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

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January 28, 2024

Abstract

Using firm-to-firm transactions, we show that starting to supply a 'superstar' firm (large domestic firms, exporters and multinationals) boosts productivity by 8% in the medium-run. Placebos on starting relationships with smaller firms and novel identification strategies support to a causal interpretation of "superstar spillovers". Consistent with a model of technology transfer, we find falls in markups and bigger treatment effects from technology-intensive superstars. We also show that the increase in new buyers is particularly strong within the superstar firm's network, a "dating agency" effect. This suggests an important role for raising productivity through superstars' supply chains regardless of their multinational status.

Key Words: Productivity, FDI, spillovers
JEL: F23, O30, F21

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We thank Sean Fulmer and Aidan Wang for excellent research assistance. We thank the National Bank of Belgium and ECOOM for providing access to their data and research facilities. Konings thanks the Methusalem grant (METH/15/004) for financial support. Van Reenen thanks the ESRC for financial support through POID. We thank participants at seminars in ERWIT, LSE, Padova, Surrey, Tel Aviv, UBC and Yale/COWLES for many helpful remarks, especially David Atkin, Andrew Bernard, Gert Bijnens, Paola Conconi, Dave Donaldson, Isabela Manelici, Felix Tintelnot, Rocco Machiavello, Steve Redding, and Stijn Vanormelingen. The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of New York or the Federal Reserve System or the National Bank of Belgium.

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), and De Loecker, Eeckhout, and Unger (2020)), mostly focused on the potential costs of these trends (Philippon (2019), White House (2021), and 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 (Eeckhout (2022), Wu (2018), Yeh, Macaluso, and Hershbein (2022), and Berger, Herkenhoff, and Mongey (2022) as well as lobbying strength (Wu (2018)). A less appreciated benefit of superstar firms is the potential positive productivity spillovers that they may confer on smaller firms. Since firms have grown to be superstars in part due to their superior managerial and technical know-how, some of this knowledge may spread to other firms in the economy, particularly through supply chain linkages - suppliers to high productivity firms may themselves benefit from such "superstar spillovers."[1]

We believe that this is the first paper to show positive spillovers from superstar firms, broadly defined to include domestic large firms, exporters, and multinational enterprises (MNE) using firm-to-firm transaction data. So far, the literature has mostly focused on firms with inward FDI, and has produced mixed results. Governments spend large sums of money to attract and retain multinational investment, partly because of their belief in the importance of these supply chain benefits (e.g. the Chips and Science Act for semi-conductors and the Inflation Reduction Act for green technologies). 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

1. These spillovers are not necessarily externalities. Indeed, we will show that some - but not all - of the spillovers are captured by the superstar through extracting a better deal from the supplier and squeezing their margins.

the downstream sector. As with the case studies, the main positive mechanism postulated is that a multinational transfers 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 superstar firm experience higher Total Factor Productivity (TFP) after a new relationship is established. The only other paper that has identified positive TFP spillovers from superstar firms to domestic firms is the seminal paper by Alfaro-Ureña, Manelici, and Vasquez (2022) who use firm transaction data from Costa Rica, but this is only for superstar firms that have inward FDI. Developing county studies cannot assess whether all types of superstar firms generate spillovers because they don't have any non-multinational superstar firms. Ours is the only econometric study that has the value of firm-to-firm transaction data to look at these issues in a developed country, where superstar firms don't have to be multinational.[2] 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

2. 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.

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 approach using superstar entry.

What are the mechanism underlying our superstar spillover effects? We write down 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 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 significant 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), Empirical Strategy (Section 3), Results (Section 4), Mechanisms (Section 5), Endogeneity (Section 6), Robustness (7) and Conclusions (Sections 8). 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 (e.g. Javorcik 2004), especially in downstream (i.e. who you sell to) industries 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.).[3]

There is a wider literature looking at production networks for large firms regardless of multinational status. Greenstone, Hornbeck, and Moretti (2010) looked at spillovers from "Million Dollar Plants" - large establishments of very big enterprises. 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 much interest in firm-to-firm networks as vectors of transmission

3. 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.

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. Iyoha (2021) develops a methodology for estimating productivity taking account of spillovers within production networks, by augmenting standard proxy variable production function estimation (beginning with Olley and Pakes (1996)). She applies this methodology to publicly listed US firms in Compustat from 1977 to 2016, and finds a cumulative TFP increase of 16% more productive due to these spillovers across the network.[4] Throughout this literature, the general empirical approach has been to condition on the existing 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. The richness of our data allows us to look at the spillovers to the full distribution of firms, and to examine the heterogeneity of the source of the spillover by FDI, exporting and size and the mechanisms underlying the spillovers.

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

4. Firm-to-firm sales in Compustat are only reported for custormers that are responsible for at least 10% of sales, resulting in a very sparse observed network.

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 with more than one full-time equivalent employee. 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 record 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.[5] 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 across all firms located in Belgium, based on the firm's total average sales over the sample period.[6] 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.

Appendix Table A1 shows the effects of our cleaning procedures on sample size (we cover 78 percent of all jobs in employer firms) and shows averages (and variances) for the main variables in our baseline analysis sample of about 88,500 companies. Most firms are small: the mean is just over six full-time

5. The wholesale sector is defined as those within 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.

6. These large superstar firms are widely dispersed across sectors: they span 176 four-digit NACE industries, and they purchase from 604 industries.

equivalent employees. Appendix 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, a supplier's sales nearly double and TFP jumps by 13 log points).

3 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.[7] 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 a 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 A.4 for more detail).

In our estimation sample, we drop any firm i that starts a new relationship with a firm j of type K if its sales share to the superstar 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 does not preclude firms that sell to other treatment type K firms, e.g. for the treatment type $K = MNE$, the control group comprises firm $i's$ that never sell anything to a multinational, but may include firm $i's$ that sell to exporters or large superstar firms. We also drop from the control group any firm i that is itself 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 none of the results are sensitive to alternative definitions of the exact thresholds or choices of sample.[8]

7. 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 D1).

8. 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 98.5 percent of the observations would have to be dropped because most firms are already buying from a superstar in the first year they appear in the sample or buying amounts that are too small to constitute a serious relationship. This is also the case if we exclude any firm in the 2-digit (NACE=35) electricity industry.

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:

$$y_{i,t} = \sum_{\ell=-5}^{5} \beta_{\ell-1} I_{i,\ell} + \delta_i + \gamma_{s,t} + \epsilon_{i,t}. \tag{1}$$

We define $I_{i,t} = \mathbf{1}(E_i = t)$ 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 the 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 examine 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 (we denote the year of the event "t1" in the Tables and "1" in the event study plots. All the specifications include firm fixed effects (δ_i) and industry-year fixed effects ($\gamma_{s,t}$) at the NACE four-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).

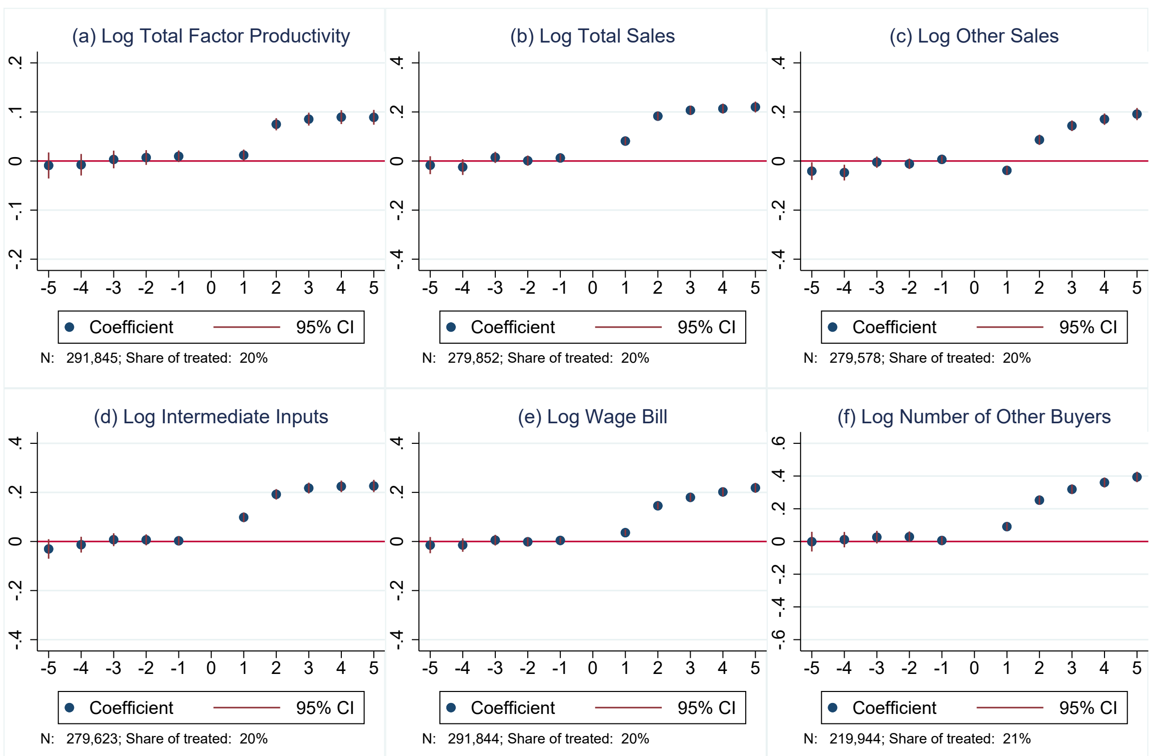
A major empirical concern is whether firms would have also had better performance even in the absence of the superstar relationship. By estimating β_{-1} to β_{-5}, we can examine pre-trends to check whether firm i was already on a positive productivity trend prior to forming a relationship. We will 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 - as we discuss in Section 5 - 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 benefits arising after superstar relationships. Second, Section 6 considers designs focusing on shocks to superstar firms independent of those to firm i in order to identify the causal impacts of superstar firms.

4 Baseline Results

4.1 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 Table 1. The first panel of Figure 1 plots the regression coefficients from equation (1), with log TFP as the dependent variable. There are no significant coefficients prior to treatment, so no evidence of pre-event trends. We see a significant rise in TFP of around one percent in the year of treatment, which increases to nearly nine percent by the end of our event window (i.e. four years after the serious relationship began).[9]

Figure 1: Gains from selling to Multinationals (MNEs)



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 multinational 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 multinational treatment firms. "N" is the number of observations. All coefficients are relative to the year before the event ("0"). All regression results are in Table 1.

We also consider the effect of starting a new relationship with a multinational on a number of

9. 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 D2.

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 22 log points (25 percent) four years later. Since mean sales are €1.38 million (see Table A1), the estimates imply about a €345,000 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 19 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.[10] Finally, in panel (f) we show that an extensive margin - the total number of buyers other than multinationals, 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).

10. 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 multinationals cause hourly wages to substantially rise as in Setzler and Tintelnot (2021), but Table D4 shows that employment increases by around 15 log points.

