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FDI and superstar spillovers: Evidence from firm-to-firm transactions[☆]

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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% after three years. Placebos on starting relationships with smaller firms and novel identification strategies support a causal interpretation of "superstar spillovers". Consistent with a model of technology transfer, we find bigger treatment effects from technology-intensive superstars and also falls in markups (in order to win superstar contracts). We also show that firms that start supplying superstar firms enjoy a 'dating agency' effect — an increase in the number of new buyers that is particularly strong within the superstar firm's network. Taken together, the results suggest an important role for raising productivity through superstars' supply chains regardless of multinational status.

1. Introduction

Do superstar firms generate positive spillovers? The increasing dominance of large firms in recent decades has attracted much attention (Autor et al., 2020; Bajgar et al., 2020; De Loecker et al., 2020), mostly focused on the potential costs of these trends (Philippon, 2019; House, 2021; Akcigit and Ates, 2023). 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 et al., 2022; Berger et al., 2022) as well as their 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 what we entitle "superstar spillovers".[1]

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[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.

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This is the first paper to show positive productivity 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 Foreign Direct Investment (FDI). 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 US Chips and Science Act for semiconductors 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 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.[2] In contrast, the econometric literature has found mixed results on FDI spillovers. However, because these 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?

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. This is consistent with Alfaro-Ureña et al. (2022) who also find TFP spillovers in Costa Rica. But because this is a small developing country, they cannot assess whether all types of superstar firms generate spillovers because they do not have 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 do not have to be multinational.[3]

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 percent 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 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 percent of the size distribution are neither multinationals nor intensive exporters. In addition to a positive growth in TFP, partnering with a superstar firm leads to growth in outputs, inputs (labor, capital and intermediates), the number of buyers, engagement in international trade and survival.

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

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

[2] 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. Additionally, Bloom et al. (2013) discuss how Indian shoe supplier Godalkas was helped by their main customer Nike to upgrade their productivity through extensive managerial training.

[3] 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 et al. (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.

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 Section 8). Appendices go into more detail on Econometrics (A) and Theory (B); and the online appendices provide more detail on the Data (OA), and Additional Results (OB).

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 et al., 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 et al. (2011), Antràs et al. (2017), Lim (2018), and Dhyne 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"), often finding negative effects. By contrast, Keller and Yeaple (2009) using US data and Alvarez and López (2008) using Chilean data found positive effects. A problem with 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 industries (*i.e.* who you sell to) 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.).

There is a wider literature looking at production networks for large firms regardless of multinational status. Greenstone et al. (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 of shocks along complex supply chains (*e.g.* Acemoglu and Azar, 2020; Acemoglu et al., 2012, 2017; Liu, 2019; Atalay et al., 2011; 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

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

on other companies. Often the debate is framed in terms of the negative impact of these firms by reducing competition and increasing lobbying. Our paper documents one positive mechanism on productivity spillovers from these superstar firms on their suppliers.

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

2. Data

The critical data source for our analysis is the Business-To-Business (B2B) transactions dataset from the National Bank of Belgium (NBB). This records the value of annual sales between all domestic supplier–buyer relationships in Belgium for the period 2002 to 2014, based on their value-added tax (VAT) declarations. Sales refer to the sum of all invoices from firm i to firm j, net of the VAT amount due, in a given year. As every firm in Belgium is required to report VAT on all sales of at least 250 euros, the data has universal coverage of all businesses active in Belgium. More details of the B2B and other data are provided in Appendix OA (and also in Dhyne et al., 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 Appendix OA 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 et al. (2015) and Gandhi et al. (2020). Details on estimation methods are provided in Appendix A.1.

Appendix Table OA1 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 equivalent employees. Appendix Table OA2 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]

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[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.

[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 OB1). 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. The data 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.

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]

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 a multinational firm, so treatment firm type K = *multinational*. Our baseline results are presented graphically in Fig. 1 with estimates of year-by-year treatment coefficients reported in Table 1. The first panel of Fig. 1 plots the regression coefficients from Eq. (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]

We also consider the effect of starting a new relationship with a multinational on a number of other outcome variables in the subsequent panels (b)–(f), again plotting the coefficients in Eq. (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 Fig. 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 OA1), the estimates imply about a €345,000 increase in sales. Of course, there is a mechanical increase in

[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.

[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 OB2.

