Domestic vs Foreign Superstars: Comparative Advantage, Pro-competitive Effects, and Productivity Spillovers

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Abstract

Superstar firms are seen as catalysts of comparative advantage and competition. This paper challenges this perception using Chinese firm-level data from 1998 to 2007, revealing that superstar firm dominance had an overall negative impact on industry export competitiveness. Only FDI-driven concentration has a positive influence on industry exports, with much heterogeneity according to how an industry is poised for growth. The importance of differentiating superstar firms by ownership extends to the impact of their dominance on the local economy, where only FDI-driven concentration generates broad pro-competitive effects on non-superstar firms. Lastly, this paper leverages an industry-specific shock to find unique and positive horizontal spillovers from superstar FDI on the productivity of local firms. These findings offer valuable insights into understanding key aspects of China's export-led growth. They particularly underscore the significance of firm ownership when applying the literature on superstar firms to emerging economies.

Keywords: Foreign Direct Investment (FDI), China, Granular Firms, Granular Comparative Advantage, Markups, Firm Ownership, Horizontal Spillovers.
JEL Codes: F14, F21, F23, F63, D20, L11, O33

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1 Introduction

The role of superstar firms in influencing the export patterns of economies has increasingly garnered attention[1]. Notably, China's massive export-led growth and the comparable significance of foreign and domestic firms for gross export volumes during the early 2000s offers an exceptional yet unexplored setting for investigating superstar firms. Using Chinese firm-level panel data spanning the period 1998 to 2007, this paper differentiates the largest local operations of foreign multinationals from the most prominent domestic firms to assess their heterogeneous impact on industry-level comparative advantage. Correspondingly, this paper addresses the implications of their presence for the local economy. Specifically, it identifies distinct pro-competitive effects stemming from superstar Foreign Direct Investment (FDI) that go beyond those from domestic superstars, and unique horizontal spillovers arising from this form of FDI.

China's FDI inflows began to pick up significantly in the early 1990's as the country further opened up its economy. Elevated FDI inflows as a percentage of GDP were maintained throughout the following two decades, even as the size of its economy grew rapidly. By 2001 FDI accounted for over 50% of Chinese exports and by 2007 China's trade balance had skyrocketed to over 300 billion USD. Understanding what form of FDI China benefited from is of vital importance for developing countries or regions positioned today similarly to China was then and seeking to replicate the success of China's industrial policy. However, there is a noticeable lack of analyses on superstar FDI within any country-specific study, and of analyses on any type of concentration into superstar firms in a developing country context. This paper seeks to bridge these gaps in the literature.

In Gaubert and Itskhoki (2021), a distinction is made between a "fundamental comparative advantage," which applies to all firms within an industry, and a "granular comparative advantage," (GCA) which arises from unique market forces or know-how possessed by industry leaders. The latter is attributed to the heavy-tailed distribution of firm sizes and the limited number of firms in each industry, which allows for out-sized firms to arise. These firms are detectable "grains" as their influence does not average out in the aggregate but instead generates a "granular residual", causing exports to deviate from what can be explained by industry-wide factors. Using French data, Gaubert and Itskhoki (2021) associate an industry's granularity, represented by the top-few firms' combined domestic market share, with increased export competitiveness, and attribute this to the positive influence of GCA. However, this paper counters that for a major emerging economy during the same period, the relationship is negative. This challenges the assumption that findings from the granular firms' literature, following Gabaix (2011), apply universally across developmental stages.

[1] Freund and Pierola (2015) noted that across 32 developing countries between 2006 and 2008, the leading firm accounted for an average of nearly 15% of total (non-oil) exports, emphasizing the significance of these firms in shaping international trade dynamics.

Yet for economies in earlier stages of development there may be at least two fundamentally different types of firms. The Chinese Industrial Enterprise Survey data allows distinguishing the firms that are primarily funded by FDI, what I refer to as Foreign-Funded-Firms (FFFs), from the Domestically-Funded-Firms (DFFs). FFFs are shown to not only be important to economy-wide outcomes, but also at the industry-level, accounting for over 40% of industry exports on average across 420 industry codes. Looking closer reveals that the group of superstar FFFs (here defined as the top-3 FFFs by exports) contribute more to this figure on average than all other FFFs combined, and nearly as much the superstar DFFs. In the context of China, the first focus of this paper is to explore how these superstar firms impact industry export dynamics.

This paper therefore derives two distinct granular residuals terms to explain variation in comparative advantage, one that corresponds to superstar FDI and one that corresponds to domestic superstars. This distinction is underpinned by systematic differences in the industry-level Pareto exponents that describe the size and productivity distributions on the group of FFFs and on the group of DFFs. The observed differences cannot be explained solely by barriers of entry faced by foreign firms as the distribution estimates have a lower bound cut-off on the right tail, whereby only the relatively larger firms from both groups are compared.

Both of these funding types in China exhibit granularity, and combining the top-3 exporters that are FFFs and the top-3 exporters that are DFFs captures over 50% of industry exports on average in each year of the sample. These two groups of granular firms are described by distinct firm-level characteristics that ultimately lead to heterogeneous and practically opposite implications for GCA.

By partitioning granularity into two categories, I can highlight the type of foreign direct investment (FDI) most prevalent in the granularity measure specific to FFFs. I demonstrate that superstar FFFs established in China for market access purposes, whereby they are granular in terms of domestic market share, have no bearing on GCA. However, if employment is used to define granularity, yielding a more unbiased set of multinationals that includes those with efficiency-seeking objectives, a positive influence on GCA emerges in China. In all applications, the coefficient on granularity from DFFs remains negative, even when removing state-owned firms. However, there is evidence of convergence in the behavior of Chinese GCA to that of a developed economy scenario by the end of the 10-year period, with the negative relationship between GCA from DFF granularity and industry exports diminishing year after year.

A primary concern of this analysis is that Chinese industries which are more comparatively advantaged simply attract more FFF granularity, and industries which are more comparatively disadvantaged attract more DFF granularity. However, Instrumental variable analysis, out of sample prediction, and various robustness checks support casual inference. Moreover, out of sample prediction offers strong evidence against reverse causality.

Heterogeneity results also fit well with a mechanism of GCA. For example, FFF granularity is more strongly associated with industry exports in industries that are either in the middle of the technology spectrum, dominated by state-owned firms, less penetrated by other FFFs, have lower aggregate productivity, or a higher ratio of young firms. This suggests that FFF granularity generates positive GCA in industries that are not too mature, yet are well-positioned for growth, rather than those industries which are well-established or already privatized. Conversely, DFF granularity has a stronger negative correlation with industry exports when interacted with proxies for fundamental comparative advantages. This result would not be expected if the negative coefficient on DFF granularity was solely due to industries with inherent disadvantages.

The fact that interacting the number of FFFs with both forms of granularity yields a negative coefficient attests to the requirement of a knowledge gap between the superstar firms and non-superstars, that if not present, diminishes the potential positive impact of such market concentration. This again supports the story of GCA, as GCA rests on the concept of the idiosyncratic contributions of firms specific know-how. In industries dominated by numerous FFFs or already privatized, there's limited space for further absorption.

At the level of the granular firms themselves, both groups generate relatively more GCA when they have higher added value relative to real assets, lower labor intensity measured in wages to real assets, or pay higher average wages per worker. This shows how superstar DFFs transition to eventually become comparable to superstar FFFs in their relationship with GCA.

To further explore the role of granular firms in shaping Chinese competitiveness, I investigate how superstar firms impact the domestic economy on a more micro level, and in doing so contribute to two very important domains within the international trade literature; the first being the central issue of pro-competitive effects, and second being horizontal spillovers from FDI. If granularity impacts comparative advantage beyond the granular firms' own contribution to industry exports, then impacts on firm-level competitiveness or productivity spillovers would be likely channels.

According to Edmond et al. (2015), international trade reduces markup distortions when exposing firms to effective competition, contingent on how domestic and foreign producers compare. Building on this, the current paper finds that granular firms can also be a pro-competitive force, but with heterogeneity depending on whether or not the granularity owes to FDI. In this exploration, I model firm-level markups as a function of both firm and industry-level variables and include terms to capture the presence and nature of granular firms as well as their interactions with the non-granular firm. Only FFF granularity induces pro-competitive effects on not only other large firms but also small firms. I attribute this to superstar FFFs inducing relatively more effective competitive pressure.

Finally, horizontal spillovers from FDI on the productivity of local firms in those same industries has traditionally been elusive of causal evidence due to endogeniety and reserve causality, such as foreign firms selecting into industries already set on a path of high productivity growth or local firms themselves attracting FDI. Existing literature on FDI spillovers in China typically finds positive spillovers on firms in upstream or downstream industries, but zero or negative horizontal spillovers on firms in the same industry.

However, by utilizing an industry-level shock resulting from the 2002 update of China's Catalog of Encouraged Industries for FDI, I establish causal inference of positive horizontal spillovers from the granular component of FDI on the TFP and labor productivity of local firms. The shock only significantly explains FFF granularity based on domestic market sales, aligning with the catalog's focus on the domestic market given that FFF exporting activity was already highly encouraged. I further show that it was primarily the granular FFFs that were able to take advantage of this incremental catalog update rather than FDI more generally. The resulting positive horizontal spillovers underscores the important role of superstar FFFs' in shaping China's competitiveness.

