer Quality

	Average				Count	
Dependent variable:	Log suppliers (1)	Log employment (2)	Log sales (3)	Log buyers (4)	Other SS buyers (5)	All other SS buyers (6)
MNE						
t1: Year of event	0.011	0.002	-0.013	-0.010	-0.547***	-0.498***
	(0.010)	(0.018)	(0.020)	(0.018)	(0.030)	(0.045)
1 or more years after event	0.252***	0.540***	0.629***	0.336***	0.582***	0.837***
	(0.010)	(0.019)	(0.021)	(0.018)	(0.034)	(0.064)
Observations	397,129	370,108	390,615	383,124	397,129	397,129
Adjusted R^2	0.616	0.618	0.609	0.522	0.711	0.762
Exporters						
t1: Year of event	0.019	0.024	0.036	0.072***	-0.322***	-0.302***
	(0.013)	(0.025)	(0.028)	(0.023)	(0.024)	(0.038)
1 or more years after event	0.124***	0.265***	0.331***	0.191***	0.430***	0.700***
	(0.013)	(0.024)	(0.027)	(0.022)	(0.028)	(0.055)
Observations	401,859	375,051	395,021	387,596	401,859	401,859
Adjusted R^2	0.619	0.623	0.606	0.529	0.668	0.725
Large						
t1: Year of event	0.037***	0.051***	0.044**	0.039**	-0.264***	-0.058
	(0.010)	(0.019)	(0.020)	(0.018)	(0.019)	(0.105)
1 or more years after event	0.203***	0.431***	0.577***	0.315***	0.393***	1.093***
	(0.010)	(0.019)	(0.022)	(0.018)	(0.019)	(0.115)
Observations	579,068	549,441	571,482	563,779	579,068	579,068
Adjusted R^2	0.628	0.618	0.609	0.524	0.723	0.770

Notes: These specifications are the same as in Table D4 except the dependent variables depict different measures of the quality of the set of buyers that firm i sells to. The dependent variable in columns (1) to (4) represents the average characteristics of firm i's buyers in terms of log number of suppliers, average employment, sales, and number of buyers, respectively. In columns (5) and (6), it is the number of buyers that are superstar firms less firm i's superstar firms. In column (5) the superstar firms are defined as a specific type K=MNE, exporter, large analogous to the treatment superstar, whereas column (6) includes the number of buyers that are of any superstar type. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D9: Odds Ratio

Treatment type k:	MNE	Exporter	Large
Total buyers (J)	319,369	319,369	319,369
Total number of in-network suppliers ($S_{SS=k}$)	13,662	8,340	26,262
Mean number of in-network suppliers	234.7	204.1	222.2
Mean number of out of network suppliers	134.0	165.9	130.2
Difference in quality (x)	75.2%	23.1%	70.6%
Casual effect on the average quality of a new buyer (β_x)	0.252	0.124	0.203
Total actual number of other buyers increase ($\hat{B}$)	4.877	3.006	6.953
Actual increase in number of in-network buyers ($\hat{B}^{in}$)	1.231	0.352	2.213
Estimated increase in number of in-network buyers ($E(B^{in})$)	0.248	0.081	0.654
Odds ratio	4.96	4.36	3.39

Notes: See Appendix D.7 for details. β_x comes from Column (1) of Table D8. $\hat{B}^{in}$ and $\hat{B}^{out}$ are from columns (1) and (2) of Table 2. $\hat{B} = \hat{B}^{in} + \hat{B}^{out}$