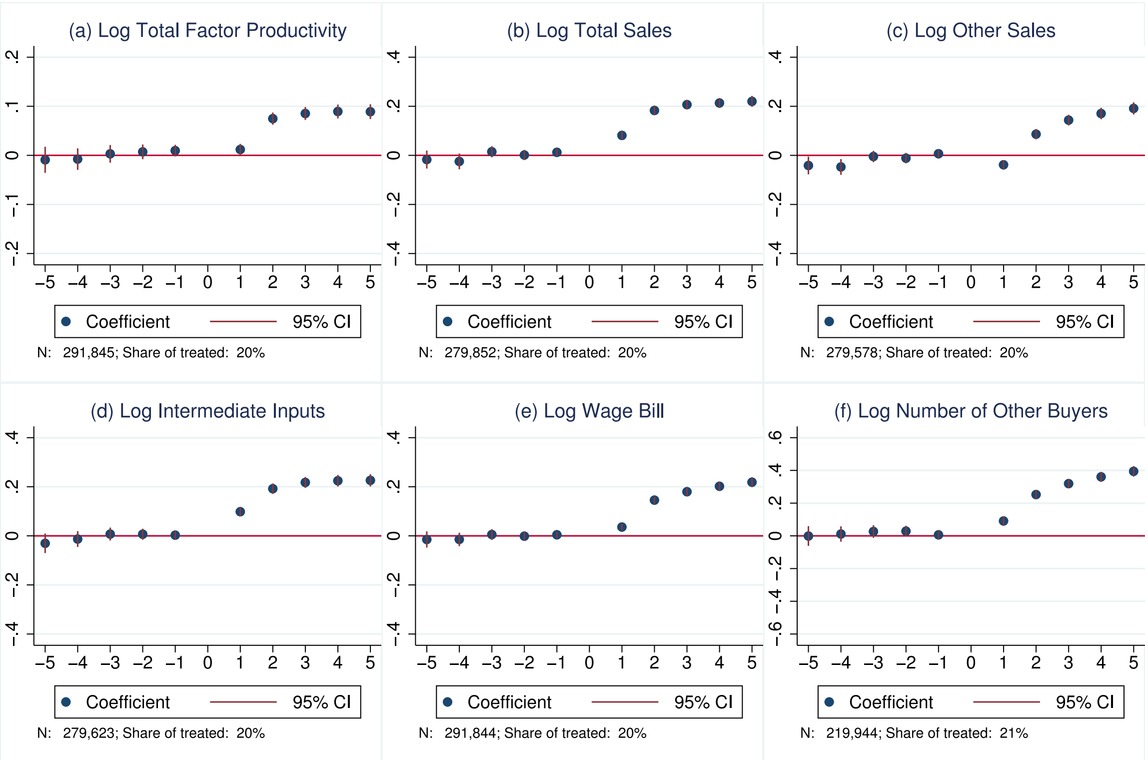

Fig. 1. Gains from selling to Multinationals (MNEs).
Notes: The horizontal axis indicates the year firm i starts selling to a multinational (MNE), defined as a firm located in Belgium with at least 10% inward or outward foreign ownership, with $t = 1$ indicating the treatment year. Each dot represents 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.

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 et al. (2022)).

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

In order to estimate whether links to exporting firms also yield spillovers, we adopt the same strategy as with multinational links, but instead define a superstar firm as one that exports at least ten percent of its sales. We plot the results from estimating

[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 OB4 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 Fig. 1.

Eq. (1) in Fig. 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 Fig. 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.

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 Fig. 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 OA4 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 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 Eq. (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 Refining Company, a large manufacturer of jewelry, Corelio (http://corelio.be),