These findings hold considerable implications for both trade and industrial policy. For developing countries aiming to enhance their comparative advantage or competitiveness in specific industries, promoting superstar FDI can be advantageous. On the other hand, concentration into domestic superstars might decrease industry export competitiveness. Heterogeneity in the characteristics of superstar firms and the industries in which they operate provides a checklist for assessing the appropriateness of particular firms. Ultimately, this research aims to ensure that empirical evidence on granular firms is inclusive of a more diverse set of countries.

The following section gives a brief review of the recent literature on granular firms as well as literature relating FDI to comparative advantage and export competitiveness. The current paper combines these two branches of literature in the context of China. Section 3 presents the data, discusses the nature of granularity in China, and gives descriptive statistics on the two groups of granular firms. The methodology and results for GCA with FDI are presented in section 4. Section 5 then explores how both groups of granular firms influence non-granular firm markups, followed the application to superstar FDI spillovers in section 6. Section 7 concludes.

2 Related Literature

The first strand of literature that this paper relates to is that on large firms. Since Bernard et al. (1995) there have been numerous literatures on the unique characteristics of large exporting firms. Along this line of literature, Eaton et al. (2004) find that sensitivity of trade to trade costs is mostly along the extensive margin. This may imply that large exporting firms are relatively more persist and thus bring stability to export competitiveness of the industries in which they operate. Further empirical evidence presented by Freund and Pierola (2015) shows the single largest firm within each of 32 developing countries as accounting for 15 percent of total exports on average, with the top 1 percent of firms taking up 53 percent of exports. Naturally it follows that a country is also exposed to additional business cycle volatility in the presence of large firms and multinationals in general. Cravino and Levchenko (2016) determine that 10 percent of aggregate productivity shocks owe to the presence of foreign affiliates transmitting shocks from abroad. Bernard et al. (2018) find that firms that are more productive take increasingly larger market shares, with costs differences magnified by productivity differences via extensive and intensive margins of trade and FDI. Taken together, these papers suggest that superstar firms have an out-sized impact on industry export competitiveness and that this relationship may crucially depend on the mix of foreign versus domestic superstar firms. Testing this hypothesis is the first point of analysis of this paper.

In looking closely at the influence individual firms have on aggregate economy or industry characteristics, Gabaix (2011) establishes the "Granular" hypothesis; that heavy-tailed firm size distributions go against the diversification argument, and therefore shocks to such large firms do not average out in the aggregate as they would for smaller, more numerous firms, but instead propagate throughout the economy. Specifically, he shows firm-level shocks from the 100 largest US firms explain one third of US variation in output growth. In a similarly motivated paper, Acemoglu et al. (2012) establish a channel whereby idiosyncratic shocks may cascade across an economy due to networks of intersectoral input–output linkages. These network effects explain how some well-known industries consist of countless suppliers or other smaller firms that are dependent on the business and are practically at the mercy of a few oversized firms with complex supply chains.

Carvalho and Gabaix (2013) puts granularity to the test to show how the U.S. great moderation (80s-90s) owes to diversification following a decrease in granular volatility (heavy manufacturing). Grassi (2018) details how the structural importance of a firm, measured by the elasticity of aggregate output to the particular firm's productivity, depends on the interaction between the competition intensity of the firm's industry, the input-output network, and the firm size. The channel through which firm-level shocks propagate through the economy is labor augmenting productivity shock's impact on oligopolistic markups.

As mentioned in the introduction, Gaubert and Itskhoki (2021) establish granularity from an industry's larges firms as a source of comparative advantage that is distinct from the fundamental comparative advantage common to all firms. Using French data, they find that idiosyncratic shocks from granular firms accounts for 20% of the variation in export intensity across sectors. They also show that concentrating an additional 10 percentage points of industry sales in the top-3 firms (as opposed to it being spread out among other firms) is associated with a 9% (log points) increase in the aggregate level of industry exports. Essentially, superstar firms in France positively affect the comparative advantage of relevant industries. Their methodology for detecting the presence of a granular comparative advantage (GCA) is extended in section 4.1 as the starting point of the current paper's empirical analysis.

The second strand of literature motivating the current paper is that on FDI and its role in international trade. Almfraji and Almsafir (2014) gather that most literature relating FDI to economic growth indicate that FDI, especially in the manufacturing sector, aids growth and development. Given this, it's logical to seek positive sources of GCA from FDI despite a negative GCA overall as found in the current paper.

FDI was nearly nonexistent in China prior to the 1978 opening-up initiated by Deng Xiaoping. Throughout the 1980s and 1990s FDI became not only allowed, but foreign firms were often given preferential treatment on multiple fronts, largely through the implementation of special economic zones (SEZs) scattered about the country's coastal areas. Restrictions remained, however, in many industries, such as requiring joint-ventures, technology sharing or some degree of local-content requirement. Yet by 1997, in preparation of it joining the WTO, average Chinese import tariffs had been cut and many additional industries opened, while the effective tariff rate given what was actually collected from imports was only 3 percent (Tseng and Zebregs, 2002).

Young (1995) shows that the high growth rates experienced by East Asian countries owes to capital accumulation, not rapid technological progress and Whalley and Xin (2006) show that 90 percent of recent growth in local Chinese firms owes to capital accumulation. While domestic resource mobilization is the most important source of capital formation for economic growth Nunnenkamp (2004), FDI both directly adds to this and has potential to catalyze domestic capital formation (Amighini et al. (2017)) and alleviate domestic credit constraints (Poncet et al. (2010)). Taken in combination with the literature on granularity, there is no reason not to expect that superstar foreign funded firms operating in China contribute to aggregate outcomes beyond that of FDI more generally, and in a manner different than that of superstar domestically funded firms.

In addition to the effect of superstar firms on industry exports, the current paper investigates their impact on the non-granular firms of the economy. Edmond et al. (2015) discusses the significance of the type of foreign firms engaging in international trade, highlighting how, depending on how foreign and domestic firms compare, pro-competitive effects can lead to lower overall markups when a country opens to trade. Section 5 of the current paper extends this perspective to examine how non-granular firms in China respond to granularity in terms of their competitive behavior.

Iacovone et al. (2015) and Bloom et al. (2013) give case study evidence of particular superstar multinationals entering a developing country and producing positive spillovers on domestic suppliers. Amiti et al. (2023) looks directly at vertical spillovers from multinationals and then superstar firms of any ownership, where they use Belgian firm-to-firm transaction data to show that beginning to supply a multinational or beginning to supply a superstar firm, regardless or not of whether it is a multinational, produce similar positive spillovers on the domestic supplier's Total Factor Productivity (TFP). However, their event study approach caries a concern that in most results there is a significant increase in TFP 2 years before a new relationship with either a multinational or superstar firm is formed, suggesting that TFP growth, either pre-existing or soon to come, may be what enables firms to secure larger contracts, rather than the contracts causing the TFP increase. To analyze horizontal spillovers from superstar FDI in 6 of the current paper I instead rely on industry level shocks for identification of the treatment group and thus avoid concerns of signalling by individual firms. Additionally, while there exists much conclusive literature on vertical spillovers on suppliers or buyers of foreign multinationals, the literature on horizontal spillovers is inconclusive, giving additional importance to analyzing the particular channel of horizontal superstar FDI spillovers on local firms in the same industry.

Several studies, such as Du et al. (2012), Lin et al. (2009), and Lu et al. (2017), have examined spillover effects of foreign direct investment (FDI) using the same dataset as the present paper, though none address the presence of superstar firms. These authors generally find evidence of positive spillovers only in forward or backward effects on suppliers or buyers, while horizontal spillovers on firms within the same industry are typically found to be negative. Lu et al. (2017) uses the same industry level shock as the current paper uses to identify the treatment group for analyzing spillovers, but arrives at a more narrowly defined list of treated industries whereas the current paper seemingly maintains a more strict criteria for an industry being in the control group, and thus the results of Lu et al. (2017) cannot be reproduced as their data has not been made available. Further comparison of their study to the present paper is left to section 6.