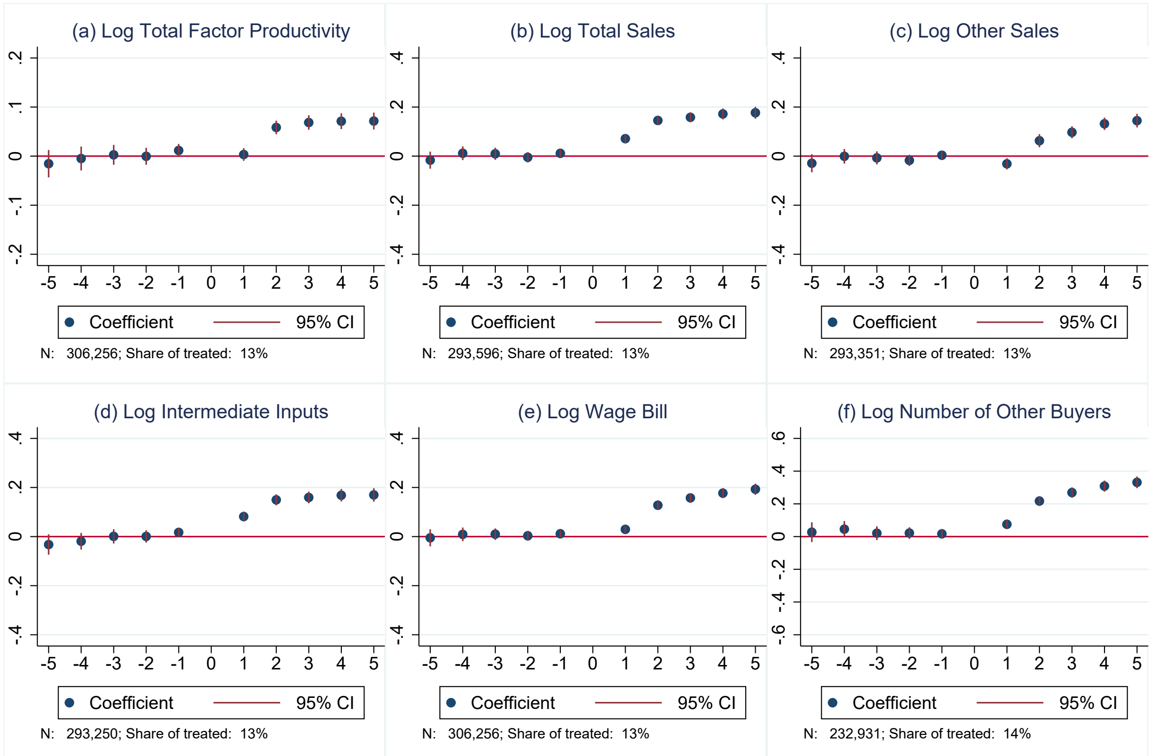
Table 1: Links to Multinational's - Full regression results

	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	-0.009	-0.017	-0.041**	-0.030	-0.015	-0.001
	(0.014)	(0.019)	(0.018)	(0.020)	(0.017)	(0.031)
t-4: 5 years before event	-0.008	-0.025	-0.047***	-0.013	-0.015	0.011
	(0.011)	(0.016)	(0.016)	(0.016)	(0.014)	(0.024)
t-3: 4 years before event	0.003	0.015	-0.005	0.007	0.005	0.027
	(0.009)	(0.012)	(0.012)	(0.013)	(0.011)	(0.020)
t-2: 3 years before event	0.007	0.002	-0.011	0.007	-0.001	0.029*
	(0.008)	(0.011)	(0.011)	(0.011)	(0.009)	(0.017)
t-1: 2 years before event	0.010	0.012	0.007	0.003	0.004	0.006
	(0.006)	(0.008)	(0.008)	(0.009)	(0.007)	(0.013)
t1: Year of event	0.012**	0.081***	-0.038***	0.098***	0.036***	0.091***
	(0.006)	(0.008)	(0.010)	(0.010)	(0.007)	(0.013)
t2: 1 year after event	0.075***	0.183***	0.086***	0.192***	0.146***	0.253***
	(0.006)	(0.009)	(0.011)	(0.011)	(0.008)	(0.014)
t3: 2 years after event	0.085***	0.207***	0.144***	0.218***	0.180***	0.319***
	(0.007)	(0.010)	(0.011)	(0.011)	(0.008)	(0.015)
t4: 3 years after event	0.089***	0.214***	0.170***	0.224***	0.202***	0.361***
	(0.007)	(0.010)	(0.012)	(0.012)	(0.009)	(0.016)
t5: 4 years after event	0.089***	0.220***	0.191***	0.226***	0.219***	0.394***
	(0.008)	(0.011)	(0.013)	(0.013)	(0.010)	(0.016)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291,845	279,852	279,578	279,623	291,844	219,944
Adjusted R^2	0.723	0.874	0.860	0.889	0.866	0.858

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.

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 2. 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 no increase in TFP in the first year of treatment, and 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.

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 coefficients are relative to the year before the event ("0"). All regression results are in Table 2.

Table 2: 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	-0.015	-0.017	-0.029	-0.032	-0.005	0.027
	(0.014)	(0.018)	(0.019)	(0.021)	(0.018)	(0.031)
t-4: 5 years before event	-0.005	0.012	-0.001	-0.019	0.009	0.046*
	(0.012)	(0.014)	(0.015)	(0.017)	(0.014)	(0.025)
t-3: 4 years before event	0.003	0.010	-0.007	0.001	0.010	0.021
	(0.010)	(0.013)	(0.014)	(0.015)	(0.012)	(0.021)
t-2: 3 years before event	-0.000	-0.005	-0.017	0.001	0.003	0.022
	(0.009)	(0.011)	(0.012)	(0.013)	(0.010)	(0.018)
t-1: 2 years before event	0.012*	0.011	0.004	0.017*	0.012	0.017
	(0.007)	(0.008)	(0.009)	(0.010)	(0.007)	(0.014)
t1: Year of event	0.003	0.071***	-0.031***	0.082***	0.030***	0.075***
	(0.007)	(0.009)	(0.012)	(0.010)	(0.007)	(0.015)
t2: 1 year after event	0.058***	0.145***	0.063***	0.150***	0.128***	0.217***
	(0.007)	(0.010)	(0.014)	(0.011)	(0.008)	(0.015)
t3: 2 years after event	0.068***	0.158***	0.097***	0.159***	0.158***	0.269***
	(0.008)	(0.010)	(0.012)	(0.012)	(0.009)	(0.016)
t4: 3 years after event	0.071***	0.172***	0.132***	0.169***	0.177***	0.308***
	(0.008)	(0.011)	(0.013)	(0.013)	(0.010)	(0.017)
t5: 4 years after event	0.071***	0.177***	0.145***	0.170***	0.193***	0.332***
	(0.009)	(0.012)	(0.014)	(0.014)	(0.012)	(0.018)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,256	293,596	293,351	293,250	306,256	232,931
Adjusted R^2	0.723	0.865	0.856	0.885	0.874	0.827

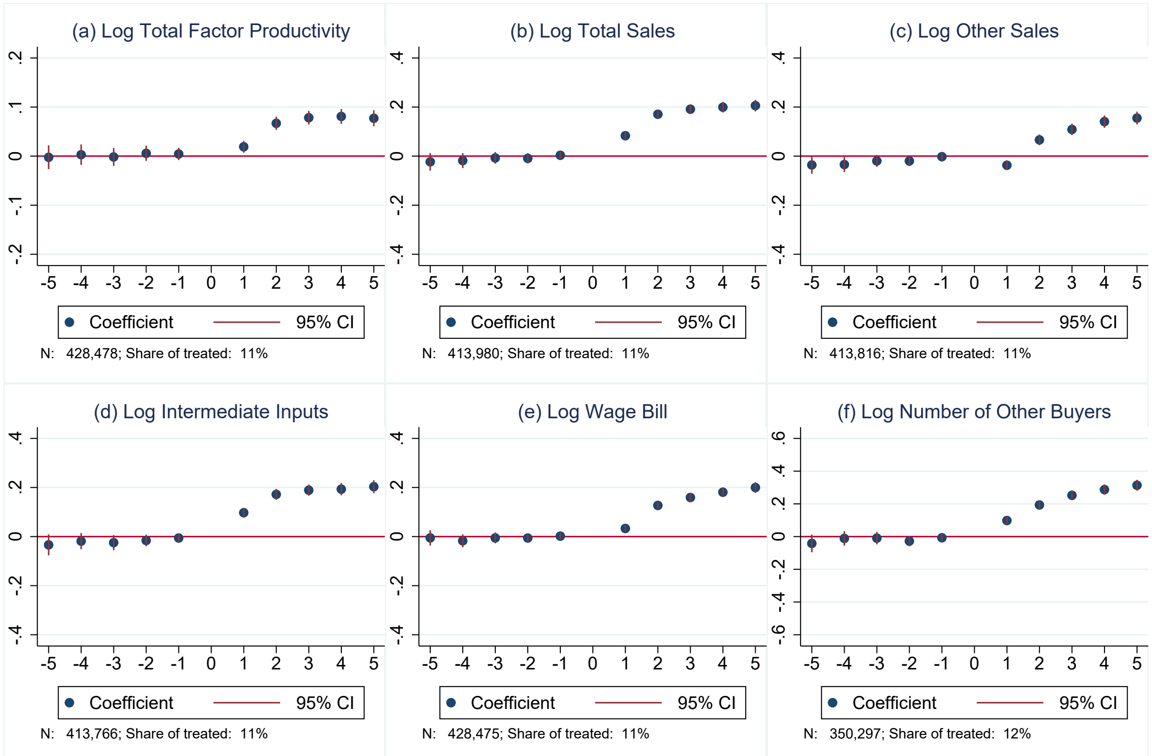
Notes: TFP is estimated using the Wooldridge methodology. All regressions include 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level. The mean of the Number of other buyers variable is 9.205. *** indicates significance at the 1% level, **5%, * 10%. These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

4.2 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 Table 3. 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 sales, inputs and the number of customers.

Although there seems to be 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. In order to investigate this issue we defined an alternative treatment indicator to be "pure superstars" in Table 4. This is a subset of the treatment group where there are non-overlapping definitions, so that a "pure large firm superstar" is in the top 0.1% of the sales distribution, but neither exports nor is a multinational. Similarly, a "pure exporter superstar" is neither

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 coefficients are relative to the year before the event ("0"). All regression results are in Table 3.

a multinational nor a very large firm and a "pure multinational superstar" is outside the top 0.1% and does not export. These treatments are strict subsets of those in Figures and Tables 1-3. Given the patterns in the event studies, we simplify the dynamics in equation (1), so that we just have three dummies: one for "1 or more years after the event" which is our main treatment effect, one for the year of the event ("t1") as this appeared to sometimes have negative effects (e.g. for other sales, as discussed above) and one for "2 or more years before the event" to check for pre-trends.

Looking over the results in Table 4 several things stand out. First, all the pre-trends are insignificant consistent with the earlier analysis. Second, the main effects, averaged one to four years after the event, are all positive and significant and in line with the magnitudes we see in Tables 1-3. In particular, the results for the purely very large firms remain robust, showing that the superstar impact does not rely on them having major overseas activity, either in the form of multinational affiliates or exporting. 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 Vanden Avenne Ooigem (https://www.vda-ooigem.be/nl), a manufacturer of food for farm animals, Industrial

Table 3: 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	-0.002	-0.023	-0.036*	-0.034	-0.005	-0.042
	(0.012)	(0.018)	(0.018)	(0.022)	(0.016)	(0.028)
t-4: 5 years before event	0.003	-0.018	-0.034**	-0.019	-0.017	-0.011
	(0.011)	(0.016)	(0.016)	(0.017)	(0.014)	(0.023)
t-3: 4 years before event	-0.002	-0.007	-0.020	-0.025	-0.005	-0.009
	(0.009)	(0.012)	(0.012)	(0.016)	(0.011)	(0.019)
t-2: 3 years before event	0.006	-0.009	-0.020*	-0.016	-0.006	-0.028*
	(0.008)	(0.011)	(0.011)	(0.012)	(0.009)	(0.016)
t-1: 2 years before event	0.004	0.004	-0.002	-0.006	0.002	-0.007
	(0.006)	(0.008)	(0.008)	(0.009)	(0.007)	(0.012)
t1: Year of event	0.019***	0.083***	-0.037***	0.097***	0.033***	0.098***
	(0.006)	(0.009)	(0.010)	(0.010)	(0.007)	(0.013)
t2: 1 year after event	0.067***	0.171***	0.066***	0.172***	0.127***	0.193***
	(0.007)	(0.009)	(0.011)	(0.011)	(0.008)	(0.014)
t3: 2 years after event	0.078***	0.191***	0.109***	0.189***	0.159***	0.252***
	(0.007)	(0.010)	(0.012)	(0.012)	(0.009)	(0.015)
t4: 3 years after event	0.081***	0.199***	0.141***	0.193***	0.181***	0.287***
	(0.008)	(0.011)	(0.013)	(0.013)	(0.010)	(0.016)
t5: 4 years after event	0.077***	0.206***	0.155***	0.203***	0.200***	0.314***
	(0.008)	(0.012)	(0.013)	(0.014)	(0.011)	(0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	428,478	413,980	413,816	413,766	428,475	350,297
Adjusted R^2	0.724	0.882	0.874	0.895	0.875	0.872

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.