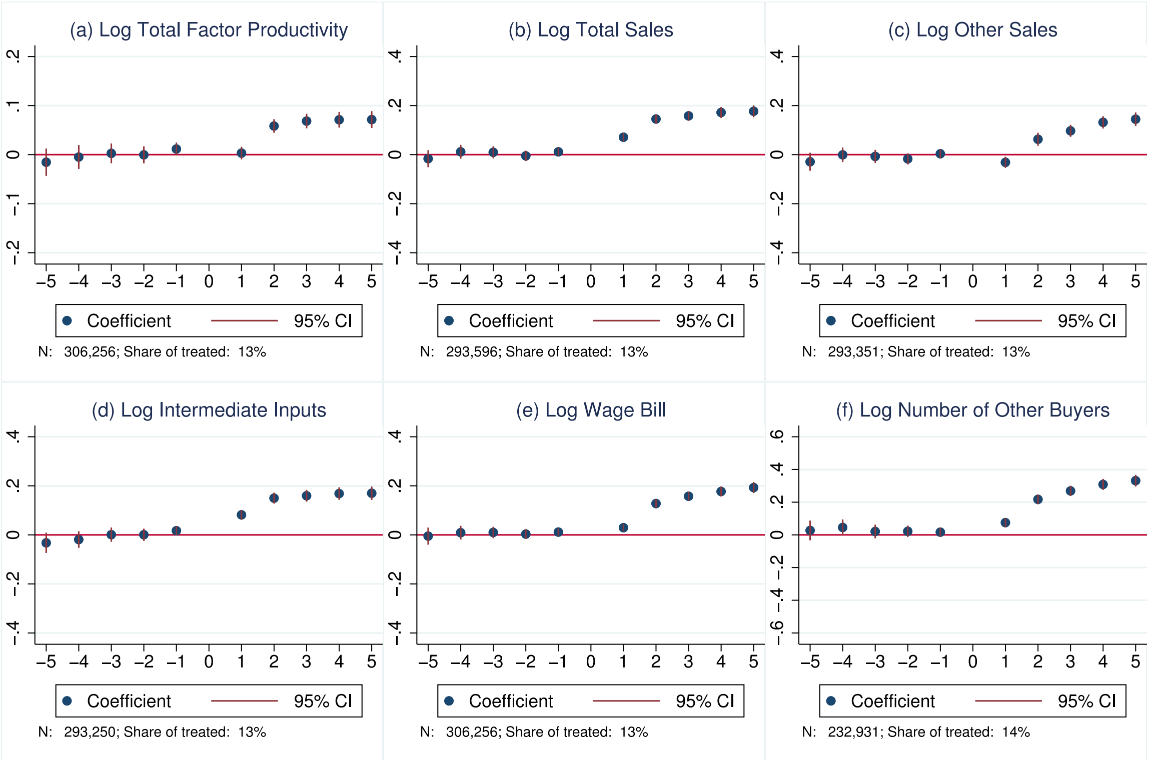

Fig. 2. Gains from selling to Exporting Firms.
Notes: The horizontal axis indicates the year firm i starts selling to an exporting firm, where exporter is defined as a firm located in Belgium, not in the wholesale industry, that exports at least 10% of its sales, with $t = 1$ the year of the treatment. 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.

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 et al. (2022), who find no effects of forming a relationship with large domestic firms. We probe the reasons for this in Appendix OB, Figure OB1 and Table OB3, 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. 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

[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 OB3, 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 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 Fig. 2.

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 Fig. 3.