3 Data and Context

3.1 Description of the panel data

The Chinese Industrial Enterprise Survey (CIES) conducted by the National Bureau of Statistics of China (NBS) is a large firm-level dataset with consistent data on firm funding and various firm-reported figures for the ten years spanning 1998 through 2007. It is meant to include all firms with total sales above five million RMB as well as all state-owned firms for these years. The survey continues past 2007 but with reduced scope and loss of some key variables. Variables reported throughout these years include total firm sales, exports, input costs, total employment, wage bill, current and fixed assets, paid-in capital, and many others. Brandt et al. (2014) provide a good description of the dataset. Largely following their suggestions and using additional text analysis, I match firms that may have had a change in ID, eliminate firms and industries that are not actually in manufacturing or are in highly restricted industries such as tobacco or weapons, and impute some additional variables such as real physical capital stocks. The result is 2,035,995 observations across the 10 years, consisting of 533,677 firms in an unbalanced panel sorting into

420 Chinese industry codes that sometimes vary within a firm from one year to the next.

There are 6 variables describing different origins of paid-in capital, each with a corresponding running total that is used to construct ownership percentages. These 6 variables are paid-in capital from each of Hong Kong/Macao/Taiwan (henceforth HKMT), foreign (all non-HKMT rest of world funding), private, corporate, state, and local collective. The categories of HKMT and foreign account for all non-mainland China funding sources, and I label a firm as an FFF if these two categories make up at least 50% of total paid-in capital. All other firms are therefore DFFs, meaning that more than 50% of their ownership is traced to mainland China. I then combine private and corporate into a single private category, and state and local collective into a single state category. A DFF can therefore be called private if the combined categories of HKMT, foreign, and private make up 50% or more of total paid-in capital, given that the firm was not already classified as an FFF. Any remaining DFFs are thus dominated by some form of state capital [2]. While I primarily maintain only two groups throughout the analysis, robustness checks are done for separating FFFs to HKMT FFFs and non-HKMT FFFs as well as for separating private DFFs from state-owned DFFs.

In 1998 FFFs accounted for 11.8% of observations, 20.0% of total manufacturing sales and 49.7% of total exports. These numbers increased to 16%, 27.4% and 61.4% by 2007, respectively. Details of this breakdown are shown in table A1 of the appendix. The next section discusses how the largest firms are remarkably important for these aggregate figures.

3.2 Granularity in China

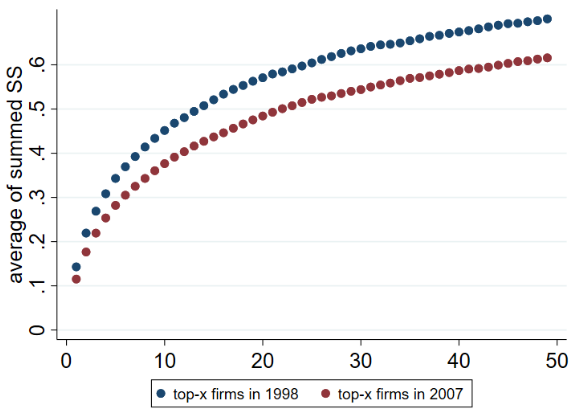
Chinese industries are indeed very granular, and not only due to a single industry leader. Figure 1 demonstrates this, where the average combined sales shares of all possible groupings of top-x firms are laid out up to the grouping of the top-50 firms. The average share of sales going to the single largest firm per industry, or group size of 1, is about 14.3% in the year 1998. The second largest firm on average takes about 7.7% of total sales, making a group total of 22%. The group of top-3 firms then averages at 27%, still a substantial increase. These figures are all roughly double if focusing on exports[3]. Soon this marginal increase from adding the next largest firm becomes less substantial, and the plot in figure 1a tappers off as less and less granular firms (firms that are closer in size to the industry average) are included.

While the average shares are lower per respective group of granular firms in 2007 compared to 1998, the expected sales share if all firms were equal decreases from an average of 0.3% in 1998 to 0.13% by 2007 due to growth in the total number of firms. Normalizing the average shares for this reveals that granularity is in fact becomes more pronounced by 2007, as shown in figure 1b.

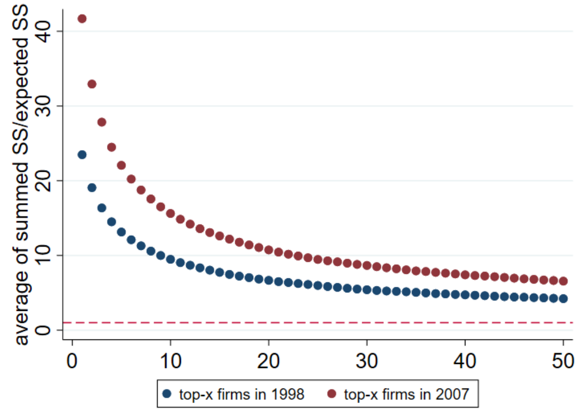
[2] Additional details on funding and the 50% threshold used to define FFFs are left for section A1 of the appendix.

[3] Average sales and export shares going to the top firm are presented for each year in table A2 of the appendix.

Figure 1: Grouping granular firms



(a) Mean SS of top X firms



(b) Number of times sector mean

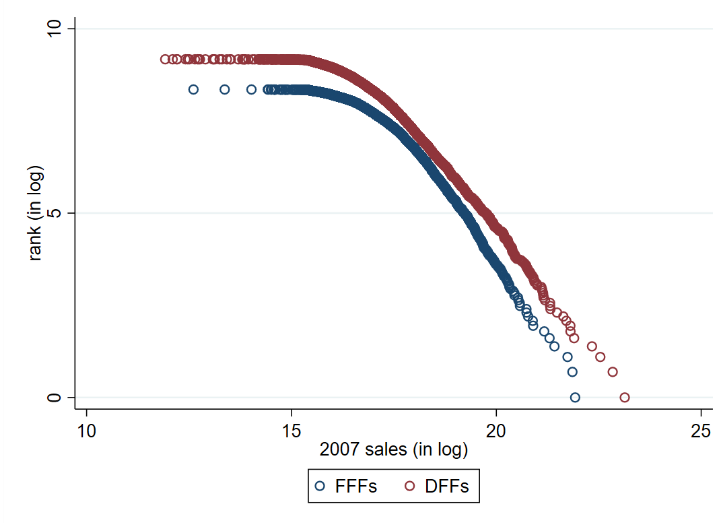
Note: Each X-axis denotes the group of top-x firms, per industry where there are at least as many firms. Left shows averaged summed sales shares (SS) across all sectors: $\sum_{z=1}^{Z}\sum_{i=1}^{x} SS_{z,i,t}/Z$. Right normalizes this by dividing it by x/I. It is the number of times greater a group's share is compared to the hypothetical homogeneous share, giving a lower bound of 1.

In 2007, the single largest firm per industry was on average 41.7 times larger than what would be expected if all firms were of equal size. The cotton textile industry had the largest firm relative to its industry, at 827 times the average of 10,308 firms in 2007, and its top-3 firms had a combined size 350 times the average for groupings of 3 firms. The auto parts and accessories industry had the second most disproportionately large firm at 435 times the average of 7,579 firms in 2007, and its top-3 firms had a combined size 189 times the average for groupings of 3 firms, which is the 4th highest of industries for that grouping. Given that this is among firms with greater than 5 million RMB of sales, these relative size figures are likely much higher for any industry with low barriers to entry.

To more formally investigate the nature of granularity in Chinese industries and motivate the separation of granularity into two distinct sources, I estimate the power-law distributions, also known as Pareto distributions, on firm sizes. This essentially describes the largest few outlier firms in relation to the firms that rank near them. Assuming the power law probability distribution $p(x) = \Pr(X = x) = Cx^{-\alpha}$ from lower bound $x_{min} > 0$ and normalization constant $C = (\alpha - 1)x_{min}^{\alpha-1}$, α is estimated separately for sub-samples of DFFs and FFFs in each industry. A lower α implies stronger potential of granularity via more inequality in the sense that small differences in firms gives large differences in size, exports, sales, etc. In the cumulative distribution function (cCDF), a higher power law exponent is reflected by a steeper drop in the right end of the distribution, where as lower exponents see it stretched further out.

A pattern emerges of statistically different alpha estimates for DFFs and FFFs, with alpha

Figure 2: Example of firm sales rank to sales cCDF: Textile and apparel industry



Note: shows the cumulative distribution function (cCDF) of sales, equivalent to the descending rank (log value) of firms by sales plotted against the firms' sales (log value).

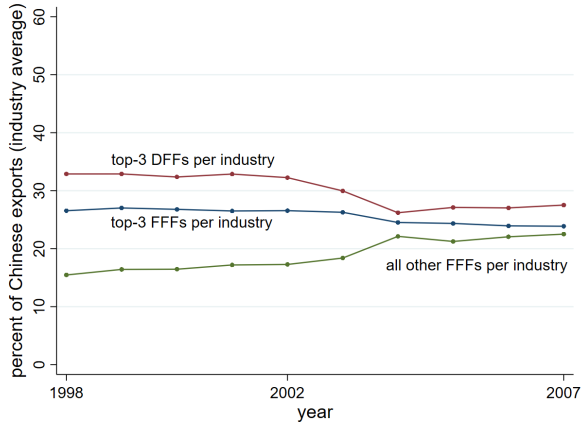
estimates for DFFs systematically lower than that of FFFs, meaning that there is more inequality among DFFs than FFFs in a typical industry, and greater dispersion at the fat-tail end. Details on how the estimates compare across industries and at different levels of aggregation are discussed in section A3 of the appendix.

As an example, figure 2 shows the cCDF of total sales, equivalent to the descending rank (logged) of firms by sales plotted against firms' log of sales, for textile and apparel manufacturing, a typical four-digit industry. The near-straight line following some minimum level of sales on the log-log scale indicates a strong power-law distribution in firm size. The estimated power-law exponents are 2.31 and 2.51 for DFFs and FFFs, respectively. This industry is also typical in that there are roughly 3 firms at the far right tail for both FFFs and DFFs whose log sales are visibly spaced apart from the next few largest firms in their respective groups, indicating their granularity, or distinct large size.