Table D10: Heterogeneity of Treatment Effects by Superstar Characteristics

Dependent variable:	Log Other Sales				Log TFP	Log Other Buyers	Log Other Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MNE							
1 or more years after event	0.068***	0.065***	0.062***	0.070***	0.045***	0.194***	0.095***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.016)	(0.016)
x R&D indicator	0.043***				0.032***	0.101***	0.067***
	(0.010)				(0.010)	(0.022)	(0.018)
x ICT		0.032***			0.019**	0.068***	0.025
		(0.009)			(0.009)	(0.018)	(0.016)
x Skill Share indicator			0.050***		0.042***	0.107***	0.049***
			(0.009)		(0.010)	(0.020)	(0.017)
x RC indicator				0.008	0.010	0.075***	0.057***
				(0.009)	(0.009)	(0.016)	(0.016)
Observations	532,790	532,790	532,790	532,790	532,790	397,129	509,146
Adjusted R^2	0.645	0.645	0.645	0.645	0.645	0.834	0.835
Exporters							
1 or more years after event	0.056***	0.056***	0.060***	0.056***	0.053***	0.193***	0.073***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.016)	(0.015)
x R&D indicator	0.022*				0.021	0.119***	0.108***
	(0.013)				(0.014)	(0.028)	(0.024)
x ICT indicator		0.010			0.008	0.012	0.023
		(0.010)			(0.011)	(0.020)	(0.018)
x Skill Share indicator			-0.001		-0.007	0.042**	-0.021
			(0.010)		(0.010)	(0.019)	(0.019)
x RC indicator				0.006	0.006	0.054***	0.063***
				(0.010)	(0.010)	(0.018)	(0.017)
Observations	537,247	537,247	537,247	537,247	537,247	401,859	512,795
Adjusted R^2	0.644	0.644	0.644	0.644	0.644	0.805	0.835
Large							
1 or more years after event	0.060***	0.062***	0.059***	0.075***	0.055***	0.197***	0.097***
	(0.006)	(0.007)	(0.006)	(0.008)	(0.009)	(0.017)	(0.016)
x R&D indicator	0.065***				0.056***	0.134***	0.080***
	(0.012)				(0.013)	(0.028)	(0.023)
x ICT indicator		0.019**			0.006	0.014	0.009
		(0.009)			(0.010)	(0.019)	(0.017)
x Skill Share indicator			0.042***		0.032***	0.109***	0.062***
			(0.011)		(0.011)	(0.023)	(0.020)
x RC indicator				-0.010	-0.007	0.060***	0.045***
				(0.009)	(0.009)	(0.018)	(0.017)
Observations	723,803	723,803	723,803	723,803	723,803	579,068	696,608
Adjusted R^2	0.648	0.648	0.648	0.648	0.648	0.850	0.851

Notes: Columns (1) to (4) are the parallel regressions to those in Table 1, replacing the dependent variable with log (other sales). Columns (5) to (7) include all four interactive indicator variables in the same regression. The dummy indicator variable in each column is as follows: (1) **"R&D"** equals 1 (and zero otherwise) if the superstar firm is in the top decile of research and development expenditure. (2) **"ICT"** equals 1 (and zero otherwise) if the superstar firm is in the top quartile of spending on information and communication technology as a share of total purchases (where total purchases includes purchases from all Belgium firms plus imports); (3) **"Skill labor"** equals 1 (and zero otherwise) if the superstar firm is in the top quartile of the skill share distribution, defined as the share of full-time-equivalent workers with a college degree; (4) **"RC"** equals 1 (and zero otherwise) if superstar firm is in the top quartile of Relationship Capability as measured by number of buyers. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D11: Treatment effects are larger for younger suppliers

	Log Total Factor Productivity	Log Total Sales	Log Other Sales	Log Intermediate Inputs	Log Wage Bill	Log Number of Other Buyers
	(1)	(2)	(3)	(4)	(5)	(6)
MNE						
1 or more years after event	0.034***	0.198***	0.133***	0.210***	0.179***	0.279***
	(0.006)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
x Young	0.127***	0.118***	0.104***	0.113***	0.166***	0.096***
	(0.008)	(0.011)	(0.014)	(0.012)	(0.015)	(0.013)
Observations	532,765	509,687	509,121	510,173	531,163	397,116
Adjusted R^2	0.646	0.851	0.835	0.869	0.804	0.834
Exporters						
1 or more years after event	0.032***	0.140***	0.090***	0.142***	0.144***	0.232***
	(0.007)	(0.010)	(0.011)	(0.011)	(0.013)	(0.013)
x Young	0.094***	0.115***	0.108***	0.109***	0.180***	0.109***
	(0.009)	(0.012)	(0.016)	(0.014)	(0.018)	(0.016)
Observations	537,206	513,172	512,754	513,507	535,534	401,824
Adjusted R^2	0.645	0.844	0.835	0.865	0.809	0.805
Large						
1 or more years after event	0.033***	0.190***	0.114***	0.204***	0.155***	0.251***
	(0.006)	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)
x Young	0.131***	0.144***	0.141***	0.132***	0.223***	0.108***
	(0.009)	(0.013)	(0.015)	(0.015)	(0.018)	(0.016)
Observations	723,763	696,879	696,568	697,507	721,679	579,037
Adjusted R^2	0.648	0.861	0.851	0.877	0.814	0.850

Notes: The Young indicator equals one if the age of the firm is less than or equal to five years. The dependent variable in each of the columns are defined as in the baseline regressions. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. In the regression sample for MNE, 31% of the treated firms are young firm observations; the share is 28% for the Exporters and Large samples. *** indicates significance at the 1% level, **5%, * 10%.