Refining Company, a large manufacturer of jewelry, Corelio (http://corelio.be), the largest company in printing and publishing of newspapers and Comfort Energy (https://www.comfortenergy.be) one of the largest distributors of heating oil to households.[11]

Our results are different from Alfaro-Ureña, Manelici, and Vasquez (2022), who find no effects of forming a relationship with large domestic firms. We probe the reasons for this in Appendix D, Figure D1 and Table D3, showing that it is not due to some obvious differences in the definition of what it means to be a domestic superstar. The most likely explanation is that in Costa Rica there are hardly any very large purely domestic firms, so there is little variation to contrast with multinational effects.

11. Another two examples are Belorta (https://belorta.be/) the largest fruit and vegetable auction in Belgium and Febelco (https://www.febelco.be/) a distributor and supplier of pharmaceutical products to local pharmacists. Some of the "pure large superstars" are state-owned, for example: Aquafin (https://www.aquafin.be), which deals with waste water treatment/sewage and purifying household and industrial water; and Belairbus (www.belairbus.be) a Belgian aerospace manufacturer. In the last column of Table D3, 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 does not have a major effect on 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.

Table 4: Links to Pure Superstars

	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)
Multinationals						
2 or more years before event	0.006	0.004	-0.006	0.005	-0.008	0.010
	(0.009)	(0.013)	(0.013)	(0.013)	(0.011)	(0.019)
t1: Year of event	0.015*	0.081***	-0.038***	0.104***	0.040***	0.085***
	(0.008)	(0.012)	(0.014)	(0.014)	(0.010)	(0.019)
1 or more years after event	0.083***	0.193***	0.137***	0.215***	0.179***	0.315***
	(0.009)	(0.013)	(0.015)	(0.016)	(0.012)	(0.020)
Observations	257,515	246,145	246,021	245,891	257,514	192,743
Adjusted R^2	0.723	0.871	0.866	0.888	0.860	0.863
% Share of Treated	8.99	8.81	8.76	8.82	8.99	7.22
Exporters						
2 or more years before event	0.006	-0.005	-0.020	-0.012	0.012	0.016
	(0.010)	(0.013)	(0.014)	(0.015)	(0.011)	(0.020)
t1: Year of event	0.003	0.063***	-0.040**	0.073***	0.019**	0.077***
	(0.009)	(0.013)	(0.018)	(0.014)	(0.010)	(0.020)
1 or more years after event	0.063***	0.139***	0.093***	0.135***	0.138***	0.257***
	(0.010)	(0.014)	(0.016)	(0.015)	(0.012)	(0.020)
Observations	284,238	271,877	271,732	271,519	284,238	215,197
Adjusted R^2	0.723	0.863	0.861	0.885	0.872	0.831
% share of treated	6.01	5.93	5.88	5.93	6.01	5.00
Large-Sales Firms						
2 or more years before event	0.015	-0.011	-0.019	-0.025	-0.008	-0.025
	(0.013)	(0.018)	(0.018)	(0.021)	(0.016)	(0.025)
t1: Year of event	0.028**	0.097***	-0.047**	0.103***	0.033**	0.075***
	(0.013)	(0.017)	(0.021)	(0.021)	(0.014)	(0.025)
1 or more years after event	0.086***	0.182***	0.065***	0.168***	0.150***	0.205***
	(0.014)	(0.019)	(0.024)	(0.023)	(0.018)	(0.027)
Observations	390,153	376,275	376,229	376,057	390,150	318,160
Adjusted R^2	0.723	0.880	0.877	0.895	0.871	0.877
% share of treated	2.44	2.39	2.38	2.39	2.44	2.12

Notes: The treated sample in this table is a subset of Tables 1-3, where the pure superstars are those with non-overlapping definitions. For example, a pure large firm superstar does not also meet the criteria to be considered a multinational or exporter superstar. Firms that are treated in the same year by both a pure superstar and a non-pure superstar are dropped from the sample entirely. The control group is identical to those in Tables 1-3. All the pre-treatment periods are grouped into one and all post-treatment periods are grouped into one. The regression includes 4-digit NACE industry-year and firm fixed effects. Standard errors are clustered at the firm level.

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.

4.3 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.

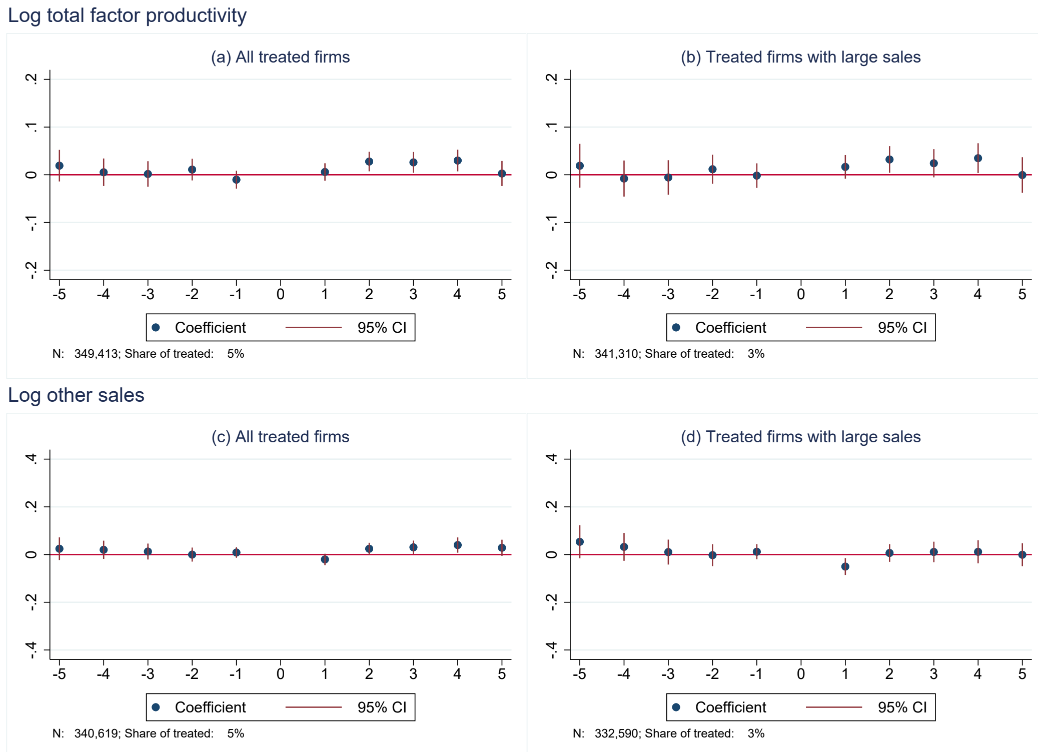
To investigate this issue, we run a placebo experiment, focusing on treatments with non-superstar firms (e.g. smaller firms) and re-estimating equation (1). We consider whether there are spillovers generated to a firm i from starting a new serious relationship with a "small" firm, which we define in 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 4 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 median sales in euros to the new customer firm is the same as the median value of 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 panels, but use sales to other firms as the outcome rather than TFP. Once again, there is essentially zero effect.

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 4: 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 further 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.

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.

4.4 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. In column (1) of Table D4, 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 89 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, as some of the low productivity firms who would have exited are kept in business due to the superstar relationship. We also show positive and significant treatment effects on jobs, tangible capital (as measured by fixed assets) and intangible capital.

Table D5 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 D6 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.

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 also exist in developed countries for firms with inward FDI or outward FDI, operating through explicit buyer-seller linkages. Moreover, we further extend the literature by showing that large domestic firms, and exporters, also generate these spillovers through explicit buyer-seller linkages. 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.

5 Exploring the Superstar Spillover Mechanisms

5.1 Modeling productivity-related superstar spillovers

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. In Appendix C we formalize a simple model of superstar spillovers. Each superstar firm seeks a preferred upstream supplier with whom she will form a long-term relational contract and 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: 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 builds on our finding that supplier firms forming a relationship with a superstar 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). These are all documented in the main results.

The model has several additional predictions which we examine in this subsection. First, since a supplier has to bid a lower price in order to win the superstar contract, its overall price-cost margin should *fall* after a superstar relationship forms. In contrast, overall profits should *rise*, as these losses per unit sold to the superstar are made up by selling more output to other firms due to higher productivity.[14] Second, we predict that *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). Third, as it is likely that the more technologically intensive superstars confer greater spillovers, the productivity effects should be larger for such firms. 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 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.

The next subsection examines these four implications.

5.2 Implications of the productivity-based Superstar Spillover Model

5.2.1 Price-Cost Margins and Profitability

Although our data allows us to distinguish sales across different customers, 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

We calculate price-cost margins following 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.[15] For all three definitions of superstar firms we see significantly negative treatment effects (of

14. The superstar firm does not, in general, extract all the profits from the supplier because there are a finite set of upstream firms who bid to supply. 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.

15. We also used the simpler "accounting" approach of Antràs, Fort, and Tintelnot (2017) and simply divide sales by

between 1 to 2 percent) on the markup of forming a relationship with a superstar firm (column (5) of Table D4).[16]

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.[17] The fact that, empirically, we see *falling* markups rules out this alternative interpretation.

We also estimate the impact on gross profit as measured by Earnings Before Interest, Tax and Amortization (EBITA), finding that total profits rise following a superstar relationship (last column of Table D4).

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

The most common mechanism posited in the literature 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 5 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. All of the nine interactions are positive and seven of these are significant at the 10% level or greater. For example, a large firm that is R&D intensive generates a spillover that is almost twice as big as a large firm that is non-R&D intensive (12% vs. 7.1%). In columns (5)-(7) we replace TFP with "other buyers" as the dependent variable. All nine interactions are positive (and seven significant) when we use "other sales" as an outcome - see Appendix Table D7. These results strongly suggest that the technology transfer mechanism is likely to be at play.

material inputs, generating similar results. Note we use 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.

16. 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.

17. 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 5: 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	0.075***	0.071***	0.073***	0.072***	0.292***	0.284***	0.282***	0.267***
	(0.006)	(0.007)	(0.007)	(0.009)	(0.014)	(0.015)	(0.014)	(0.017)
x indicator variable	0.045***	0.036***	0.038***	0.016*	0.127***	0.096***	0.134***	0.072***
	(0.010)	(0.009)	(0.010)	(0.009)	(0.026)	(0.020)	(0.022)	(0.019)
Observations	291,845	291,845	291,845	291,845	219,944	219,944	219,944	219,944
Adjusted R^2	0.724	0.724	0.724	0.723	0.858	0.858	0.858	0.858
Exporters								
1 or more years after event	0.060***	0.059***	0.061***	0.060***	0.250***	0.253***	0.232***	0.238***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.015)	(0.016)	(0.017)	(0.017)
x indicator variable	0.041***	0.019*	0.010	0.011	0.136***	0.050**	0.077***	0.062***
	(0.013)	(0.010)	(0.010)	(0.010)	(0.032)	(0.022)	(0.021)	(0.021)
Observations	306,256	306,256	306,256	306,256	232,931	232,931	232,931	232,931
Adjusted R^2	0.723	0.723	0.723	0.723	0.827	0.827	0.827	0.827
Large								
1 or more years after event	0.067***	0.070***	0.068***	0.072***	0.228***	0.230***	0.217***	0.220***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.014)	(0.016)	(0.015)	(0.017)
x indicator variable	0.055***	0.013	0.028**	0.005	0.156***	0.051**	0.145***	0.052***
	(0.012)	(0.010)	(0.011)	(0.010)	(0.031)	(0.021)	(0.025)	(0.020)
Observations	428,478	428,478	428,478	428,478	350,297	350,297	350,297	350,297
Adjusted R^2	0.724	0.724	0.724	0.724	0.872	0.872	0.872	0.872

Notes: Columns (1) to (4) regress our baseline measure of TFP on the post-treatment indicators (as in column (1) of Table D2) 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 =multinational, 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, and a pre-event dummy, but coefficients are 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.