3.3 Defining the granularity proxies

The panel data provides at least 5 common metrics for sorting firms according to size: total sales, exports, domestic market sales, total employment, and total wage bill. Section A2 of the appendix discusses the representation of each funding type among the top-6 firms according to each of these metrics. Trends to note are the growing presence of FFFs, the composition of top FFFs according to HKMT versus rest of world funding, the declining presence of state-owned firms, and the increasing dominance of private DFFs. While there are many top-6 firms that happen to be

Figure 3: Accounting for China's industry-level exports



Note: The graph shows average combined industry export share of the top-3 DFFs, top-3 FFFs, and all other FFFs not in the top-3 per industry.

FFFs, as shown in table A3, I instead build the granularity proxies by taking the top-3 FFFs and top-3 DFF per industry to maintain an equal representation of firms in each group.

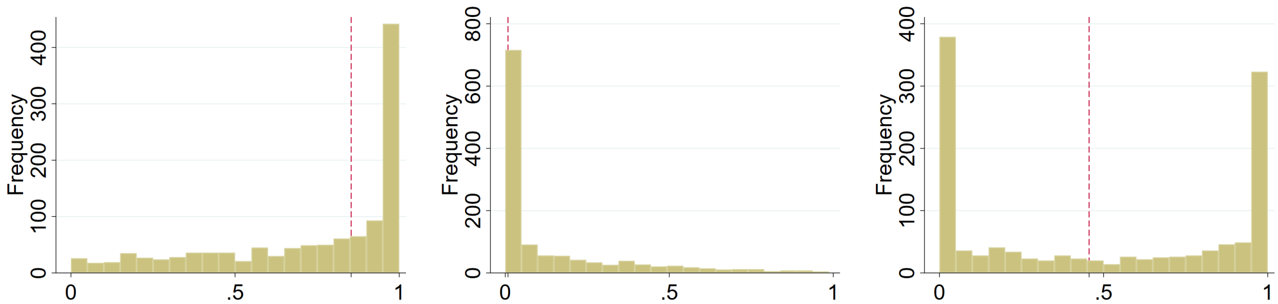
Figure 3 shows that on average across the 420 industries, the top-3 FFFs by exports contribute more than all other FFFs combined, and are almost at the same level as the top-3 DFFs, indicating the importance of superstar FFFs across a broad set of industries. Table A2 of the appendix details the year by year breakdown. These figures may suggest that aspects of China's FDI success story may more specifically be a success story of superstar FDI.

The methodology for detecting granular comparative advantage (GCA) discussed in section 4.1 below arrives at combined domestic market sales shares of top firms as a preferred measure of granularity, which avoids systematic correlation with exports and is the metric used in Gaubert and Itskhoki (2021). The issue with applying this approach to a developing country is that there are many large exporters that do not sell to the domestic market, but instead use the country only as an export base to other markets. At the same time, China's large market is able to sustain manufacturing firms that are very large despite zero exports. Thus, many granular FFFs either only export or only focus on local market.

Figure 4 shows histograms for the export intensity of all top-3 FFFs for the year 2007 as defined by exports (left), domestic market sales (middle), and by employment (right). Among the top-3 FFFs by exports there is a mass of firms with an export intensity of 1, many of which are indeed very large. Conversely, there is a mass of top domestic market sellers with an export intensity of 0. Top employers represent a more equal mix.

Defining granularity by domestic sales creates a horizontal FDI (domestic market access) bias. Defining granularity by employment is more neutral and captures large exporters, large domestic market sellers, as well as more firms in the middle of the spectrum. I therefore primarily rely

Figure 4: Export intensities of top-3 FFFs in 2007



(a) FFFs granular in terms of exports

(b) FFFs granular in terms of domestic market sales

(c) FFFs granular in terms of employment

Note: The red dashed line indicates the median among the top firms.

on two proxies for granularity when describing industry exports in the next section; both that by domestic market sales and that by employment. Defining by total wage bill is also used for robustness checks. The heterogeneous characteristics of granular firms captured by employment shares versus wage bill shares is discussed in section A4 of the appendix, where I argue that defining granularity by employment shares is most representative of vertical (efficiency seeking) superstar FDI, or least biased towards horizontal superstar FDI.

I also utilize the definition by total sales in the application to pro-competitive effects, while only the definition by domestic market sales ends up being relevant for the application to horizontal spillovers, as discussed in those sections.

A comparison between the two groups of granular DFFs and FFFs as defined by employment is shown in table 1, where firm characteristics are regressed on dummies for top-3 FFFs and top-3 DFFs, while including industry and year fixed effects. For more insight, I also include dummies for other large, but not necessarily granular FFFs and DFFs, defined as those firms with more than 100 employees but not in their respective top-3 spot. All other firms are excluded for ease of comparison. The granular DFF dummy is set as the reference group, meaning that the estimated coefficients are relative to granular DFFs. Firm age and a state-owned firm dummy are also included, but coefficients generally see only small changes in the expected directions if these two control variables are left out.

Compared to granular DFFs, granular FFFs have a higher export intensity by 0.26 on the range 0 to 1, lower markups by 0.017 log points, a higher real capital-labor ratio by 0.297 log points, a higher labor productivity by 0.184 log points, and a higher average wage rate by 0.268 log points. Not controlling for state-owned firms leads to a doubling of the labor productivity coefficient, but all other coefficients see only minor adjustments (not shown). Compared to non-granular DFFs, granular DFFs have a higher real capital-labor ratio by 0.289 log points, higher labor productivity

Table 1: Characteristics of granular and other large firms (defining $\widetilde{s}$ by employment)

	(1) export intensity	(2) ln markups	(3) ln KL ratio	(4) ln labor productivity	(5) ln mean wage rate	(6) ratio grads to staff (2004)
top-3 FFFs	0.260***	-0.017***	0.297***	0.184***	0.268***	0.004
other large FFFs	0.219***	-0.072***	0.200***	0.021	0.176***	-0.005
other large DFFs	-0.057***	-0.086***	-0.289***	-0.126***	-0.119***	-0.020***
State-owned dummy	-0.033***	-0.016***	-0.003	-0.266***	-0.109***	0.004***
firm age	0.000	-0.000	0.008***	-0.011***	0.002***	-0.000***
Constant	0.239***	0.355***	3.678***	3.907***	2.472***	0.060***
Industry & Year FE	Y	Y	Y	Y	Y	Y
Observations	1058852	1058852	1055558	1058852	119773	86794

Granular DFF is the reference dummy. KL ratio is real capital / workers, labor productivity is real value added / workers. Not controlling for state-owned firms leads to a doubling of the labor productivity coefficient on the dummy for granular FFFs, but all other coefficients see only minor adjustments (not shown).

by 0.126 log points, and higher average wage rate by 0.119 log points. Additionally, non-granular DFFs employ relatively less college graduates. Notably, only granular FFFs have an average labor productivity significantly higher than granular DFFs, setting them apart from non-granular FFFs or FDI in general.

The granularity proxies are built by summing the share of industry activity going to the top-3 firms per funding type. Let $\widetilde{s}_{z,i,t}$ denote the relevant share of industry z activity concentrated in firm i in year t. The corresponding measure for granularity used in the following analysis is then:

$$\sum_{i=1}^{3} \widetilde{s}_{z,i,t} \tag{1}$$

where $\widetilde{s}$ denotes one of either *domestic sales share*, *employment share*, *wage bill share*, or *total sales share*, depending on the specific application below.

Note that while granularity is defined at the industry level for each group of DFFs and FFFs separately, the calculated shares for the top-3 FFFs or top-3 DFFs are out of the industry total, with all firms included in the total without respect to funding type. For example, if the top-3 FFFs together account for 10% of industry employment, and the top-3 DFFs together account for 15%, then the remaining non-granular firms account for 75% of industry employment. Granularity in this case would measure 0.10 for FFFs and 0.15 for DFFs.

The measures of granularity as pertains to the methodology of detecting GCA with FDI are derived from a decomposition of industry exports intensity in the following section.

4 Granular Comparative Advantage (GCA) with FDI

4.1 Methodology for Detecting GCA

Gaubert and Itskhoki (2021) put forth a Ricardian comparative advantage model that builds on Dornbusch et al. (1977) with Melitz (2003) firm heterogeneity but with a finite number of firms as in Eaton et al. (2012). Their model distinguishes between a Fundamental Comparative Advantage (FCA) that pertains to things common to all firms in an industry, such as the availability of specific human capital, infrastructure, and technology, and a Granular Comparative Advantage (GCA) that arises from the idiosyncratic contributions of individual firms, such as their specific know-how. GCA is treated as coming from a mean zero residual, thus holding a positive influence on some industries and an offsetting negative influence on others, where their interest is in describing the amount of total variation in comparative advantage that comes from this residual. The current paper is instead interested in the nature of the relative contributions to an industry's comparative advantage of granularity from superstar DFFs versus granularity from superstar FFFs. I therefore expand the accounting framework of Gaubert and Itskhoki (2021) to expose two distinct granular residuals and analyze their relationship with industry export performance.