Table D12: Superstar Entry

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
MNE						
t1: Year of event	0.015	0.169***	0.034	0.162***	0.133***	0.122***
	(0.021)	(0.029)	(0.036)	(0.028)	(0.034)	(0.034)
1 or more years after event	0.061***	0.235***	0.175***	0.221***	0.226***	0.276***
	(0.020)	(0.032)	(0.037)	(0.032)	(0.038)	(0.035)
Observations	419,259	399,148	399,100	397,581	396,351	301,967
Adjusted R^2	0.644	0.847	0.845	0.875	0.794	0.846
Inward FDI						
t1: Year of event	0.001	0.144***	0.011	0.136***	0.120***	0.086**
	(0.022)	(0.030)	(0.038)	(0.028)	(0.037)	(0.036)
1 or more years after event	0.053**	0.225***	0.177***	0.212***	0.234***	0.244***
	(0.021)	(0.033)	(0.039)	(0.033)	(0.041)	(0.037)
Observations	418,252	398,180	398,137	396,618	395,390	301,104
Adjusted R^2	0.644	0.847	0.846	0.875	0.793	0.846
Exporters						
t1: Year of event	0.024	0.056**	-0.167***	0.049*	0.088**	0.029
	(0.023)	(0.028)	(0.053)	(0.029)	(0.041)	(0.034)
1 or more years after event	0.057**	0.124***	-0.061	0.086***	0.183***	0.151***
	(0.022)	(0.031)	(0.055)	(0.033)	(0.046)	(0.036)
Observations	461,409	438,610	438,565	436,867	435,492	335,192
Adjusted R^2	0.644	0.842	0.839	0.871	0.804	0.813

Notes: TFP is estimated using the Wooldridge methodology. In this Table, treatments are defined a firm i that starts selling at least 10% of its sales in t or $t+1$ to a firm j that has changed its status between t and $t-1$ to become a superstar. In the first panel the superstar entry is defined as a new inward or outward FDI of at least 10% in period t. In the middle panel, the superstar entry is defined just for inward FDI. In the lower panel, it is defined for exporting. The share of observations treated is 2% in the MNE panel and 1-2% in the FDI and Exporters panels. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D13: Effect of Ending Superstar Relationship

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
MNE						
1 or more years after event	0.106***	0.335***	0.175***	0.357***	0.331***	0.379***
	(0.006)	(0.010)	(0.013)	(0.012)	(0.012)	(0.014)
x End of relationship	-0.049***	-0.155***	-0.014	-0.174***	-0.155***	-0.113***
	(0.006)	(0.009)	(0.011)	(0.010)	(0.011)	(0.011)
Observations	532,790	509,712	509,146	510,198	531,188	397,129
Adjusted R^2	0.645	0.851	0.835	0.870	0.804	0.834
Exporters						
1 or more years after event	0.096***	0.271***	0.153***	0.272***	0.278***	0.333***
	(0.007)	(0.011)	(0.014)	(0.013)	(0.015)	(0.015)
x End of relationship	-0.056***	-0.149***	-0.048***	-0.149***	-0.126***	-0.108***
	(0.007)	(0.010)	(0.013)	(0.011)	(0.014)	(0.013)
Observations	537,247	513,213	512,795	513,548	535,575	401,859
Adjusted R^2	0.644	0.844	0.835	0.865	0.809	0.805
Large						
1 or more years after event	0.105***	0.338***	0.168***	0.357***	0.318***	0.357***
	(0.007)	(0.011)	(0.014)	(0.013)	(0.013)	(0.015)
x End of relationship	-0.060***	-0.179***	-0.026**	-0.195***	-0.171***	-0.132***
	(0.007)	(0.010)	(0.013)	(0.011)	(0.013)	(0.013)
Observations	723,803	696,919	696,608	697,547	721,719	579,068
Adjusted R^2	0.648	0.861	0.851	0.877	0.814	0.850