5.2.3 Larger Spillovers *to* Treated firms with more Absorptive Capacity

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 receive greater benefits from technological spillovers. First, we consider the same three technology indicators as above but now for the treated firm i instead of the superstar firm j. In Appendix Table D8, we show that treatment firms with higher technological capabilities, either more R&D incentive, ICT intensive or human capital intensive, receive higher spillovers from starting a serious relationship with a superstar firm.[18] In the last column, we explore the possibility that firms who have "much to learn" would 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. Appendix Table D8 shows that the treatment effects are significantly larger for young firms. For example, for large firm superstars, the TFP effect is three log points for old firms and 17 log points (nearly six times higher) for young firms.

5.2.4 What type of firms supply superstars?

We predicted that the larger and more productive firms should bid more aggressively to supply a superstar 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 (€1.9 million vs €1.1 million) and 6.3% higher TFP. Consistent with the greater effects on young firms, we also find that they are about two years younger.

Summary on productivity mechanisms of superstar spillovers The simple model we outlined at the start if this subsection seems to have some support in the data. First, there are positive causal effects of supplying a superstar firm on productivity and therefore on outputs, numbers of buyers and inputs. Second, markups fall, but profits rise. Third, productivity treatment effects are larger when a superstar has more to teach and a supplier has more to learn. Fourth, superstar suppliers are *ex ante* more productive.

5.3 Superstar Spillovers through non-productivity mechanisms

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

18. Including interactions of these technology variables for both firm i and firm j does not affect the magnitudes or significance.

Table 6: 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	1.03	12.90	0.18	10.17	0.75	18.00
Year of event	0.389	-0.148	0.047	0.059	1.842**	0.000
	(0.251)	(0.261)	(0.078)	(0.191)	(0.932)	(0.345)
1 or more years after event	1.178***	3.722***	0.474***	2.840***	2.549***	4.187***
	(0.201)	(0.384)	(0.105)	(0.212)	(0.770)	(0.573)
Observations	219,944	219,944	232,931	232,931	350,297	350,297
Adjusted R^2	0.939	0.864	0.882	0.894	0.802	0.927
Expected number of buyers in network	0.251		0.089		0.631	
Odds of actual number compared to expected number	4.69:1		5.32:1		4.04:1	

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), is the number of other buyers outside the superstar's network. All regressions include a pre-event dummy, but coefficients are 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% 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 A.5 for details on these calculations.

two alternative mechanisms outside of our formal model. We label these "relationship capabilities" and "dating agency" effects.

5.3.1 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 5 interacts high RC with the treatment dummy. Although the coefficients are positive, none are significant at the 5% level. However, when we look at the number of other buyers as an outcome in column (8), we do see a positive and significant interaction.

These results suggest that relationship capability 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 4.

5.3.2 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 6 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 out of network vs in-network in columns (1) and (2) is over three (3.72 vs. 1.18), but the average firm has twelve times (12.9 vs. 1.03 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 A.5 details our calculations, with the odds ratio given in the final row of Table 6. 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.

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.

6 Potential Endogeneity of Superstar Links

Our event studies establish that a firm i that starts a serious relationship with a superstar firm gains 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 4.3 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 4 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 two more 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.[19] Second, we 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 positive superstar spillovers.

19. 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).

6.1 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. To build intuition, 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 (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.[20]

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 using the Amiti and Weinstein (2018) methodology. 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).

By including the $Control_{it}$ from equation (6) in equation (2), we net out any contemporaneous change in firm i's TFP due to factors arising in firm i, e.g. an improvement in its management quality. Hence, the coefficient β should only captures changes in firm i's TFP due to changes in firm j. Although our methodology for constructing the $Control_{it}$ allows for new bilateral relationships, a firm must be in the sample in $t-1$ to be included, 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 7 to the sub-sample with non-missing $Control_{it}$, in column (2). This point estimate of 0.083 drops to 0.061 in column (2). When we additionally include

20. 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).

Table 7: 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	0.012**	0.017**	0.005	0.003	0.002	-0.005	0.019***	0.008	-0.008
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)
1 or more years after event	0.083***	0.061***	0.046***	0.066***	0.056***	0.044***	0.075***	0.052***	0.035***
	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Control$_{it}$			0.037***			0.037***			0.042***
			(0.001)			(0.001)			(0.001)
Observations	291,845	169,616	169,616	306,256	178,494	178,494	428,478	278,223	278,223
Adjusted R^2	0.723	0.747	0.750	0.723	0.745	0.748	0.724	0.744	0.748

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 a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

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 0.061 to 0.046. 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 0.056 in column (5) to 0.044 in column (6). For the links to large firms, the reduction is from 0.052 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 only a bit smaller than our baseline results. We should consider these as lower bounds, because some of the genuine treatment effect may be taken out by including this type of control. 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.

6.2 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 domestic firm and then expands by seeking out new suppliers. This approach uses only shocks that are large enough to change the extensive margin such that we observe the entry of a superstar firm.[21] In the top panel of Appendix Table D9, 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

21. 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.

with similar magnitudes to our baseline estimates.

7 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 D10 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 11.2% increase in productivity for an unbroken relationship, but this falls to 6.4% 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.[22] 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.[23] 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 Table D11 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 11 to 21 percent of our sample are treated). In Appendix Table D12, 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 0.073, compared to 0.083 in our baseline.

22. 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.

23. 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.

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 from the transferal of knowledge. Subsection 4.3 showed that it was not simply an increase in the first moment (sales demand) causing our spillover effects because an equivalent growth in sales to 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 0.08 (from 1.54 in the three pre-event years to 1.62 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 D1. 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,[24] 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. 7% 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 a multinational in Table D13. First, we considered links to inward FDI and outward FDI separately and found essentially the same results (0.086 and 0.083, respectively) as in the baseline where these are combined (0.083). Second, instead of the 10% ownership threshold to define a multinational, we considered an alternative such as 50% or more, which generated similar results (0.085).[25] 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 in less developed countries, like India or China.

24. For example, for large firm spillovers, insisting on having the initial sales threshold at 50% generated treatment effect of 7%, compared to only 5% if we included any new sales to a superstar.

25. 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.

We change the definition of exporters and large superstar firms in analogous ways in Table D14, 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%) and allow for different 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 similar results to our baseline.

Alternative Samples We experimented with different samples in Table D15. Rather than include all firms with more than one full-time equivalent (FTE) employment, we experimented with keeping all firms with non-missing employment, those with more than 5 FTEs and more than 10 FTEs. Next, instead of 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 show that including firms in the control that are not in the B2B data i.e. firms that only sell to final consumers directly instead of dropping them from the sample makes no difference to the results 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 8% to 4% for multinational superstars). This is consistent with the larger treatment effects we found for young firms in subsection 5.2.3 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 six to nine 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 D16 by replacing the industry by year dummies with just 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 D16, 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 D16 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 produce slightly larger effects, suggesting there are positive spillovers beyond those formed by direct buyer-supplier relationships as argued by Javorcik (2004), for example. In any case, this suggests that upwards biases from business stealing are not a major concern in our context.

8 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 superstar firm for the first time. We uncover an increase in productivity (that rises by about 8 percent after four years) and other performance measures (e.g. sales to firms other than the new superstar partner). Interestingly, we find TFP spillovers of similar magnitude for events of starting a serious relationship with multinational firms and non-multinational "superstar firms" - defined as those who are in the top thousandth of the size distribution and/or export intensively. 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 also predicts negative impacts on supplier markups, 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 productivity related spillovers, 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 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 size-dependent 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.[26] 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

26. 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 for consistency. 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 have more than one full-time equivalent employee. This drops 68 percent of the firms: 55 percent of the samplehad missing employment; and 13 percent of the sample had between zero and 1 (accounting for 1.6 percent of total employment). Observations with zero or missing full-time equivalent employment (i.e. the self-employed) are not included because we cannot estimate TFP for those observations. 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 another 4 percent of the sample, most of which are very small firms accounting for only 3.2 percent of total employment, as shown in the top panel of Table A1. Finally, since our main interest is in estimating TFP spillovers, we drop any firm for which we cannot calculate their TFP. We lose another 4 percent of firms because of missing TFP, which is due to zeros or missing values on capital or value added. After all this cleaning, we end up with an average of 88,510 thousand firms per year.

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. 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.

The upper part of Table A1 shows the implications of the cleaning. Although the number of firms drops quite substantially from 368,190 employer firms to 88,510 firms in the analysis sub-sample , we cover 77.8% of all jobs (i.e. we lose only 22.2% of jobs). The lower part of the Table reports the summary statistics on this analysis sample which covers about 494,618 observations.The average firm has 6.35 FTE workers and has sales of 1.38 million euros at the mean (and 3.0 and 500,000 euros at the median). TFP growth is about 2% per annum. We also include a robustness where we extend the sample of firms with less than one FTE worker, and firms that are not in the B2B because they only sell directly to final consumers.

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.[27] 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. 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

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

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 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)[28], 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, applied for patents, have received tax credits for R&D expenditures, received R&D subsidies; as well as including 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 other potential R&D-active firms. We include R&D expenditures as a share of total sales, averaged over the sample period.

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 4-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), and averaged over time.

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

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

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.

Relationship Capability (RC) This is measured as simply the number of customer firm $j's$ that a firm i 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).[29] 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 a multinational, 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 a multinational 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 multinational; we focus only on the relationship that has the largest sales with a particular multinational. 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 multinational, but which does not exceed more than 10% of its total sales. If a firm starts selling to more than one multinational we keep the relationship with the lowest fraction of sales.

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

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 multinational in 2004, 57 percent of them still continue selling to this multinational in 2005, 43 percent in 2006, etc.

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 multinational 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 a multinational 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 multinational 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 multinational 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 multinational 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.

A.5 Odds Ratio: Calculating the Probability of obtaining an in-network customer by random chance

In Table 6, 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 by 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 6, the treatment effect is 1.14 vs. 0.68 (the mean number of in-network firms) compared to 3.6 vs. 10.8 (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 D6). Both of these effects make the odds of 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:

$$Pr(k) = \frac{J_{SS=k}}{J}(\frac{S_{SS=k}}{J_{SS=k}}) = \frac{S_{SS=k}}{J} \tag{7}$$

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 be uprated by $1 + \beta_x$ to reflect this. Denote this quality adjusted probability as $Pr(k')$:

$$Pr(k') = Pr(k)(1 + \beta_x x) = \frac{S_{SS=k}}{J}(1 + \hat{\beta}_x x) \tag{8}$$

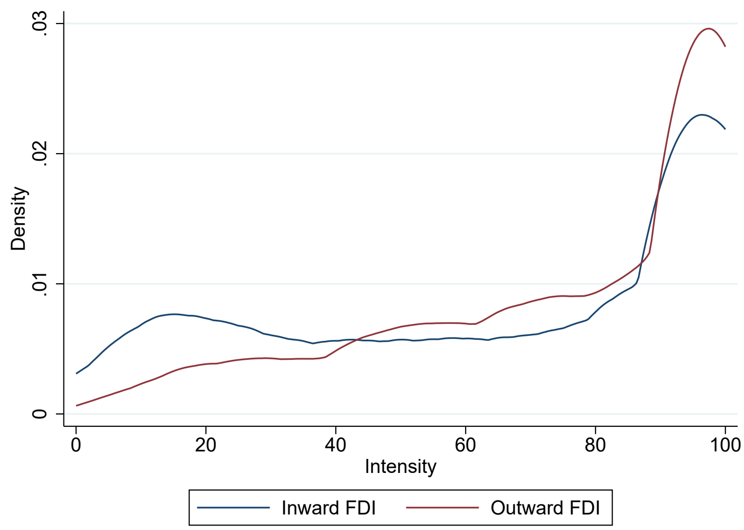
To calculate the expected number of in-network buyers that could arise by random chance ($E(B^{in})$), we take the estimated treatment effect on the total number of buyers ($\hat{B}$) and multiply this by $Pr(k')$, i.e.

$$E(B^{in}) = \hat{B}Pr(k') = \hat{B}\frac{S_{SS=k}}{J}(1 + \hat{\beta}_x x) \tag{9}$$

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:

$$ODDS = \frac{\hat{B}^{in}}{E(B^{in})} = \frac{\hat{B}^{in}}{\hat{B}\frac{S_{SS=k}}{J}(1 + \hat{\beta}_x x)} \tag{10}$$

Figure A1: Kernel Density of Multinational 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.