For industry exports, X_z, and domestic industry expenditure, Y_z, define the export intensity of industry z as $\Lambda_z = X_z/Y_z$. Y_z is the sum of domestic sales and imports and represents domestic absorption. As this is a cross-sectional within-country analysis, variation in Λ_z directly reflects movement in the comparative advantage of Chinese industries.

Λ_z can be decomposed into the sum of the products of firm-level domestic market shares and export intensities. For domestic market shares $s_{zi} = d_{zi}/Y_z$, where d_{zi} is the sales of firm i to the domestic Chinese market, and export intensities $\lambda_{zi} = x_{zi}/d_{zi}$, where x_{zi} is the exports of firm i from China to the rest of the world, this decomposition is expressed as:

$$\Lambda_z = \sum_{i=1}^{N_z} s_{zi}\lambda_{zi} = \mathbf{s}'_z\lambda_z \tag{2}$$

where N_z is the finite number of firms in industry z and $\mathbf{s}'_z\lambda_z$ is the corresponding matrix notation. This summation makes clear the exposure of an industry's export intensity to granular elements at the firm level. A disproportionately large firm may have a disproportionately large impact on industry level Λ_z via either s_{zi} or λ_{zi} without a continuum of firms to guarantee it averages out in the aggregate. The export ratio of a granular firm is also likely to be different than if the same resources were divided among many smaller firms, though in the context of the current paper, it is not immediately obvious whether granular firms in a large developing country would have a bias towards exports or towards the domestic market.

Besides the export ratios of granular firms themselves, the presence of such large firms may also boost or hinder the export performance of other firms in the industry. This could owe to crowding out smaller firms from the domestic market, forcing them to seek opportunities in international markets, or spillover effects that affect productivity or entire supply chains. Thus, non-granular firms may also be affected by the idiosyncratic activity of granular firms, which in turn is also detectable in the aggregate given the finite number of firms in the summation in equation 2. These second-order effects are especially relevant to the case of a developing country.

In the literature on firm productivity, draws are typically from a single distribution for some level of disaggregation, as is the case in Gaubert and Itskhoki (2021). The current paper argues that, especially in the context of developing economies, there are at least two fundamentally different categories of firms within each industry. Specifically, there is the group of local domestically-funded firms (DFFs) and the group of foreign-funded firms (FFFs) that are the product of FDI. Foreign multinationals enter a country to take advantage of local comparative advantages (vertical FDI), or to capitalize on a growing domestic market (horizontal FDI). Upon entry, they often already have extensive supply and demand networks, and years of expertise. Their utilization of technology may be vastly different from local firms, as is evident in the literature on FDI spillovers, even if they are subsequently exposed to the same local resources.

Equation 2 can be expanded to distinguish between the contribution of DFFs and FFFs:

$$\Lambda_z = \sum_{i=1}^{N_z^{DFF}} s_{zi}\lambda_{zi} + \sum_{i=N_z^{DFF}+1}^{N_z^{DFF}+N_z^{FFF}} s_{zi}\lambda_{zi} = \mathbf{s}_z'^{DFF}\lambda_z^{DFF} + \mathbf{s}_z'^{FFF}\lambda_z^{FFF} \tag{3}$$

On the summations N_z^{DFF} represents the number of DFFs in industry z, N_z^{FFF} represents the number of FFFs in industry z, and $N_z^{DFF} + N_z^{FFF} = N_z$. The right hand side is again the corresponding vector notation with the suffixes denoting each element's funding type.

In every industry, two distinct stochastic data generating processes, represented by $(\lambda, \mathbf{s}) \sim F_z^{DFF}(\cdot)$ for DFFs and $(\lambda, \mathbf{s}) \sim F_z^{FFF}(\cdot)$ for FFFs, give rise to observed realizations of firm-level market shares and export intensities per respective funding category. Both $F_z^{DFF}(\cdot)$ and $F_z^{FFF}(\cdot)$ encapsulate industry characteristics, or the benefits of comparative advantage, that are accessible to their respective firm categories within industry z. As Y_z is the same regardless of funding type within industry z, the expected value of Λ_z can be computed as the sum of the expected value of the components of Λ_z from each funding type:

$$\Phi_z = \mathbb{E}_z\{\Lambda_z\} = \int \mathbf{s}_z'^{DFF}\lambda_z^{DFF}\ dF_z^{DFF}(\mathbf{s}_z^{DFF}, \lambda_z^{DFF}) + \int \mathbf{s}_z'^{FFF}\lambda_z^{FFF}\ dF_z^{FFF}(\mathbf{s}_z^{FFF}, \lambda_z^{FFF}). \tag{4}$$

where Φ_z is the expected value of industry export intensity and represents the fundamental comparative advantage (FCA) realized at the industry level. Deviations from this expected value for a particular industry owes to the granular component of industry export intensity provided by outlier firms that do no average out in the aggregate, which may arise within either the group of DFFs or FFFs. Λ_z therefore has the decomposition:

$$\Lambda_z = \Phi_z + \Gamma_z^{DFF} + \Gamma_z^{FFF} \tag{5}$$

where $\Gamma_z^{DFF} + \Gamma_z^{FFF} = \Lambda_z - \Phi_z$ is the granular component that is the sum of the two granular residuals. Each Γ_z represents two distinct sources of granular comparative advantage (GCA) coming from the idiosyncratic activity of superstar firms. GCA has the potential to push an industry's comparative advantage beyond its FCA, and could be a vital source of export competitiveness where just a few superstar firms shape a country's key export sectors. Conversely, this granular residual could be negative in the case where superstar firms are suffocating, inefficient, or over-reliant on the domestic market for survival.

The goal of the following is to ascertain the existence of granular comparative advantage by regressing industry exports on granularity proxies, namely a simple concentration ratios describing how dominant the top-few DFFs and FFFs are per industry, and to evaluate how granularity brought on by domestic superstars contributes to industry level comparative advantage differently from the granularity brought on by foreign superstars.

The domestic market share s_{zi} defined above requires imports data, which is not available at the level of disaggregation desired for this paper. I also want to test other definitions of granularity as mentioned in section 3.3. Thus, $\widetilde{s}_{z,i,t}$ denotes an alternative share of industry activity or size.

First, I follow Gaubert and Itskhoki (2021) by computing $\widetilde{s}_{z,i,t}$ from domestic market sales. This gives $\widetilde{s}_{z,i,t} = \textit{domestic sales share} = d_{z,i,t}/\sum_{i=1}^{N_z} d_{z,i,t}$, where $d_{z,i,t}$ is a firm's domestic market sales and is equal to their total sales originating from their mainland-China production minus what is exported out of main-land China, and N_z is the total number of firms in industry z. This definition of $\widetilde{s}_{z,i,t}$ is not mechanically correlated with exports and thus is the preferred share to use in building granularity proxies. However, ranking firms by domestic sales leads to a proxy of granularity excessively biased towards firms established in the emerging economy for horizontal-type, market access reasons, as was discussed in section 3.3. Therefore, I also define $\widetilde{s}_{z,i,t}$ as a firm's share of industry employment (or number of workers), whereby $\widetilde{s}_{z,i,t} = \textit{employment share} = e_{z,i,t}/\sum_{i=1}^{N_z} e_{z,i,t}$ and $e_{z,i,t}$ is a firms' total number of workers. A firm's share of the industry wage bill is also used in robustness checks, whereby $\widetilde{s}_{z,i,t} = \textit{wage bill share} = wb_{z,i,t}/\sum_{i=1}^{N_z} wb_{z,i,t}$ and $wb_{z,i,t}$ is total the wage bill paid out by the firm, with a contrast of this definition and that by employment given in section A4 of the appendix. I maintain the notation of $\widetilde{s}_{z,i,t}$ for the three definitions for simplicity and to make clear that only one is used at a time with the idea to compare result when using the different definitions.

The granularity proxies are defined as the concentration ratio among the top-3 DFFs, $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$ and the top-3 FFFs, $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$, which seems ideal for capturing any obvious presence of granularity from these two groups of firms for the case of China, as discussed in section 3.2. Empirical results remain similar if reducing or slightly enlarging the number of top firms. The maximum for both of these concentration ratios added together is 1.

While generally the granular FFFs and granular DFFs proxies have very low correlations across industries, there are some industries where both may become large, and thus have a higher covariance either in levels or in changes. It is therefore important to include both sources of granularity despite there being much space between granularity from FFFs and DFFs in most industries. The granular terms are left as shares as taking logs does not improve the normality and would also go against the point of capturing the fat tail Pareto distributions.