Notes: TFP is estimated using the Wooldridge methodology. "End of relationship" is a dummy equal to 1 for all years after the serious superstar relationship ended. If a firm i formed a new serious relationship with more than one superstar, we track the one that received the largest sales share. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D14: Event studies using matching (Nearest Neighbor)

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
MNE						
t1: Year of event	0.055***	0.182***	0.066***	0.198***	0.193***	0.120***
	(0.006)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)
1 or more years after event	0.071***	0.231***	0.155***	0.237***	0.261***	0.286***
	(0.006)	(0.010)	(0.010)	(0.011)	(0.012)	(0.012)
Observations	147,207	143,337	143,142	143,429	146,810	108,310
Adjusted R^2	0.651	0.851	0.829	0.862	0.820	0.768
Exporters						
t1: Year of event	0.036***	0.137***	0.037***	0.143***	0.164***	0.099***
	(0.006)	(0.008)	(0.010)	(0.009)	(0.011)	(0.012)
1 or more years after event	0.059***	0.167***	0.108***	0.175***	0.214***	0.238***
	(0.007)	(0.010)	(0.011)	(0.011)	(0.014)	(0.013)
Observations	103,373	101,585	101,476	101,640	103,103	78,921
Adjusted R^2	0.637	0.847	0.824	0.860	0.812	0.738
Large						
t1: Year of event	0.054***	0.179***	0.065***	0.199***	0.187***	0.153***
	(0.006)	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)
1 or more years after event	0.064***	0.216***	0.129***	0.229***	0.239***	0.258***
	(0.007)	(0.010)	(0.011)	(0.012)	(0.013)	(0.013)
Observations	123,456	120,605	120,482	120,653	123,178	98,334
Adjusted R^2	0.657	0.874	0.857	0.876	0.840	0.810

Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D15: Robustness to Alternative Definitions of what counts as a "serious relationship" with a Superstar

	Dependent variable: Log Total Factor Productivity					
	Alternative cutoffs for serious relationship					
	> 0%	> 1%	> 5%	> 15%	> 20%	> 50%
	(1)	(2)	(3)	(4)	(5)	(6)
MNE						
2 or more years before event	-0.014***	-0.007	0.006	0.002	0.004	0.001
	(0.003)	(0.004)	(0.005)	(0.007)	(0.007)	(0.010)
t1: Year of event	0.019***	0.018***	0.027***	0.024***	0.030***	0.027***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.009)
1 or more years after event	0.061***	0.068***	0.079***	0.076***	0.080***	0.071***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.010)
Observations	727,485	652,422	571,540	511,284	496,958	455,895
Adjusted R-squared	0.653	0.648	0.647	0.645	0.645	0.644
Exporters						
2 or more years before event	-0.014***	-0.004	0.012**	0.006	0.004	0.006
	(0.004)	(0.004)	(0.006)	(0.008)	(0.009)	(0.012)
t1: Year of event	0.017***	0.019***	0.022***	0.013*	0.012	0.016
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.012)
1 or more years after event	0.053***	0.063***	0.070***	0.064***	0.063***	0.062***
	(0.004)	(0.004)	(0.006)	(0.008)	(0.008)	(0.012)
Observations	720,511	646,670	569,642	520,248	509,517	482,116
Adjusted R-squared	0.654	0.648	0.645	0.645	0.644	0.645
Large						
2 or more years before event	-0.014***	-0.006	0.007	0.003	0.003	0.016
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.011)
t1: Year of event	0.023***	0.025***	0.031***	0.030***	0.030***	0.029***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.011)
1 or more years after event	0.050***	0.061***	0.072***	0.073***	0.074***	0.078***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.011)
Observations	940,257	841,212	759,294	705,447	692,888	660,276
Adjusted R-squared	0.660	0.652	0.649	0.648	0.648	0.647