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 1.139 from column (1) of Table 6 and reproduced in the third from bottom row of Table A6. The expected number from random chance from equation (9) is $\hat{B}\frac{S_{SS=k}}{J}(1+\hat{\beta}_x x)$ = 4.75*(13,662/319,369)*(1 + (0.253*0.75)) = 0.253 (given in the fifth to last row of Table A6). All these numbers are given on different rows of column (1) in Table A6 which are taken either directly from the data or our econometric estimates (i.e. $\hat{\beta}_x$ comes from column (1) of Table D6; $\hat{B}^{in}$ and $\hat{B}^{out}$ are from columns (1) and (2) of Table 6 and $\hat{B} = \hat{B}^{in} + \hat{B}^{out}$). The Odds ratio of equation (10) is $\frac{\hat{B}^{in}}{E(B^{in})}$ = 1.231/0.248 = 4.96, which is given in the final row of Table A6 and in the last row of Table 6 in the main text. These imply that we would expect to see on average 0.24 new buyers from a superstar firm's network, whereas in reality we observe five times as many (1.1).

The other superstar treatments are calculated in the same way in Table A6 and also suggest substantially larger effects on obtaining more in-network than out-network buyers as discussed in subsection 5.3.2.

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 and ≤ 1 emp	117.92	1.87	68.0	1.6
firms not in B2B	103.28	1.81	4.0	3.2
observations missing TFP	88.51	1.48	4.0	17.4

Summary statistics

Variable	P50	Mean	SD
$ln(TFP_{WR})$	-0.31	-0.34	0.60
$\Delta ln(TFP_{WR})$	0.03	0.02	0.34
Sales (millions euros)	0.50	1.38	8.48
Intermediate inputs (millions euros)	0.29	1.03	6.88
Wage bill (millions euros)	0.10	0.26	1.55
# buyers (hundreds)	0.06	0.18	0.67
Employment (FTE)	3.00	6.35	19.46
Total fixed assets (millions euros)	0.08	0.53	6.64
Export value (millions euros)	0.00	0.11	1.91
Export dummy	0.00	0.06	0.24
Export varieties	0.00	1.60	36.19
Import value (millions euros)	0.00	0.12	1.85
Import dummy	0.00	0.11	0.31
Import varieties	0.00	2.93	20.44
Firm survival	1.00	0.59	0.49
Intangible assets (millions euros)	0.00	0.06	2.65
Purchases (millions euros)	0.22	0.80	5.71
Operating profit (thousands euros)	17.65	51.71	149.28
Markup (de Loecker and Warzynski (2012))	1.20	1.26	0.39

Notes: These descriptive statistics are based on our main analysis sample of firms with non-missing TFP (88,510 firms). The average number of observations is 494,618.

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
$ln(TFP_{WR})$	-0.371	-0.238	-0.412	-0.385	-0.247	-0.363	-0.304	-0.188	-0.367
	(0.601)	(0.614)	(0.599)	(0.576)	(0.593)	(0.603)	(0.604)	(0.620)	(0.595)
Sales (millions euros)	1.178	2.015	0.852	1.188	1.624	0.971	1.899	2.813	1.056
	(5.093)	(10.418)	(3.829)	(12.153)	(11.116)	(8.513)	(6.979)	(10.743)	(3.472)
Intermediate inputs (millions euros)	0.903	1.627	0.620	0.895	1.236	0.663	1.483	2.260	0.769
	(4.233)	(11.069)	(3.625)	(11.724)	(10.226)	(5.281)	(5.779)	(10.730)	(3.538)
Wage bill (millions euros)	0.227	0.338	0.164	0.205	0.299	0.232	0.350	0.487	0.206
	(1.363)	(1.343)	(0.401)	(1.041)	(1.256)	(1.776)	(1.914)	(2.619)	(0.559)
# buyers (thousands)	0.006	0.021	0.013	0.006	0.014	0.010	0.010	0.029	0.018
	(0.010)	(0.108)	(0.028)	(0.008)	(0.035)	(0.023)	(0.019)	(0.194)	(0.037)
Total fixed assets (millions euros)	0.530	0.670	0.394	0.388	0.610	0.563	0.686	1.300	0.392
	(4.594)	(5.858)	(3.967)	(3.336)	(6.524)	(6.082)	(5.535)	(18.969)	(3.554)
Employment	6.348	7.972	4.661	5.677	7.079	5.689	8.711	10.324	5.457
	(27.887)	(24.028)	(9.930)	(20.922)	(20.546)	(18.113)	(36.237)	(38.093)	(11.804)
Age of firm	11.343	10.484	13.122	11.535	11.230	13.081	11.971	11.605	13.839
	(10.686)	(9.908)	(10.936)	(9.808)	(9.838)	(11.282)	(10.829)	(10.485)	(11.300)
Average N	18,402	40,094	232,036	13,835	26,068	264,561	17,046	31,175	379,630

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
Mean number of suppliers	207	174	620
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. For example, the last column tells us there are a total of 491 large superstar firms, comprising 0.1 percent of the share of firms, 21% of total employment, with an average of 944 full-time employees. Out of these large superstar firms, 72 percent are also multinational, 32 percent are exporters (with most of the MNE being exporters) - out of the total large firms 74 percent are either multinational or exporters or both.

Table A5: The Persistency of a Relationship with a Multinational

(a) Serious Relationship with a Multinational

	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 Multinational

	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 Multinational, 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 Multinational, 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 multinational 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.

Table A6: 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)	0.263	0.127	0.199
Total actual number of other buyers increase ($\hat{B}$)	4.90	3.31	6.73
Actual increase in number of in-network buyers ($\hat{B}^{in}$)	1.178	0.474	2.550
Estimated increase in number of in-network buyers ($E(B^{in})$)	0.251	0.089	0.631
Odds ratio	4.69	5.32	4.04

Notes: This table provides all the data needed to calculated the odds ratio of selling to a buyer in the superstar's network. See Appendix D.7 for details. β_x comes from Column (1) of Table D6. $\hat{B}^{in}$ and $\hat{B}^{out}$ are from columns (1) and (2) of Table 6. $\hat{B} = \hat{B}^{in} + \hat{B}^{out}$

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:

$$Q_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} \tag{11}$$

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:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \varepsilon_{it} \tag{12}$$

$$ln(A_{it}) = a_{it} = \alpha_0 + \varepsilon_{it} \tag{13}$$

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:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + v_{it} + e_{it}, \tag{14}$$

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:

$$m_{it} = f_t(\omega_{it}, k_{it}, FX, FM, MNE). \tag{15}$$

By inverting (15), 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:

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_l k_{it} + v_{it} + \epsilon_{it} \tag{16}$$

with $w_{it} = \beta_0 + v_{it}$ representing firm level log productivity, and ϵ_{it} is a white noise error term. We 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

$$i_{it} = f_t(w_{it}, k_{it}, l_{it}, FX, FM, MNE). \tag{17}$$

Inverting (17) allows us to substitute out productivity w_{it} in (16) and we obtain:

$$q_{it} = \beta_m m_{it} + \theta(i_{it}, k_{it}, l_{it}, FX, FM, MNE) + \epsilon_{it}. \tag{18}$$

Equation (18) can be estimated with OLS to obtain an estimate of β_m.To obtain the markup we need to divide $\hat{\beta_m}$ 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 (16) we obtain an estimate of ϵ_{it}. Thus the corrected expenditure share is given by

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

.

The markup is then given by $\frac{\hat{\beta_m}}{\hat{\mu_{it}}}$.

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

To construct the control variable in Table 7, 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. 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:

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

and

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

However, if we want to include the change in total sales, the growth rates need to be calculated to include new relationships that form between these firms between t and $t-1$, i.e. 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 $t-1$. 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. 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).

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.[30]

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[31] 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.[32] Firms with superstar contracts supply both the superstar and the competitive markets, firms without superstar contracts

30. 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.

31. 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.

32. 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.

just supply the competitive market.

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:

$$\frac{p_i - c_i}{p_i} = \frac{1}{\eta}, \tag{19}$$

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

$$\pi_i = \widetilde{\eta} \left(\frac{1}{c_i} \right)^{\eta - 1}, \tag{20}$$

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:

$$\max_{Z_i} (Z_i - \sigma_i) Pr(D_i = 1 | Z_i) \tag{21}$$

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)):

$$s_i = \sigma_i \delta_i; \; where \; \delta_i = 1 + \frac{\int_{\sigma_i}^{\bar{\sigma}} [1 - F(\bar{\sigma})]^{I-1} d\bar{\sigma}}{\sigma_i [1 - F(\sigma_i)]^{I-1}} \tag{22}$$

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 (22) 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).[33] Focusing on the first element, we know from equation (20) this is:

$$\widetilde{\eta} \left\{ \gamma^{1-\eta} \left(\frac{1}{c_i} \right)^{\eta-1} - \left(\frac{1}{c_i} \right)^{\eta-1} \right\} = \left(\frac{1}{c_i} \right)^{\eta-1} \widetilde{\eta}(\gamma^{1-\eta} - 1) \tag{23}$$

This expression is decreasing in marginal cost, c, as $(1-\eta)\widetilde{\eta}(\gamma^{1-\eta}-1) < 0$.[34] In other words, high TFP firms will get a greater benefit from a superstar contract.[35]

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,

33. 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.

34. 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 $(\gamma^{1-\eta} - 1) > 0$

35. This follows from the convexity of the profit function in marginal costs from equation (20): 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 19), whereas they will be lower to the superstar firm due to bidding more aggressively in the auction due to the spillover benefits (see equation (22)). 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 (20)). Profits for winners are strictly positive so long as the 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 (23).

The evidence for Proposition 1 was established in the main results section 4. The evidence for Proposition 2 is in subsection 5.2.1. 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 5 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 D8).

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 A.5 above. Subsection 5.3.2 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.

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 D1 shows various alternative thresholds to 10% from anything at all (">0") to greater than 1%, 5%, 15%, 20% and 50%. Column (4) has our baseline results (with the 10% cutoff), 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, as well as a dummy for all pre-event years.

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 (7)) compared to five percent for any sales to a superstar (column (1)). 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. Table D1 suggests that our 10% threshold helps screen out these more endogenous relationships, and effectively balance the pre-trend between treatment and control.

Alternative Productivity Measures We include our baseline result (pooling the pre- and post-event years) in column (1) of Table D2 for comparison, but we don't report the coefficient on the pre-event years in all subsequent tables to save space. 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 D4, 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.[36]

36. 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

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 (16 percent for multinational) and the smallest ones coming from the methods which do not control for endogeneity (e.g. OLS generates a 5.2 percent effect in column (8) for multinational superstars).