As $\widetilde{s}$ is a share, the granularity proxies are not necessarily correlated with industry exports unless through a granular residual. In other words, if industry exports are not correlated with the size of the largest firms relative to other firms or relative to the industry norm in a manner that does not extend beyond the direct effect on industry size, then the coefficient on these shares in explaining industry exports would be zero. Thus the baseline regression for detecting GCA in China is:

$$X_{z,t} = \alpha + \beta^{DFF} \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF} + \beta^{FFF} \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \log D_{z,t} + \delta_z + \delta_t + \varepsilon_{z,t}, \tag{6}$$

where β^{FFF} and β^{DFF} are the estimates of interest that relate granularity owing to FFFs and DFFs, respectively, to industry exports, $X_{z,t}$. $D_{z,t}$ is a control for the industry size according to whichever definition of $\widetilde{s}$ is used, so either the aggregate domestic sales among firms in mainland China, the aggregate number of workers, or the aggregate wage bill. δ_z and δ_t are industry and year fixed effects, respectively.

The non-linear Poisson pseudo-maximum likelihood estimator is appropriate for handling zeros or near zero values in the dependent variable, and is therefore used to estimate equation 6, as there are 47 industry-year observations out of 4,200 that have zero industry exports. This estimator helps with addressing the fact that China had a relatively less diversified economy during this period, as these zeros describe the worst performing industries in terms of export competitiveness, and taking logs whereby they become missing values can induce a large bias.

In this Poisson estimator, the conditional mean of the exponential form $E(X|regressors) = exp(regressors'\beta)$, given that industry exports are non-negative. The first order conditions on the corresponding log-likelihood function are of the form $\sum_{i=1}^{N} X_{z,t} - exp(regressors'_{z,t}\beta) = 0$, where $\hat{\beta}$ is found numerically as there is no explicit solution. The partial elasticity for the FFF granularity term is then

$$\frac{\partial \log E(X_{z,t}|regressors_{z,t})}{\partial \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}} = \beta^{FFF} \tag{7}$$

and similar for the partial elasticity of the DFF granularity term.

Indeed, since Santos Silva and Tenreyro (2006), the Poisson estimator has been shown to be more appropriate for analyzing exports under the presence of heteroskedasticity, regardless whether or not zero values are present. As it is a pseudo-maximum likelihood estimator, the data is not required to be count data or follow a Poisson distribution and in fact remains consistent for any distribution on the data. Additionally, the Poisson estimator in particular is consistent in the presence of two-way fixed effects, whereas, for example, the tobit estimator is not due to the incidental parameters problem. The Poison estimator is also scale invariant.

The different forms of $\widetilde{s}_{z,i,t}$ yield different empirical specifications according to 6. Comparisons between these empirical specifications allows looking at the association of GCA with a set of relatively market seeking foreign firms versus a less biased set including more efficiency seeking firms. To address endogeneity between the granularity proxies and industry exports, a Poisson 2sls exercise using capital investments as an IV as well as an out-of-sample prediction exercise follow the baseline results and discussion of other robustness checks specific to the Chinese data.

4.2 GCA Results

This subsection examines whether a granular residual characterizes Chinese exports and how this residual varies according to the funding type of granular firms.

Table 2 shows results from estimating equation 6 using domestic sales share to identify and sum together the top firms in each industry. While defining granularity by domestic sales shares biases the analysis towards a representation of horizontal FDI for the case of China, it also carries the least empirical concerns as domestic sales shares are not systematically correlated with exports. Furthermore, the variables for DFF domestic sales granularity and FFF domestic sales granularity have a near zero correlation of -0.05.

$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$ in columns (1), (4), and (7) is for the top-3 firms by domestic sales regardless of funding type. Columns (1) and (4) are directly comparable to columns (4) and (5) in table 1 of Gaubert and Itskhoki (2021). Whereas they found a positive association for the application to France, the current paper finds evidence of a strong negative relationship between industry granularity and industry exports. That is, larger industry concentration among top-firms in China associates with lower total exports in their respective industries, thereby providing evidence that granularity hinders comparative advantage in China overall, and by extension that superstar firms in developing economies may indeed have the opposite impact on over all comparative advantage compared with developed economies.

Table 2: Granular CA via domestic sales share

	1998-2007 full FEs			first-diff 2-dig FE			Poisson full FEs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-1.952***			-1.088***			-0.814***		
	(0.73)			(0.41)			(0.24)		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-1.370**			-0.710*			-0.809***	
		(0.65)			(0.37)			(0.23)	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			0.358			0.124			-0.471
			(0.60)			(0.43)			(0.34)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-2.070***			-1.219**			-1.194***
			(0.76)			(0.49)			(0.29)
$D_{z,t}$	1.023***	1.034***	0.964***				0.396***	0.384***	0.359***
	(0.20)	(0.21)	(0.20)				(0.07)	(0.07)	(0.07)
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.445	0.439	0.450	0.012	0.009	0.016			
Observations	4200	4200	4200	3780	3780	3780	4200	4200	4200

Note: DV is industry exports. In all columns $\widetilde{s}$ is defined by domestic sales and $D_{z,t}$ is industry domestic sales. Columns (4) - (6) takes first differences and includes year and two-digit industry fixed effects. Columns (7) - (9) repeat (1) - (3) (all with year and 4-digit industry fixed effects) using a Poisson regression, where the DV is not logged so that zero-export industries are included without needing to add 1 unit before taking logs as is done in columns (1) - (6). Robust errors; * p<0.10, ** p<0.05, *** p<0.01.

Some industry-years have zero exports in China over the panel of analysis, and thus exports were incremented by one unit to obtain the results shown in columns (1) through (6) of table 2. Columns (7) - (9) re-estimate columns (1) - (3) with the preferred Poison pseudo-maximum likelihood estimator, which accommodates for zero-export industry-years without needing to increment the data, as discussed in section 4.1. For the Poison regression in column (7) the interpretation is that an additional 10% of total domestic market sales (from operations located within mainland China) concentrated among the top-3 firms (without respect to funding-type) associates with a 7.82% (exp(-0.814x0.10)-1) decrease in industry exports. In other words, there is a negative granular residual.

Columns (2), (5), and (8) add the domestic sales shares of the top-3 FFFs and top-3 DFFs together, or $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$. This is done to show what happens when the two groups of aggregated top-firms are then split into two different sources of granularity, $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$ and $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$, in columns (3), (6), and (9). Looking at the Poisson specifications; from the granularity proxy made from only 3 firms per industry-year in column (7) to expanding to 6 firms in column (8), there almost no difference in the estimated coefficients. Splitting the 6 firms into two groups in column (9) shows that the negative granular residual is coming from the more dominant granular DFFs, while granular FFFs do not produce a granular residual.

Columns (4) - (6) capture a more dynamic story by regressing first-differences of all variables and implementing 2-digit industry fixed effects. The dynamic specification strongly maintains

Table 3: Granular CA via industry wage and worker shares

	Defining $\widetilde{s}$ by wage bill			Defining $\widetilde{s}$ by employment		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-0.697***			0.120		
	(0.24)			(0.29)		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-0.692***			0.272	
		(0.23)			(0.27)	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			-0.033			1.495***
			(0.35)			(0.40)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-1.350***			-0.807**
			(0.26)			(0.39)
$D_{z,t}$	0.860***	0.838***	0.804***	0.793***	0.795***	0.728***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Industry & Year FE	Y	Y	Y	Y	Y	Y
pseudo-R-sqr	0.980	0.980	0.981	0.979	0.979	0.980
Obs	4200	4200	4200	4200	4200	4200

Note: All are Poisson regressions, comparable to columns (7) - (9) of previous table. $\widetilde{s}$ is wage bill shares for columns (1) - (3) and employment shares for columns (4) - (6). Both resulting proxies capture vertical FDI more than domestic market share, with worker share more so than wage bill share. $D_{z,t}$ is industry total wage bill for columns (1) – (3) and total number of workers for columns (4) – (6). Robust errors; * p<0.10, ** p<0.05, *** p<0.01.

that as the degree of granularity in an industry increases there is an associated decrease in that industry's export stance, again indicating a negative granular residual.

Given that the only difference between columns (1) and (7) are that (1) is a log-linear regression while (7) is a Poisson regression, the different coefficient estimates of -1.952 and -0.814 indicate that the log-linear model may suffer from heterogeneity-induced bias as discussed in Santos Silva and Tenreyro (2006). If excluding the 47 zero export industry-year observations, the coefficient of interest in column (7) hardly changes, while the coefficient when re-estimating column (1) adjusts drastically to -0.590 with a standard error of 0.343. In other words, the Poisson estimator is stable and the log-linear OLS model is not.

Table 3 offers a different perspective by using the two alternative methods of sorting firms to proxy for industry granularity, which as mentioned, allow better representation of vertical FDI. Firms are ranked by wage bill shares for columns (1) through (3) and ranked by employment shares for columns (4) through (6), with the granularity proxies built from the corresponding shares and the and Poison regressions of columns (7) through (9) in table 2 reproduced, respectively. The coefficient on granularity from a single source remains negative for wage bill shares, but zeros out when using employment shares. Similarly, the coefficient on granularity from FFFs remains indistinguishable from zero when using wage bill shares but turns strongly positive at 1.495 when using employment shares. The interpretation is that an additional 10% of total employment concentrated among top-3 FFFs associates with a 16.1% ([exp(1.495x0.10)-1]) increase in industry exports. In other words, placing 10% of an existing workforce into the top-3 FFFs by employment is equivalent to increasing the total workforce (D_z, t) by roughly 2 log-points due to the strong positive FFF granular residual.