Notes: These specifications are the same as in column (1) of Tables D1, D2, and D3, except we pool all of the pre indicators and pool all of the indicators from $t = 2$. Each columns adjusts the 10% baseline cutoff that defines a serious relationship with a superstar (i.e. at least 10 percent of firm i's sales must be to the superstar). The adjustment runs from having any sales ("$>$0%) in column (1), to having at least half of the firm's sales going to the superstar ("$>$50%") in column (6). TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D16: Alternative Superstar Definition: MNE

	Dependent variable: Log Total Factor Productivity				
	Inward FDI	Outward FDI	FDI > 50%	Include indirect FDI	By source/destination
	(1)	(2)	(3)	(4)	(5)
t1: Year of event	0.025***	0.025***	0.022***	0.023***	
	(0.006)	(0.006)	(0.006)	(0.005)	
1 or more years after event	0.077***	0.077***	0.076***	0.076***	
	(0.006)	(0.005)	(0.006)	(0.005)	
EU, t1: Year of event					0.025***
					(0.007)
EU, 1 or more years after event					0.072***
					(0.006)
US, t1: Year of event					0.029**
					(0.012)
US, 1 or more years after event					0.094***
					(0.011)
Other developed, t1: Year of event					0.012
					(0.023)
Other developed, 1 or more years after event					0.084***
					(0.022)
Less developed, t1: Year of event					-0.002
					(0.017)
Less developed, 1 or more years after event					0.052***
					(0.016)
Observations	611,742	610,123	516,471	529,892	532,790
Adjusted R-squared	0.647	0.649	0.646	0.645	0.645
Share of treated	17%	18%	20%	23%	23%

Notes: Column (1) defines MNE firms as only those with inward FDI. Column (2) defines MNE firms as only those with outward FDI. Column (3) changes the threshold for MNE to 50%. Column (4) includes indirect FDI in addition to direct FDI. Column (5) splits links to MNE firms by the source/destination country type of the inward or outward FDI. The "other developed" category comprises Australia, Canada, Japan, and New Zealand based on the UN classifciation. The "less developed" category comprises all countries not in one of the other three catgories. For firms with links to multiple MNE firms of different country types, the country type is assigned in order of US, Other developed, Less developed, EU. In another version where firms with links to multiple MNE firms of different country types are assigned to the country type to which the link has the highest share of the firm's sales, results are the same. TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D17: Alternative Superstar Definitions: Exporters and Large Firms

	Dependent variable: Log Total Factor Productivity						
	Exporters					Large	
		Alternative thresholds for FX					
	Include wholesalers	> 0%	> 20%	> 50%	By destination	Top 0.2 percentile sales	Top 0.2 percentile TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
t1: Year of event	0.011**	0.019***	0.015**	0.025***		0.016***	0.025***
	(0.005)	(0.006)	(0.007)	(0.009)		(0.005)	(0.007)
1 or more years after event	0.057***	0.071***	0.060***	0.060***		0.075***	0.053***
	(0.005)	(0.006)	(0.007)	(0.009)		(0.005)	(0.007)
EU, t1: Year of event					0.006		
					(0.009)		
EU, 1 or more years after event					0.053***		
					(0.009)		
US, t1: Year of event					0.006		
					(0.011)		
US, 1 or more years after event					0.070***		
					(0.010)		
Other developed, t1: Year of event					0.097***		
					(0.033)		
Other developed, 1 or more years after event					0.134***		
					(0.029)		
Less developed, t1: Year of event					0.008		
					(0.011)		
Less developed, 1 or more years after event					0.063***		
					(0.010)		
Observations	457,986	456,730	521,806	493,513	537,247	613,084	915,927
Adjusted R-squared	0.646	0.646	0.645	0.645	0.644	0.646	0.655
Share of treated	24%	23%	13%	8%	15%	18%	7%

Notes: Column (1) includes wholesalers as exporters. Columns (2) - (4) vary the threshold for exporters from 0% to 50%. Column (5) splits links to exporters by the destination country type. The "other developed" category comprises Australia, Canada, Japan, and New Zealand based on the UN classifciation. The "less developed" category comprises all countries not in one of the other three catgories For firms with links to multiple exporters of different country types, the country type is assigned in order of US, Other developed, Less developed, EU. In another version where firms with links to multiple exporters of different country types are assigned to the country type to which the link has the highest share of firm's sales, results are the same. TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D18: Robustness to Alternative Samples