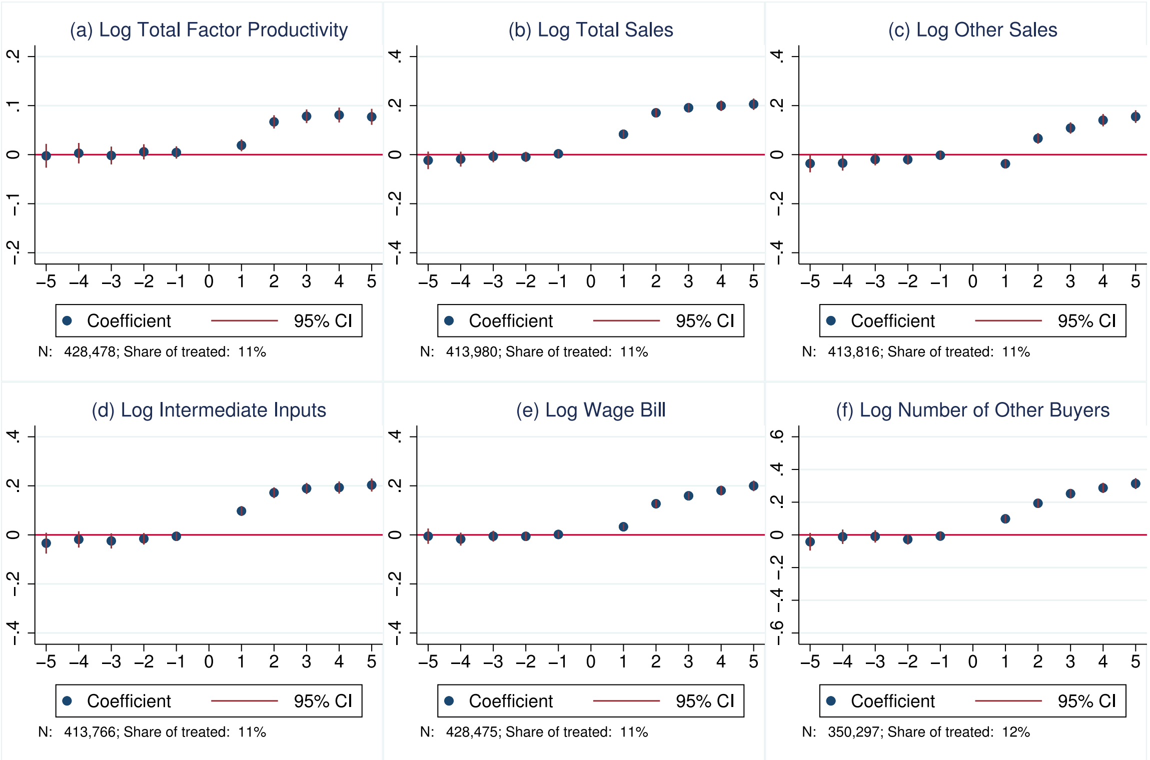

Fig. 3. Gains from selling to Large Firms.
Notes: The horizontal axis indicates the year firm i starts selling to a large firm, where large is defined as the top 0.1 percentile according to total sales, with $t = 1$ the year of the treatment. Each dot represents the coefficient of the treated firm relative 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.

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 Figs. 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 Eq. (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 Fig. 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 €3000 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 Fig. 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.

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.

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[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.

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.

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 OB4, 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), intangible capital, and international trade. 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 OB5 shows that there are effects on the *quality* as well as the quantity of new buyers. We look across all of 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.

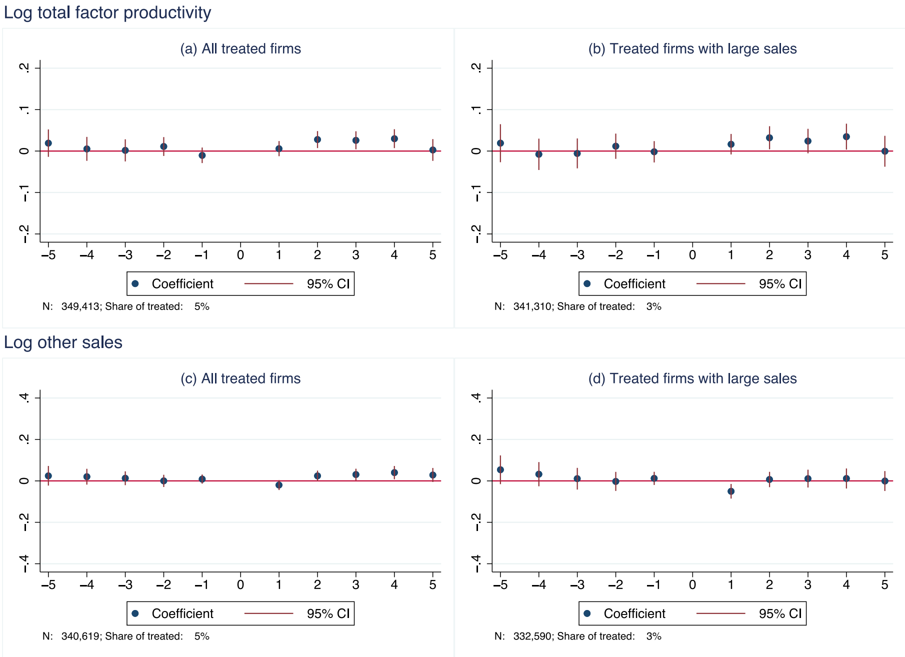

Fig. 4. Placebo: No Gains from selling to Smaller Firms.
Notes: The dependent variable in panels (a) and (b) is the log TFP estimated using the Wooldridge (2009) methodology. The dependent variable in panels (c) and (d) is the log of total sales net of sales to the treatment firms. Rather than the event being starting to supply to a superstar firm, the 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 3000 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 Fig. 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.

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 B 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

[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.