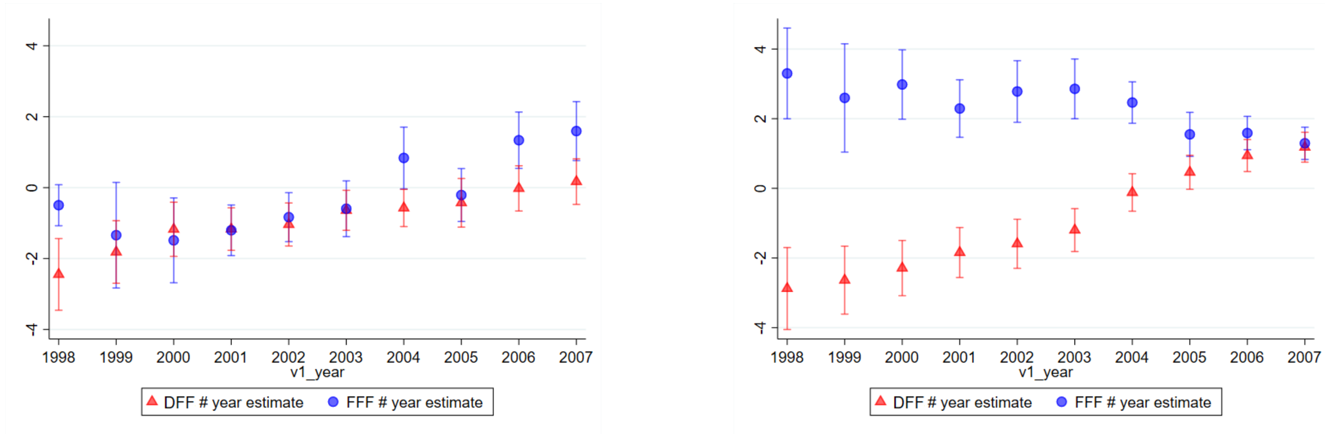
For context, 75 industries out of the 420 see the FFF granularity in employment proxy increasing by 0.05 or more from the year 1998 to 2007 and 32 industries increase by 0.10 or more, with the largest increase being 0.45. At the same time, 32 industries see the proxy decreasing by 0.05 or more and 16 by 0.10 or more, with the largest decrease being 0.47. By these thresholds and given the estimated coefficient, the change in concentration of industry employment into the top-3 FFFs is therefore a sizable source of industry export variation in over 25% of Chinese industries. Nearly half of industries had more than 5% of total employment concentrated in the top-3 FFFs by 2007.

Meanwhile, a coefficient of -0.807 implies that placing 10% of an existing workforce into the top-3 DFFs by employment is equivalent to decreasing the total workforce by roughly 1 log-point on average. The IV strategy discussed later and shown in table A10 strengthens these results. Taken together, these results suggest that letting in the largest efficiency seeking firms is the only source of positive GCA.

Additionally, the results seem to be driven by industries where FFF granularity and DFF granularity are more similar, and thus not where there might be a single domestic monopoly or a total lack of domestic superstars. This is detected by dropping all industries where the distance between FFF granularity and DFF granularity is greater than the median across industries, and is robust to choosing any reference year.

Granularity does, however, show signs of changing its relationship with comparative advantage over the years of the panel in China. When modifying the regression in column (6) of table 3 by introducing the interaction of year dummies with the granularity terms while retaining both year and industry fixed effects, a convergence becomes evident. Figure 5b illustrates this result, where by 2007 the estimated coefficients on industry DFF and FFF granularity (by employment) are indistinguishable from each other. Meanwhile, Figure 5a shows that while both groups see a negative association with exports of their granularity when proxying by domestic sales in the initial years of the survey data, there seems to be an upward trend. In particular, this relatively domestic market-oriented proxy for granularity sees significantly positive coefficients by the end of the sample for FFFs, with coefficients becoming very similar to when proxying by employment shares.

Figure 5: Convergence of coefficients on granularity proxies



(a) defining $\widetilde{s}$ by domestic sales

(b) defining $\widetilde{s}$ by employment

Note: Plots coefficients of a single Poisson regression equivalent to column (9) in table 2 except for adding year interactions on each of the two granularity proxies. Industry and year fixed effects included. Robust errors with solid fill indicates significance past the 90 percent level.

4.3 Ruling out bias from state-owned firms

Granularity owing to state-owned firms could arguably go in both directions. It could help build positive granular residual in comparative advantage due to the fact that state-owned firms often prevail in industries where large private firms may face fundamental comparative disadvantage, especially in this era of privatization of more competitive industries. However, state-owned firms may potentially constrain industries if they absorb available funding or underbid others, for example. It is therefore a useful robustness check to adjust the analysis by separating state-owned firms from private DFFs.

Table 4 presents the same Poisson regressions as tables 2 and 3 for the two sources of granularity, and also adds to equation 6 the term $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{SDFF}$ to control for granularity from state-owned Chinese-funded firms, where $\widetilde{s}_{z,i,t}^{SDFF}$ is a given state-owned firms' share and $n = 1$, 2, and 3 are the three largest state-owned firms by the specified method of sorting and calculating industry shares. The term $\widetilde{s}_{z,i,t}^{DFF}$ is therefore now calculated excluding any state-owned firms, and thus represents private DFFs in China. The similarity of coefficients for granularity proxies from both FFFs and modified DFFs suggests that the inclusion of state-owned firms does not skew the results. Granularity from these firms yields a comparable granular residual to that from private DFFs.

4.4 Predictive power out of sample

Reverse causality is a potential source of endogeneity for granularity explaining exports. Export growth at the industry level could fuel consolidation by the fact that opening an industry to trade

Table 4: Separating state-owned firms from granular proxies

	$\widetilde{s}$ by domestic sales		$\widetilde{s}$ by wage bill		$\widetilde{s}$ by employment	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	-0.109	-0.601*	0.204	-0.110	1.642***	1.400***
	(0.41)	(0.33)	(0.36)	(0.35)	(0.40)	(0.40)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$, private	-0.598**	-1.168***	-0.811***	-1.452***	-0.476**	-0.843***
	(0.25)	(0.25)	(0.18)	(0.24)	(0.24)	(0.29)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$, state		-1.396***		-1.320***		-1.024**
		(0.40)		(0.31)		(0.44)
$D_{z,t}$	0.358***	0.358***	0.788***	0.786***	0.729***	0.716***
	(0.07)	(0.07)	(0.05)	(0.04)	(0.04)	(0.04)
Industry & Year FE	Y	Y	Y	Y	Y	Y
pseudo-R-sqr	0.970	0.971	0.980	0.981	0.980	0.980
Obs	4200	4200	4200	4200	4200	4200

Note: All are Poisson regressions. State-owned firms are excluded from computation of the granularity proxies and given their own granularity proxy in (2), (4), and (6). The first two columns use domestic market shares to proxy for granularity, the next two use wage bill shares, and the last two use employment shares. Robust errors; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

brings import competition and more economies of scale to those firms that begin to export. Though while openness is certainly a prerequisite of foreign firms entering a country and scaling production, it is unclear whether the granular firms are primarily responsible for scaling industry exports or if their operations are heavily influenced by the presence or absence of industry exports. In contrast, import competition may have resulted in reallocation to more productive granular DFFs firms.

Reverse causality from industry exports onto either granularity from FFFs or DFFs would imply that variation in granularity is explained by past exports or industry characteristics beyond dynamics from mean reversion. This is tested in table 5, where in column (1) I first regress 10-year change in worker granularity from DFFs on the 1998 levels of log industry exports, the size control of log industry employment, the two granularity proxies, and a full set of 2-digit industry fixed effects. 10-year change in granularity from DFFs is explained only by its partial mean reversion. Of note is that only granularity from DFFs is predictive of granularity from DFFs, with not even the industry employment being significant, an indication that granularity is not simply a feature of industry size or lack thereof. Column (2) repeats for granular FFFs. There is still no predictive power from exports onto the 10-year change in granularity. However, granularity from FFFs is pulled down by industry size in terms of workers, meaning any bias from a correlated size variable is likely negative, giving more validity to its positive coefficient in explaining industry exports. Adding industry export intensity and its interaction with exports in column (3) still does not help