Further refinements to the definition of large domestic superstars We already showed in the main text that pure large superstar firms generate the same level of TFP spillovers as MNEs (compare the coefficients in column 1 of Table 4 in the top and bottom panels). This is illustrated again in D1, where we reestimate the baseline regression from Table 3, but allow for a different coefficient for large firms that are also MNEs. The graph shows that spillovers to large firms that are not MNEs are actually a big higher than those to large firms that are MNEs. Table D3 probes the definition of large domestic superstars further. First, we present the results from the figure in table form in column (1) where we allow separate treatment effects for large domestics vs. large MNE superstars. Here, we take the full set of large superstar firms from our baseline, and allow for different coefficients for large firms that are also MNEs, thus excluding MNEs from the large domestic coefficients in the first two rows (and pool the pre and post-treatment coefficients). Again, we see that the impact of a large domestic superstar is not smaller than a large multinational (if anything, it is a bit larger: 8 percent vs. 7 percent). Since some of the non-multinational domestic firms are intensive exporting superstars, it could be that our results are driven by these type of firms. Column (2) also removes exporters from the large domestic definition and includes them in the "large global" definition alongside multinationals. The results are almost unchanged. Some domestic superstars may do indirect FDI, i.e. they do not have serious foreign ownership or overseas affiliates directly, but they are owned by a domestic firm which does have such an ownership structure Column (3) further refines the large domestic superstar defintion by switching this group from domestic into global, reducing the fraction that is large domestic to only 1.3%. 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 a separate category. The final column shows that the purely domestic, non-government superstars still create significant spillovers.[37]

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.

37. An interesting finding is that this publicly owned group of firms 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. 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 distribution. They are engaged in various innovation projects. See main text and footnote 11 for examples of large domestic private firms.

Other Performance Outcomes Tables D4 and D5 has a variety of other performance outcomes. Note that the positive effect on survival effects in column (1) of Table D4 implies that we are underestimating the full benefits of superstars because the event studies on productivity, etc. are conditional on being alive. We show positive and significant effects on employment, tangible assets, intangible assets and total profits. Column (5) shows the negative and significant effects on the price-cost margin, which is what our Appendix C model predicts.

Quality of Average Buyers Table D6 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).

Heterogeneity of Treatment Effects Table D7, columns (1) to (4) show that superstar firms that are more intensive in R&D, ICT, skill share, or RC lead to larger sales to other buyers. Columns (5) to (7) show the results are robust to including all four of these interactive indicators together for the outcome variables log TFP, log other buyers and log other sales.

Absorptive Capacity Table D8, columns (1) to (3) interacts firm i with indicators for intensity in R&D, ICT, and skill share, showing that firms that are more intensive in these characteristics enjoy higher spillovers. In column (4), we show the largest gains accrue to young firms.

Superstar Entry Table D9 reports the results for the superstar entry design used in subsection 6.2. Here we use only connections to firms who become superstars in the previous period to identify the spillover effects.

Ending relationship with superstar Table D10 shows that firms continue to enjoy positive spillovers even after a relationship ends with a superstar albeit the magnitudes are smaller than for firms that continue their relationship with SS firms.

Cohort-Specific Diff-In-Diff designs Table D11 show the event studies using the Sun and Abraham (2021) approach for all our main outcomes for the three definitions of superstars.

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.[38] We use the multi-variate Mahalanobis distance[39] to find close matches on

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

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

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 four-digit sector. We also ensured that a firm is not matched to a firm that it is linked through cross-ownership relationships, by using a group-firm variable from Dhyne, Kikkawa, et al. (2021). We experimented also with matching on other variables, such as TFP, as well with non-exact matching, yielding very similar results. Table D12 contains the results, which are remarkably similar to the baseline results even though the sample is much smaller.

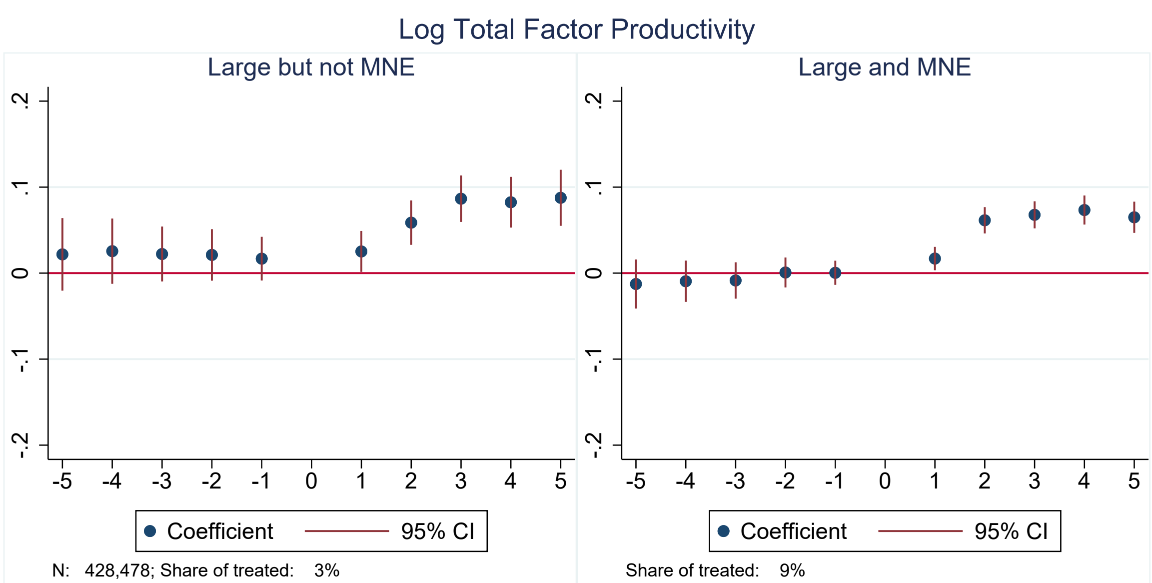
Multinational Definition and country of origin Table D13 explores some alternative definitions of multinational superstar. Recall that in our baseline results we define a multinational if it has inward (i.e. foreign owned) or outward (i.e. domestically owned but with overseas affiliates) FDI. Column (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 indirect 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 (9.8%) and less-developed countries the least (6.3%). EU and other developed are in between, around 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)).

Other thresholds for non-multinational superstars Table D14 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 qualitatively similar to the baseline.

Alternative Samples Table D15 examines a variety of alternative sampling assumptions. We show robustness to alternative employment cutoffs (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.

Business Stealing Table D16 simplifies the basic specification. Instead of including a full set of industry-by-year fixed effects, we instead just include year fixed effects (with the industry fixed effects absorbed by the firm fixed effects). The results show slightly higher coefficients than in the baseline specifications

Figure D1: 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.

Table D1: 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 greater than or equal to:						
	0%	1%	5%	10%	15%	20%	50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MNE							
2 or more years before event	-0.008**	-0.003	0.006	0.005	0.001	-0.003	-0.012
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.010)
t1: Year of event	0.015***	0.010**	0.016***	0.012**	0.009	0.013*	0.004
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.010)
1 or more years after event	0.068***	0.074***	0.084***	0.083***	0.080***	0.080***	0.063***
	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.010)
Observations	397,217	353,944	311,548	291,845	280,983	273,949	254,110
Adjusted R-squared	0.732	0.727	0.725	0.723	0.723	0.723	0.723
Exporters							
2 or more years before event	-0.014***	-0.009**	0.007	0.004	-0.002	-0.006	-0.004
	(0.003)	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)	(0.012)
t1: Year of event	0.012***	0.009**	0.011*	0.003	-0.003	-0.005	-0.007
	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)	(0.008)	(0.012)
1 or more years after event	0.054***	0.061***	0.069***	0.066***	0.063***	0.060***	0.059***
	(0.004)	(0.004)	(0.006)	(0.007)	(0.008)	(0.009)	(0.012)
Observations	408,749	363,879	322,861	306,256	297,658	292,335	278,978
Adjusted R-squared	0.732	0.726	0.724	0.723	0.723	0.723	0.724
Large							
2 or more years before event	-0.013***	-0.007*	0.003	0.003	-0.003	-0.006	0.007
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.011)
t1: Year of event	0.018***	0.016***	0.021***	0.019***	0.015**	0.015*	0.010
	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.011)
1 or more years after event	0.053***	0.063***	0.072***	0.075***	0.072***	0.069***	0.071***
	(0.003)	(0.004)	(0.005)	(0.007)	(0.007)	(0.008)	(0.012)
Observations	553,219	492,944	447,698	428,478	418,843	412,328	395,374
Adjusted R-squared	0.734	0.728	0.725	0.724	0.723	0.723	0.723

Notes: These specifications are the same as in column (1) of Tables 1, 2, and 3, 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). The baseline cutoff of 10% is reported in column (4) for comparison. 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 D2: 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	0.012**	0.017***	0.005	0.033***	0.027***	0.007	0.003	-0.000	0.016***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
1 or more years after event	0.083***	0.098***	0.058***	0.157***	0.060***	0.069***	0.072***	0.052***	0.072***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Observations	291,845	291,844	291,845	291,845	278,944	291,845	291,772	291,845	286,318
Adjusted R^2	0.724	0.731	0.698	0.833	0.816	0.700	0.691	0.650	0.737
Exporters									
t1: Year of event	0.003	0.003	-0.001	0.020***	0.022***	-0.000	-0.004	-0.006	0.008
	(0.007)	(0.006)	(0.007)	(0.008)	(0.005)	(0.007)	(0.007)	(0.007)	(0.006)
1 or more years after event	0.066***	0.073***	0.048***	0.130***	0.049***	0.054***	0.059***	0.041***	0.060***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.005)	(0.007)	(0.008)	(0.007)	(0.007)
Observations	306,256	306,256	306,256	306,256	292,569	306,256	306,205	306,256	300,529
Adjusted R^2	0.724	0.737	0.692	0.843	0.761	0.695	0.687	0.638	0.738
Large									
t1: Year of event	0.019***	0.023***	0.014**	0.041***	0.030***	0.015**	0.009	0.009	0.022***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
1 or more years after event	0.075***	0.089***	0.054***	0.145***	0.058***	0.063***	0.063***	0.048***	0.063***
	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)	(0.007)	(0.006)
Observations	428,478	428,475	428,478	428,478	413,000	428,478	428,352	428,478	421,876
Adjusted R^2	0.725	0.734	0.696	0.838	0.812	0.698	0.690	0.647	0.739

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 pre-treatmentt and after treatment. We do not report the pre-event coefficients to save space. 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 D3: TFP gains from selling to Large Domestic Firms

	Dependent Variable: Log Total Factor Productivity			
Alternative large domestic definition:	Exclude MNE (1)	& Exclude exporters (2)	& Exclude indirect MNE (3)	& Exclude govt. (4)
Large domestic, t1: Year of event	0.022	0.023*	0.017	-0.031
	(0.014)	(0.014)	(0.017)	(0.027)
Large domestic, 1 or more years after event	0.076***	0.078***	0.075***	0.058**
	(0.014)	(0.015)	(0.017)	(0.028)
Large global, t1: Year of event	0.016**	0.015**	0.016**	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)
Large global, 1 or more years after event	0.066***	0.066***	0.069***	0.069***
	(0.008)	(0.008)	(0.007)	(0.007)
Large govt., t1: Year of event				0.047**
				(0.022)
Large govt., 1 or more years after event				0.085***
				(0.022)
Firm FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Percentage of treated large domestic	2.15	2.11	1.31	0.50
Observations	424,050	424,204	425,725	425,699
Adjusted R^2	0.723	0.723	0.723	0.723

Notes: Regressions are specified as in the baseline Table 3 but allowing for separate coefficients for treatment to "pure" large domestic superstars and other large superstars (and with pooled pre and post-treatment variables). The number of of observations differ slightly because we drop any treated firm that sells to more than one type of large superstar. Column (1) defines large, domestic firms as those large firms that are non-multinational. Column (2) defines large, domestic firms as those large firms that are non-multinational and non-exporting. Column (3) defines large, domestic firms as those large firms that are non-multinational, non-exporting, and non-indirect-multinational. Column (4) defines large, domestic firms as those large firms that are non-multinational, non-exporting, non-indirect-multinational, and non-government. TFP is estimated using the Wooldridge methodology. All regressions include a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D4: Gains from selling to Superstars on other Performance Outcomes