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 input 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 between 1 to 2 percent) on the markup of forming a relationship with a superstar firm (column (5) of Table OB4).[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 OB4).

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 OB6. These results strongly suggest that the technology transfer mechanism is likely to be at play.

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

[15] We also used the simpler "accounting" approach of Antràs et al. (2017) and simply divide sales by 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 et al. (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 Indicator Variable				Log Other Buyers 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)
	(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***	0.061***	0.061***	0.062***	0.250***	0.253***	0.232***	0.238***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.015)	(0.016)	(0.017)	(0.017)
	(0.013)	(0.010)	(0.010)	(0.010)	(0.032)	(0.022)	(0.021)	(0.021)
Observations	329,274	329,274	329,274	329,274	232,931	232,931	232,931	232,931
Adjusted R^2	0.727	0.727	0.727	0.727	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)
	(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 OB2) 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.

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 OB7, 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 OB7 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 OA2 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 two alternative mechanisms outside of our formal model. We label these "relationship capabilities" and "dating agency" effects.

[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		5.30:1		4.25:1	

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 OA.1.3 for details on these calculations.

5.3.1. *Relationship capability*

In an important contribution, Bernard et al. (2022) argue that the high sales of many superstar firms are 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 OA.1.3 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 Eq. (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 Section 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 Fig. 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.

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 Eq. (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 Eq. (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 et al. (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 Eq. (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 A.3 describes how we recover μ_{it} incorporating these new relationships using the Amiti and

[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).

[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 Eq. (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%.

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 Eq. (1).

By including the $Control_{it}$ from Eq. (6) in Eq. (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 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 effects, 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 OB8, we present the results for multinationals across all six of our main outcome variables (the middle panel has it just for inward FDI and the last panel for exporters). Although the share of treated firms is smaller now, all treatment effects are positive and significant with similar magnitudes to our baseline estimates.

7. Robustness

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

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 OB9 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 an 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.

[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.

Heterogeneous treatment effects: cohort-specific estimators. A recent literature has emphasized problems of interpreting estimates of Eq. (1) in the presence of heterogeneous treatment effects. Even when OLS estimation of Eq. (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 OB10 for the results).[24]

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. Section 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 OB1. First, we chose to define a "serious relationship" if 10% or more of firm *i*'s sales went to superstar firm *j*. This was in order to avoid firms who sold trivial amounts to the new firm. We looked at various other thresholds (up to fifty percent). As one might expect, there was a tendency for impacts to become slightly larger as we increase the importance of the new relationship,[25] but things generally stabilized after a five percent threshold. However, if we do not impose any threshold (*i.e.* include any new relationship with a superstar firm), we detect significant pre-trends. Although these were smaller in magnitude than the post-event effect (*e.g.* −1% vs. 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.

Next, we varied the definition of a multinational in Table OB11. 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).[26] Third, we include links to Belgium firms with indirect inward or outward FDI. Finally, we split the baseline multinational treatment by source and destination country, where we allow effects to differ for multinationals in the EU, US, other developed, and less-developed countries. We find the largest treatment effects come from American multinationals and the smallest are from multinationals whose origin is in less-developed countries, like India or China.

We change the definition of exporters and large superstar firms in analogous ways in Table OB12, 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 OB13. 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

[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 et al. (forthcoming) 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.

[24] 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 unreported results, we found 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.

[25] 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.

[26] Appendix Figure (OA1) 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.

(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 Section 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 OA2 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 OB14 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 Eq. (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 OB14, 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 OB14 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 these spillovers remain opaque. Our paper addresses this issue using 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 three years) and other performance measures (*e.g.* sales to firms other than the new superstar partner). Interestingly, we find TFP spillovers of similar magnitude when starting a serious relationship with a multinational firm or a large firm (defined as those who are in the top thousandth of the size distribution) or a firm that intensively exports. 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 effectively auction (long-term) contracts with potential suppliers. This model also predicts negative impacts on supplier markups, treatment effect heterogeneity (*e.g.* spillovers larger from 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 et al. (2016) on size-dependent regulatory barriers).