	Dependent variable: Log Total Factor Productivity							
	Drop firms with low employment							
	≤ 1	≤ 5	≤ 10	Put dropped treated in controls	Min 1 year of pre and post treatment	Include non-B2B firms in controls	Drop wholesalers	Balanced panel
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MNE								
t1: Year of event	0.001	0.004	-0.007	0.021***	0.025***	0.023***	0.025***	0.038***
	(0.007)	(0.012)	(0.017)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
1 or more years after event	0.069***	0.078***	0.052***	0.080***	0.072***	0.074***	0.074***	0.043***
	(0.006)	(0.012)	(0.018)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Observations	249,703	54,223	19,092	1,332,512	574,921	681,663	492,407	293,605
Adjusted R-squared	0.681	0.726	0.753	0.693	0.648	0.661	0.644	0.660
Exporters								
t1: Year of event	-0.003	-0.015	-0.002	0.009	0.013**	0.010	0.010	0.022***
	(0.007)	(0.015)	(0.024)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
1 or more years after event	0.059***	0.082***	0.094***	0.064***	0.057***	0.059***	0.059***	0.043***
	(0.007)	(0.014)	(0.022)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	257,896	60,136	23,239	1,069,331	562,567	684,876	537,247	299,711
Adjusted R-squared	0.681	0.726	0.740	0.691	0.646	0.660	0.644	0.662
Large								
t1: Year of event	0.015**	0.011	0.007	0.023***	0.026***	0.026***	0.025***	0.034***
	(0.007)	(0.011)	(0.015)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
1 or more years after event	0.066***	0.065***	0.067***	0.072***	0.066***	0.069***	0.070***	0.041***
	(0.007)	(0.011)	(0.015)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	362,970	93,439	36,940	1,333,869	755,001	872,950	661,286	421,691
Adjusted R-squared	0.684	0.725	0.742	0.698	0.651	0.660	0.647	0.664

Notes: These specifications are the same as in column (1) of Tables D1, D2, and D3, except we pool all of the pre indicators and pool all of the indicators from $t = 2$. Columns (1), (2), and (3) drop from the sample firms with employment less than or equal to 1, 5, or 10, respectively. Column (4) puts treated firms that were dropped from the baseline sample into the control sample instead. Column (5) drops firms that started a new relationship in the first year and the last year in the sample instead of the dropping the first and last two years (that we did in our baseline approach). Column (6) puts firms that are not in the B2B data, which were dropped from the baseline sample, into the controlsample instead. Column (7) drops wholesaler firms from the sample. Columns (8) restricts to the balanced sample, i.e. the set of firms that were present for the full 13 years between 2002 and 2014. TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D19: Results robust to using linear industry and year fixed effects instead of industry by year fixed effects

	Log Total Factor Productivity (1)	Log Total Sales (2)	Log Other Sales (3)	Log Intermediate Inputs (4)	Log Wage Bill (5)	Log Number of Other Buyers (6)
MNE						
Year of treatment	0.019***	0.121***	-0.019**	0.142***	0.058***	0.075***
	(0.005)	(0.008)	(0.009)	(0.008)	(0.009)	(0.010)
1 or more years after event	0.078***	0.236***	0.166***	0.245***	0.236***	0.314***
	(0.005)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)
Observations	533,643	510,580	510,016	511,073	532,048	398,012
Adjusted R^2	0.641	0.847	0.831	0.866	0.802	0.832
Exporters						
Year of treatment	0.007	0.080***	-0.033***	0.088***	0.055***	0.064***
	(0.006)	(0.008)	(0.010)	(0.009)	(0.011)	(0.011)
1 or more years after event	0.060***	0.167***	0.115***	0.168***	0.194***	0.260***
	(0.006)	(0.009)	(0.010)	(0.010)	(0.012)	(0.012)
Observations	538,166	514,135	513,708	514,475	536,490	402,726
Adjusted R^2	0.641	0.840	0.830	0.862	0.807	0.803
Large						
Year of treatment	0.023***	0.128***	-0.008	0.148***	0.066***	0.112***
	(0.006)	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)
1 or more years after event	0.074***	0.230***	0.151***	0.233***	0.222***	0.286***
	(0.006)	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)
Observations	724,569	697,691	697,382	698,321	722,486	579,854
Adjusted R^2	0.645	0.857	0.848	0.875	0.812	0.849

Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry, year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.