	Firm survival	Log employment	Log tangible fixed assets	Log intangible assets	Log markup	Profits
	(1)	(2)	(3)	(4)	(5)	(6)
MNE						
t1: Year of event	0.078***	0.038***	0.072***	0.256***	-0.006***	0.204
	(0.001)	(0.006)	(0.011)	(0.037)	(0.002)	(1.273)
1 or more years after event	0.056***	0.153***	0.151***	0.266***	-0.010***	10.736***
	(0.002)	(0.007)	(0.015)	(0.039)	(0.002)	(1.406)
Observations	935,626	291,845	291,322	287,156	229,034	291,845
Adjusted R^2	0.088	0.847	0.817	0.621	0.850	0.665
Exporters						
t1: Year of event	0.076***	0.024***	0.063***	0.156***	-0.005***	-1.235
	(0.002)	(0.007)	(0.013)	(0.043)	(0.002)	(1.420)
1 or more years after event	0.062***	0.124***	0.119***	0.197***	-0.007***	8.681***
	(0.003)	(0.008)	(0.017)	(0.045)	(0.002)	(1.554)
Observations	1,048,974	306,256	305,755	301,279	242,218	306,256
Adjusted R^2	0.089	0.854	0.816	0.638	0.851	0.661
Large						
t1: Year of event	0.074***	0.034***	0.078***	0.172***	-0.008***	3.938**
	(0.002)	(0.006)	(0.012)	(0.037)	(0.002)	(1.755)
1 or more years after event	0.057***	0.138***	0.147***	0.221***	-0.010***	15.129***
	(0.003)	(0.008)	(0.016)	(0.038)	(0.002)	(1.997)
Observations	1,269,427	428,478	427,778	423,057	344,674	428,478
Adjusted R^2	0.084	0.859	0.814	0.630	0.846	0.660

Notes: These specifications are the same as in Table D2 except with a different outcome variable as the dependent variable. All regressions include a pre-event dummy, but coefficients are 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. 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 0.89. 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), profits are in thousands of euros. The variables in columns (5) and (6) have been winsorized at the 1st and 99th percentiles.

Table D5: 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	0.006	0.003	0.279***	0.003	0.009***	0.092
	(0.009)	(0.002)	(0.082)	(0.014)	(0.003)	(0.143)
1 or more years after event	0.061***	0.012***	0.527***	0.071***	0.024***	0.596***
	(0.012)	(0.002)	(0.099)	(0.014)	(0.003)	(0.201)
Observations	291,845	291,845	291,845	291,845	291,845	291,845
Adjusted R^2	0.935	0.694	0.882	0.846	0.672	0.775
Exporters						
t1: Year of event	0.008	-0.000	-0.076	0.010	0.007**	0.246
	(0.005)	(0.002)	(0.143)	(0.010)	(0.003)	(0.151)
1 or more years after event	0.016	0.006**	-0.462	0.033***	0.015***	0.490***
	(0.010)	(0.002)	(0.628)	(0.012)	(0.003)	(0.165)
Observations	306,256	306,256	306,256	306,256	306,256	306,256
Adjusted R^2	0.664	0.538	0.314	0.613	0.574	0.757
Large						
t1: Year of event	0.045***	0.006**	0.353***	0.027	0.010***	0.178
	(0.017)	(0.003)	(0.106)	(0.020)	(0.004)	(0.150)
1 or more years after event	0.121***	0.015***	0.619***	0.128***	0.023***	0.935***
	(0.023)	(0.003)	(0.182)	(0.027)	(0.004)	(0.210)
Observations	428,478	428,478	428,478	428,478	428,478	428,478
Adjusted R^2	0.831	0.711	0.757	0.798	0.700	0.787

Notes: These specifications are the same as in Table D2 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 a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D6: Effects on Average Buyer Quality

	Average			
Dependent variable:	Log suppliers (1)	Log employment (2)	Log sales (3)	Log buyers (4)
MNE				
t1: Year of event	0.024*	-0.005	0.012	0.002
	(0.013)	(0.025)	(0.028)	(0.025)
1 or more years after event	0.263***	0.536***	0.653***	0.362***
	(0.014)	(0.026)	(0.029)	(0.026)
Observations	219,944	206,545	216,445	212,347
Adjusted R^2	0.631	0.628	0.626	0.528
Exporters				
t1: Year of event	0.010	0.029	0.040	0.036
	(0.017)	(0.033)	(0.037)	(0.033)
1 or more years after event	0.127***	0.305***	0.377***	0.169***
	(0.017)	(0.033)	(0.037)	(0.031)
Observations	232,931	219,243	229,143	224,986
Adjusted R^2	0.637	0.638	0.622	0.538
Large				
t1: Year of event	0.034***	0.063***	0.055**	0.046**
	(0.011)	(0.020)	(0.022)	(0.020)
1 or more years after event	0.199***	0.431***	0.575***	0.317***
	(0.011)	(0.021)	(0.024)	(0.021)
Observations	558,277	529,266	550,928	543,305
Adjusted R^2	0.629	0.616	0.607	0.524

Notes: These specifications are the same as in Table D2 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. All regressions include a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D7: 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	0.122***	0.121***	0.124***	0.104***	0.050***	0.207***	0.075***
	(0.011)	(0.012)	(0.011)	(0.016)	(0.010)	(0.019)	(0.019)
x R&D indicator	0.081***				0.034***	0.091***	0.066***
	(0.018)				(0.010)	(0.025)	(0.018)
x ICT		0.046***			0.025***	0.053***	0.029*
		(0.016)			(0.009)	(0.020)	(0.016)
x Skill Share indicator			0.048***		0.027***	0.109***	0.035**
			(0.016)		(0.010)	(0.023)	(0.017)
x RC indicator				0.047***	0.016	0.069***	0.045**
				(0.018)	(0.010)	(0.019)	(0.018)
Observations	279,578	279,578	279,578	279,578	291,845	219,944	279,578
Adjusted R^2	0.860	0.860	0.860	0.860	0.724	0.858	0.860
Exporters							
1 or more years after event	0.060***	0.059***	0.061***	0.060***	0.051***	0.199***	0.041**
	(0.007)	(0.008)	(0.008)	(0.009)	(0.010)	(0.020)	(0.017)
x R&D indicator	0.041***				0.036**	0.115***	0.111***
	(0.013)				(0.014)	(0.033)	(0.026)
x ICT indicator		0.019*			0.013	0.016	0.036*
		(0.010)			(0.011)	(0.023)	(0.019)
x Skill Share indicator			0.010		0.000	0.047**	-0.028
			(0.010)		(0.010)	(0.021)	(0.023)
x RC indicator				0.011	0.009	0.046**	0.081***
				(0.010)	(0.010)	(0.021)	(0.021)
Observations	306,256	306,256	306,256	306,256	306,256	232,931	293,351
Adjusted R^2	0.723	0.723	0.723	0.723	0.723	0.827	0.856
Large							
1 or more years after event	0.067***	0.070***	0.068***	0.072***	0.057***	0.167***	0.058***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.010)	(0.019)	(0.018)
x R&D indicator	0.055***				0.051***	0.139***	0.062***
	(0.012)				(0.013)	(0.031)	(0.023)
x ICT indicator		0.013			0.003	0.006	0.000
		(0.010)			(0.010)	(0.021)	(0.018)
x Skill Share indicator			0.028**		0.019	0.122***	0.054**
			(0.011)		(0.012)	(0.026)	(0.021)
x RC indicator				0.005	0.007	0.056***	0.050***
				(0.010)	(0.010)	(0.020)	(0.018)
Observations	428,478	428,478	428,478	428,478	428,478	350,297	413,816
Adjusted R^2	0.724	0.724	0.724	0.724	0.724	0.872	0.874

Notes: Columns (1) to (4) are the parallel regressions to those in Table 5, 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 the year of event dummy, and a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D8: Absorptive Capacity: Treatment effects are larger for firms who are Hi-tech, Skilled and Young

Dependent variable:	Log TFP			
	Indicator Variable			
	R&D (1)	ICT (2)	Skill labor (3)	Young (4)
MNE				
1 or more years after event	0.081***	0.077***	0.070***	0.026***
	(0.006)	(0.006)	(0.007)	(0.007)
x Indicator Variable	0.164***	0.031***	0.058***	0.177***
	(0.045)	(0.012)	(0.011)	(0.009)
Observations	291,845	291,845	291,845	291,845
Adjusted R^2	0.724	0.723	0.724	0.724
FX				
1 or more years after event	0.066***	0.063***	0.053***	0.024***
	(0.007)	(0.007)	(0.007)	(0.007)
x Indicator Variable	-0.001	0.017	0.054***	0.143***
	(0.066)	(0.014)	(0.013)	(0.011)
Observations	306,256	306,256	306,256	306,256
Adjusted R^2	0.723	0.723	0.723	0.723
FLS				
1 or more years after event	0.073***	0.069***	0.067***	0.026***
	(0.007)	(0.007)	(0.007)	(0.007)
x Indicator Variable	0.097***	0.029**	0.035***	0.173***
	(0.035)	(0.012)	(0.012)	(0.011)
Observations	428,478	428,478	428,478	428,478
Adjusted R^2	0.724	0.724	0.724	0.724

Notes: These specifications are the same as in Table D2, except we include an additional interactive dummy variable based on firm $i's$ characteristic. The dummy indicator variable in each column is time-invariant and defined as follows: (1) **"R&D"** equals 1 (and zero otherwise) if the treated firm has positive research and development expenditures. (2) **"ICT"** equals 1 (and zero otherwise) if the treated firm is in the top quartile of treated firms' spending on ICT 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 treated firm is in the top quartile of the treated firms' skill share distribution, defined as the share of full-time-equivalent workers with a college degree; (4) **"Young"** equals 1 if the age of the firm is less than or equal to five years. The dependent variable is log TFP. All regressions include the year of event dummy, and a pre-event dummy, but coefficients are 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. In the regression sample for multinational, 36% of the treated firms are young firm observations; the share is 31% for the Exporters sample and 30% for the Large sample. *** indicates significance at the 1% level, **5%, * 10%.

Table D9: 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	0.042**	0.050*	-0.024	0.034	0.042*	0.066
	(0.021)	(0.028)	(0.033)	(0.026)	(0.022)	(0.040)
1 or more years after event	0.070***	0.152***	0.132***	0.136***	0.157***	0.196***
	(0.022)	(0.032)	(0.034)	(0.031)	(0.026)	(0.042)
Observations	237,370	226,417	226,407	225,499	225,498	174,465
Adjusted R^2	0.723	0.872	0.871	0.894	0.855	0.870
Inward FDI						
t1: Year of event	0.039*	0.041	-0.036	0.025	0.035	0.054
	(0.023)	(0.028)	(0.035)	(0.026)	(0.023)	(0.044)
1 or more years after event	0.076***	0.152***	0.135***	0.138***	0.171***	0.183***
	(0.024)	(0.032)	(0.035)	(0.031)	(0.028)	(0.046)
Observations	236,721	225,792	225,782	224,874	224,873	173,894
Adjusted R^2	0.723	0.872	0.871	0.894	0.855	0.870
Exporters						
t1: Year of event	-0.010	-0.014	-0.171***	-0.001	0.034	0.020
	(0.023)	(0.026)	(0.065)	(0.027)	(0.026)	(0.047)
1 or more years after event	0.036	0.085***	-0.094	0.069**	0.111***	0.159***
	(0.024)	(0.028)	(0.074)	(0.034)	(0.033)	(0.049)
Observations	269,058	256,891	256,865	255,826	255,826	200,199
Adjusted R^2	0.723	0.863	0.859	0.890	0.869	0.834