Declaration of competing interest

Mary Amiti, Cédric Duprez and Jozef Konings declare that they have no relevant or material financial interests that relate to the research described in this paper. John Van Reenen declares the following: I would like to disclose I have received honorarium, speaking, teaching or consulting fees from CRA International and Keystone. I have received grants from Economic and Social Research Centre, European Research Council, National Science Foundation, International Growth Center, PEDL, Smith Richardson Foundation, Sloan Foundation, IBM Global Universities Programs, Accenture, and Kauffman Foundation

Data availability

FDI and Superstar Spillovers (Original data) (Mendeley Data)

Appendix A. Econometric details

A.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:

$$Q_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} \tag{7}$$

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:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \varepsilon_{it} \tag{8}$$

$$ln(A_{it}) = a_{it} = \alpha_0 + \varepsilon_{it} \tag{9}$$

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:

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + v_{it} + e_{it}, \tag{10}$$

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 et al. (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:

$$m_{it} = f_t(\omega_{it}, k_{it}, FX, FM, MNE). \tag{11}$$

By inverting (11), 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 et al. (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 et al. (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 et al. (2015) is then used to identify the remaining coefficients on the other inputs.

A.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:

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_l k_{it} + v_{it} + \epsilon_{it} \tag{12}$$

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

$$i_{it} = f_t(w_{it}, k_{it}, l_{it}, FX, FM, MNE). \tag{13}$$

Inverting (13) allows us to substitute out productivity w_{it} in (12) and we obtain:

$$q_{it} = \beta_m m_{it} + \theta(i_{it}, k_{it}, l_{it}, FX, FM, MNE) + \epsilon_{it}. \tag{14}$$

Eq. (14) 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 (12) 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 $\frac{\hat{\beta_m}}{\hat{\mu_{it}}}$.

A.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 Eq. (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 Eq. (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 Eq. (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).

Appendix B. 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.

B.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.[27]

The upstream market has N firms indexed $i = 1, \dots, N$, 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

[27] 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.

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[28] 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.[29] Firms with superstar contracts supply both the superstar and the competitive markets, firms without superstar contracts 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.

B.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:

$$\frac{p_i - c_i}{p_i} = \frac{1}{\eta}, \tag{15}$$

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

$$\pi_i = \widetilde{\eta}\left(\frac{1}{c_i}\right)^{\eta-1}, \tag{16}$$

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).

B.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 are 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:

$$\max_{Z_i}(Z_i - \sigma_i)Pr(D_i = 1|Z_i) \tag{17}$$

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; Maskin and Riley, 1984):

$$s_i = \sigma_i\delta_i;\ where\ \delta_i = 1 + \frac{\int_{\sigma_i}^{\bar{\sigma}}[1 - F(\bar{\sigma})]^{I-1}d\bar{\sigma}}{\sigma_i[1 - F(\sigma_i)]^{I-1}} \tag{18}$$

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,

[28] 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.

[29] 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.

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, Eq. (18) 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.

B.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).[30] Focusing on the first element, we know from Eq. (16) this is:

$$\widetilde{\eta}\left\{\gamma^{1-\eta}\left(\frac{1}{c_i}\right)^{\eta-1} - \left(\frac{1}{c_i}\right)^{\eta-1}\right\} = \left(\frac{1}{c_i}\right)^{\eta-1}\widetilde{\eta}(\gamma^{1-\eta} - 1) \tag{19}$$

This expression is decreasing in marginal cost, c, as $(1-\eta)\widetilde{\eta}(\gamma^{1-\eta} - 1) < 0$.[31] In other words, high TFP firms will get a greater benefit from a superstar contract.[32]

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, 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.

B.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 the fact that price-cost markups are constant to non-superstars (Eq. (15)), whereas they will be lower to the superstar firm due to bidding more aggressively in the auction due to the spillover benefits (see Eq. (18)). 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 (Eq. (16)). 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 Eq. (19).*

The evidence for Proposition 1 was established in the main results Section 4. The evidence for Proposition 2 is in Section 5.2.1. The analysis of Section 5.2.4 also confirms Proposition 3: firms who form serious superstar relationships also had higher TFP and were relatively larger prior to forming these relationships.

B.6. Extensions to the basic model

B.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

[30] 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.

[31] 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 $(\gamma^{1-\eta} - 1) > 0$.

[32] This follows from the convexity of the profit function in marginal costs from Eq. (16): a small fall in marginal costs benefits a low-cost firm by more as their sales are higher so they get more total profits.

B.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 OB7).

B.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, Section 5.3.1 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.

B.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 OA.1.3 above. Section 5.3.2 shows that there is evidence for these dating agency effects in our data.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jinteco.2024.103972.

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