Notes: TFP is estimated using the Wooldridge methodology. In this Table, treatments are defined as 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 of at least 10% in the year of entry. The share of observations treated is 2% in the multinational panel and 1-2% in the FDI and Exporters panels. All regressions include a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D10: 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	0.109***	0.281***	0.160***	0.302***	0.238***	0.388***
	(0.007)	(0.011)	(0.014)	(0.014)	(0.010)	(0.017)
x End of relationship	-0.045***	-0.137***	-0.041***	-0.157***	-0.102***	-0.128***
	(0.007)	(0.010)	(0.013)	(0.012)	(0.009)	(0.014)
Observations	291,845	279,852	279,578	279,623	291,844	219,944
Adjusted R^2	0.724	0.874	0.860	0.889	0.866	0.858
Exporters						
1 or more years after event	0.098***	0.238***	0.131***	0.241***	0.217***	0.336***
	(0.008)	(0.013)	(0.018)	(0.015)	(0.011)	(0.019)
x End of relationship	-0.053***	-0.128***	-0.048***	-0.133***	-0.096***	-0.109***
	(0.008)	(0.011)	(0.016)	(0.013)	(0.011)	(0.016)
Observations	306,256	293,596	293,351	293,250	306,256	232,931
Adjusted R^2	0.723	0.865	0.856	0.885	0.874	0.827
Large						
1 or more years after event	0.106***	0.273***	0.128***	0.279***	0.225***	0.326***
	(0.008)	(0.012)	(0.015)	(0.014)	(0.010)	(0.017)
x End of relationship	-0.059***	-0.156***	-0.034**	-0.171***	-0.121***	-0.143***
	(0.008)	(0.011)	(0.014)	(0.013)	(0.011)	(0.016)
Observations	428,478	413,980	413,816	413,766	428,475	350,297
Adjusted R^2	0.724	0.882	0.874	0.895	0.875	0.872

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 the year of event dummy, and a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D11: Gains from selling to superstars, Robustness using Sun and Abraham (2021) approach

	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						
Year of event	0.012**	0.082***	-0.037***	0.099***	0.037***	0.092***
	(0.006)	(0.008)	(0.010)	(0.010)	(0.007)	(0.013)
1 or more years after event	0.084***	0.203***	0.138***	0.213***	0.179***	0.317***
	(0.006)	(0.009)	(0.010)	(0.011)	(0.008)	(0.014)
Observations	291,845	279,852	279,578	279,623	291,844	219,944
Adjusted R^2	0.723	0.874	0.860	0.889	0.866	0.858
FX						
Year of event	0.003	0.071***	-0.031***	0.082***	0.030***	0.075***
	(0.007)	(0.009)	(0.012)	(0.010)	(0.007)	(0.015)
1 or more years after event	0.068***	0.164***	0.106***	0.164***	0.160***	0.277***
	(0.007)	(0.010)	(0.012)	(0.012)	(0.009)	(0.015)
Observations	306,256	293,596	293,351	293,250	306,256	232,931
Adjusted R^2	0.723	0.865	0.856	0.885	0.874	0.827
FLS						
Year of event	0.019***	0.083***	-0.036***	0.097***	0.034***	0.099***
	(0.006)	(0.009)	(0.010)	(0.010)	(0.007)	(0.013)
1 or more years after event	0.076***	0.187***	0.107***	0.188***	0.162***	0.253***
	(0.007)	(0.009)	(0.010)	(0.011)	(0.009)	(0.014)
Observations	428,478	413,980	413,816	413,766	428,475	350,297
Adjusted R^2	0.724	0.882	0.874	0.895	0.875	0.872

Notes: Regressions are specified as in the baseline Tables 1, 2, and 3 but using the robust difference-in-differences estimator from Sun and Abraham (2021) (and with pooled pre and post-treatment variables). All regressions include a pre-event dummy, but coefficients are 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.

Table D12: Nearest-neighbor matching

	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)
t1: Year of event	0.058***	0.131***	0.039***	0.143***	0.125***	0.119***
	(0.006)	(0.008)	(0.009)	(0.009)	(0.006)	(0.013)
1 or more years after event	0.073***	0.183***	0.119***	0.190***	0.179***	0.273***
	(0.007)	(0.010)	(0.011)	(0.012)	(0.009)	(0.015)
Observations	74,247	72,589	72,524	72,585	74,247	53,804
Adjusted R^2	0.729	0.881	0.863	0.888	0.878	0.790
Exporters						
t1: Year of event	0.040***	0.114***	0.031***	0.122***	0.096***	0.087***
	(0.007)	(0.008)	(0.011)	(0.010)	(0.007)	(0.015)
1 or more years after event	0.059***	0.141***	0.088***	0.147***	0.147***	0.238***
	(0.008)	(0.011)	(0.013)	(0.013)	(0.011)	(0.017)
Observations	55,268	54,439	54,381	54,441	55,268	42,138
Adjusted R^2	0.710	0.864	0.837	0.880	0.871	0.753
Large						
t1: Year of event	0.059***	0.139***	0.037***	0.146***	0.114***	0.136***
	(0.006)	(0.009)	(0.009)	(0.010)	(0.007)	(0.014)
1 or more years after event	0.074***	0.179***	0.096***	0.179***	0.162***	0.231***
	(0.007)	(0.011)	(0.012)	(0.013)	(0.010)	(0.016)
Observations	69,590	68,111	68,069	68,100	69,588	55,786
Adjusted R^2	0.729	0.895	0.881	0.895	0.896	0.829

Notes: Regressions are specified as in the baseline Tables 1, 2, and 3 but using the nearest neighbor difference-in-differences estimator (and with pooled pre and post-treatment variables).TFP is estimated using the Wooldridge methodology. All regressions include a pre-event dummy, but coefficients are not reported to save space. All regressions include year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.

Table D13: Alternative Superstar Definition: Multinational

	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	0.021***	0.012**	0.012**	0.014**	
	(0.006)	(0.006)	(0.006)	(0.006)	
1 or more years after event	0.086***	0.083***	0.085***	0.084***	
	(0.006)	(0.006)	(0.007)	(0.006)	
EU, t1: Year of event					0.014**
					(0.007)
EU, 1 or more years after event					0.081***
					(0.008)
US, t1: Year of event					0.010
					(0.013)
US, 1 or more years after event					0.098***
					(0.013)
Other developed, t1: Year of event					0.019
					(0.024)
Other developed, 1 or more years after event					0.082***
					(0.026)
Less developed, t1: Year of event					-0.003
					(0.018)
Less developed, 1 or more years after event					0.063***
					(0.018)
Observations	348,353	346,257	284,358	289,925	291,845
Adjusted R-squared	0.724	0.727	0.723	0.724	0.723
Share of treated	14	16	18	20	20

Notes: Regressions are specified as in the baseline Table 1 but using alternative definitions of multinational superstar firms (and with pooled pre and post-treatment variables). Column (1) defines multinational firms as only those with inward FDI. Column (2) defines multinational firms as only those with outward FDI. Column (3) changes the threshold for multinational to 50%. Column (4) includes indirect FDI in addition to direct FDI. Column (5) splits links to multinational 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 classification. The "less developed" category comprises all countries not in one of the other three catgories. For firms with links to multiple multinational 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 multinational 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 a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D14: 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	0.004	0.005	0.006	0.016		0.020***	0.008
	(0.006)	(0.006)	(0.007)	(0.010)		(0.006)	(0.007)
1 or more years after event	0.064***	0.074***	0.065***	0.062***		0.090***	0.049***
	(0.006)	(0.006)	(0.008)	(0.010)		(0.006)	(0.008)
EU, t1: Year of event					0.003		
					(0.010)		
EU, 1 or more years after event					0.061***		
					(0.011)		
US, t1: Year of event					0.001		
					(0.012)		
US, 1 or more years after event					0.088***		
					(0.011)		
Other developed, t1: Year of event					0.085**		
					(0.034)		
Other developed, 1 or more years after event					0.145***		
					(0.031)		
Less developed, t1: Year of event					0.008		
					(0.011)		
Less developed, 1 or more years after event					0.069***		
					(0.011)		
Observations	249,532	249,130	298,914	285,131	307,254	346,934	579,153
Adjusted R-squared	0.726	0.728	0.723	0.723	0.723	0.723	0.729
Share of treated	21	20	11	6	13	16	6

Notes: Regressions are specified as in the baseline Tables 2, and 3 but using alternative definitions of exporter and large superstar firms (and with pooled pre and post-treatment variables). 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 classification. 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 a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D15: Robustness to Alternative Samples

	Dependent variable: Log Total Factor Productivity							
	Sample of firms with employment greater than:							
	0	5	10	Put dropped treated in controls	Include non-B2B firms in controls	Min 1 year of pre and post treatment	Drop wholesalers	Balanced panel
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MNE								
t1: Year of event	0.030***	0.003	0.026*	0.012**	0.012**	0.014***	0.016***	0.020***
	(0.006)	(0.009)	(0.014)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
1 or more years after event	0.084***	0.078***	0.091***	0.092***	0.083***	0.080***	0.081***	0.035***
	(0.006)	(0.010)	(0.015)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
Observations	501,628	68,728	24,633	942,566	367,153	308,280	272,016	162,852
Adjusted R-squared	0.645	0.777	0.796	0.758	0.738	0.725	0.722	0.745
Exporters								
t1: Year of event	0.019***	-0.017	-0.007	0.004	0.004	0.005	0.003	0.008
	(0.006)	(0.011)	(0.019)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)
1 or more years after event	0.070***	0.063***	0.077***	0.072***	0.066***	0.061***	0.066***	0.038***
	(0.007)	(0.011)	(0.018)	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)
Observations	516,416	77,196	29,809	739,949	380,829	315,833	306,256	173,412
Adjusted R-squared	0.645	0.773	0.787	0.760	0.736	0.724	0.723	0.748
Large								
t1: Year of event	0.034***	0.019**	0.014	0.018***	0.019***	0.019***	0.021***	0.017**
	(0.006)	(0.009)	(0.013)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
1 or more years after event	0.080***	0.078***	0.081***	0.080***	0.075***	0.073***	0.076***	0.033***
	(0.006)	(0.009)	(0.014)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)
Observations	700,161	116,380	45,262	944,755	504,010	441,435	394,753	255,895
Adjusted R-squared	0.648	0.775	0.792	0.763	0.734	0.725	0.721	0.745

Notes: These specifications are the same as in column (1) of Tables 1, 2, and 3, 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 control sample 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 a pre-event dummy, but coefficients are 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% level, **5%, * 10%.

Table D16: Results robust to dropping industry by year fixed effects

	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						
Year of treatment	0.013**	0.081***	-0.041***	0.098***	0.034***	0.094***
	(0.006)	(0.009)	(0.010)	(0.010)	(0.007)	(0.013)
1 or more years after event	0.094***	0.214***	0.147***	0.221***	0.191***	0.327***
	(0.006)	(0.010)	(0.010)	(0.011)	(0.008)	(0.014)
Observations	292,864	280,882	280,604	280,652	292,863	220,936
Adjusted R^2	0.717	0.869	0.855	0.885	0.862	0.856
Exporters						
Year of treatment	0.003	0.065***	-0.041***	0.078***	0.027***	0.076***
	(0.007)	(0.009)	(0.012)	(0.011)	(0.008)	(0.015)
1 or more years after event	0.071***	0.161***	0.099***	0.163***	0.162***	0.276***
	(0.007)	(0.010)	(0.012)	(0.012)	(0.009)	(0.015)
Observations	307,171	294,525	294,277	294,172	307,171	233,815
Adjusted R^2	0.718	0.859	0.850	0.881	0.871	0.825
Large						
Year of treatment	0.019***	0.084***	-0.039***	0.095***	0.033***	0.100***
	(0.006)	(0.009)	(0.010)	(0.010)	(0.007)	(0.013)
1 or more years after event	0.084***	0.201***	0.117***	0.193***	0.173***	0.257***
	(0.007)	(0.010)	(0.011)	(0.012)	(0.009)	(0.014)
Observations	429,358	414,847	414,687	414,642	429,355	351,160
Adjusted R^2	0.718	0.878	0.870	0.892	0.872	0.870

Notes: Regressions are specified as in the baseline Tables 1, 2, and 3 but without industry x year fixed effects (and with pooled pre and post-treatment variables). TFP is estimated using the Wooldridge methodology. All regressions include a pre-event dummy, but coefficients are not reported to save space. All regressions include year and firm fixed effects. Standard errors are clustered at the firm level. *** indicates significance at the 1% level, **5%, * 10%.