Table 5: Predictive power of key variables

Dependent Variable:	$gDFFs_{z,07}-gDFFs_{z,98}$	$gFFFs_{z,07}-gFFFs_{z,98}$			$X_{z,07}-X_{z,98}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$X_{z,98}$	-0.005	0.004	-0.001	0.002	-0.501***	-0.489***	-0.568***
	(0.003)	(0.002)	(0.003)	(0.004)	(0.043)	(0.059)	(0.060)
$\sum_{i=1}^{3}\widetilde{s}_{z,i,98}^{FFF}$	0.031	-0.741***	-0.755***	-0.768***	1.644*	1.530*	6.207***
	(0.073)	(0.046)	(0.047)	(0.048)	(0.909)	(0.898)	(2.022)
$\sum_{i=1}^{3}\widetilde{s}_{z,i,98}^{DFF}$	-0.455***	0.044*	0.045*	0.060**	0.341	0.647	1.128**
	(0.042)	(0.026)	(0.027)	(0.027)	(0.532)	(0.523)	(0.523)
$log\ workers_{z,98}$	0.008	-0.017***	-0.012**	-0.013***	0.311***	0.174*	0.310***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.078)	(0.095)	(0.097)
$export\ intensity_{z,98}$			0.141	0.168		-12.574***	-10.813***
			(0.153)	(0.157)		(2.958)	(2.944)
$\times X_{z,98}$			-0.006	-0.008		0.841***	0.733***
			(0.010)	(0.010)		(0.187)	(0.187)
$X_{z,07}-X_{z,98}$				0.004			
				(0.008)			
$\times X_{z,98}$				0.000			
				(0.001)			
$FDI\ cap\ share_{z,98}$							1.971***
							(0.477)
$\times \sum_{i=1}^{3}\widetilde{s}_{z,i,98}^{FFF}$							-11.200***
							(3.394)
2-digit industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sqr	0.453	0.481	0.487	0.509	0.431	0.462	0.490
Observations	413	413	413	412	412	412	412
dfres	380	380	378	375	379	377	375

Note: All include 2-digit fixed effects. Granularity proxy from $\widetilde{s}$ defined by employment only. Regresses 1998 values on 10-year change for indicated DV. Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.

in predicting 10-year change in granularity from FFFs. Finally, even when adding the 10-year change in exports and its interaction with 1998 exports in column (4), with these being the only contemporaneous variables, all measures of exports remain insignificant in explaining variation in granularity from FFFs, strong evidence against reverse causality.

Conversely, column (5) shows granularity from FFFs is predictive of positive export growth over the 10-year period, even after controlling for mean reversion and the positive effect from industry worker size. This is robust to controlling for industry export intensity and its interaction with log industry exports. Further, adding the share of aggregate industry invested capital that is from FDI and its interaction with granularity from FFFs brings much significance to the main variable of interest, and it is revealed that granularity when not accompanied by existing high levels of FDI penetration in particular is predictive of positive export growth at the industry level, a result in line with the heterogeneity analysis below. Note that if standardizing the beta coefficients here, granularity from FFFs and the percent of industry invested capital from FDI both have equally large coefficients of around 0.18, while their interaction would be -0.12, meaning the net effect of granularity from FFFs is still very positive on 10-year change in industry exports.

4.5 Instrumental variable approach

Granularity in financial capital is correlated with granularity in domestic sales shares, wage bill, and employment. In order to address endogeneity with a 2SLS approach, I argue that injecting financial capital into a firm causes growth in scalables, such as wage bill or employment levels, and only through these scalables does financial capital translate to variation in exports. This logic is more direct for wage bill and employment than for domestic sales, but results when instrumenting for domestic sales and wage bill are very similar, and the fact the coefficient on DFF granularity remains negative is convincing.

The first stage thus regresses each granularity proxy on the available exogenous variables according to $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$ *and* $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} = \sum_{i=1}^{3} \widetilde{k}_{z,i,t}^{DFF} + \sum_{i=1}^{3} \widetilde{k}_{z,i,t}^{FFF} + \log D_{z,t}$, where $\widetilde{k}_{z,i,t} = \frac{financial\ capital_{z,i,t}}{financial\ capital_{z,t}}$, the share of industry financial capital belonging to firm i, whether it is a DFF or FFF. The set of firms used to build each granularity proxy are the same set used to build the corresponding instrument.

Exogeneity here means that financial capital remains uninfluenced by unobservable factors that might also affect industry exports. While it's possible that large financial injections are in anticipation of changes in industry exports, this should occur independently of fixed effects or industry size controls for the exogeneity requirement to possibly be violated. Additionally, although many multinational firms aspire to succeed in China, only a select few attain superstar status in its vast economy, not to mention that their aspirations may be based in domestic market access, with export activity only as a byproduct. This reduces the likelihood of significant unobserved factors violating the exogeneity of financial capital. Moreover, results stay robust even when considering lagged financial capital.

2SLS with log industry exports will exclude 47 zero-export observations, and likely bias estimates. Yet a non-Poisson 2SLS regression allows easy computation of test statistics, and thus these results are presented here in table 6, with the direction of the estimated coefficients all robust the alternative Poisson 2SLS estimator using the technique suggested in Lin and Wooldridge (2017), for which results are presented table A10 of the appendix to save space. The Poisson regression includes the residuals of each first stage as controls in the second stage. Shown here are the results for granularity by domestic sales shares and by employment shares are displayed here, with wage bill shares by both estimation techniques left to table A11 of the appendix.

Columns (1) and (4) maintain that overall granularity negatively impacts industry exports.

Table 6: 2sls using invested capital shares as IVs

	Defining $\widetilde{s}$ by domestic sales			Defining $\widetilde{s}$ by employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-1.430***			-1.173***			
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-1.812***			-1.774***		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			-0.317			1.421**	2.210***
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-1.567***			-1.836***	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$; private only							-0.647**
$D_{z,t}$	0.688***	0.679***	0.657***	0.903***	0.844***	0.884***	0.958***
LM-stat	836	598	406	879	675	595	688
CD-F-stat	938	626	201	1000	723	311	370
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4153	4153	4153	4153	4153	4153	4153

Note: Capital shares serve as the instruments for the granularity variables. Adding industry total paid-in capital as a control does not change signs or significance levels. Underidentification test rejection of the null with a p-value < 0.001 all indicates that the instruments are relevant, and the model is identified. Cragg-Donald Wald F stat of above 100 imply instruments are not weak. As regression is not Poisson here, log exports excludes zero export industry-years. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

Only when splitting firms into the two groups of DFFs and FFFs in column (6) is there a positive and significant coefficient on granularity from FFFs. Column (7) removes state-owned firms before building the granularity proxy for DFFs to further show that the result of superstar DFFs negatively impacting GCA is not driven by state-owned firms, but the fundamental differences between superstar DFFs and superstar FFFs.

FFFs are the only source of positive association of granularity with comparative advantage in China. These results are also robust to including real fixed assets as a firm-level control (not shown), something else financial capital might influence exports through. They are also robust to including the percentage of firms that are FFFs in an industry (not shown), meaning the granularity terms are not simply proxying for FDI other than in the sense of granular FDI. Furthermore, adding industry total paid-in capital as a control does not affect results, and thus only the relevant industry size control, D_z, t, is included.

4.6 Heterogeneity in GCA

Industry estimates characterizing GCA exhibit heterogeneity across various dimensions, which can be explored through comprehensive analysis of the Chinese firm-level database. The following discusses three categories of interaction variables: industry technology classification, other time-varying industry characteristics, and the attributes of the superstar firms themselves.

4.6.1 Industry Technology Classification

To examine heterogeneity of granular residuals with respect to the technology class of industries, I match the Chinese industry codes to ISIC revision 3 codes, which have OECD classifications based on standardized R&D intensities. These classifications categorize industries into four groups: high-tech, mid-high-tech, mid-low-tech, and low-tech. For ease of interpretation and also because the cutoff of classifications is less pronounced in the middle, I combine mid-high and mid-low into one group.

Table 7 presents the results for each of the three definitions of granularity, with the combined mid-tech classification used as the reference group for the interactions with both DFF and FFF granularity. Among the 420 industries, 236 fall into the mid-tech category, 131 into low-tech, and 53 into high-tech. For the reference group of mid-tech, the coefficients on FFF granularity move from statistically insignificant when using domestic sales shares to a significant 0.761 when using wage bill shares, and further increase to a significant 2.532 when using employment shares. Conversely, the negative association of DFF granularity with industry exports is shown to be predominately coming from mid-tech industries, with low-tech industries seeing a net zero association.

Mid-tech industries had much less FFFs as a percentage of all firms and aggregate FFF activity compared to both low-tech and high-tech industries. While non-granular FDI accounted for only 10% of exports on average in mid-tech industries in 1998, granular FFFs were already relatively important, accounting for around 25%. There is also relatively more focus on the domestic market in mid-tech industries, and generally more room for sustainable export growth. The next subsection shows that these are compatible with industry level characteristics that enable FFF granularity to boost industry exports and while DFF granularity would hold back industry exports.

Meanwhile, the net zero DFF granular residual in low-tech sectors may be due to the more competitive nature of these industries that prevent DFF superstars from crowding out firms, or that they benefit from strong low-tech economies of scale that they cannot yet reproduce in mid-tech industries.

4.6.2 Industry characteristics

The next two subsections focus on granularity defined by employment shares so to break down the FFF and DFF granular residuals. Table A13 in the appendix presents results from the interaction of these granularity measures with various industry-level controls, highlighting heterogeneity based on industry characteristics.

When examining the ratio of firms younger than 5 years old, which proxies for industry dy-

Table 7: Interacting with industry tech dummies

	$\widetilde{s}$ by dom sales	$\widetilde{s}$ by wage bill	$\widetilde{s}$ by employment
	(1)	(2)	(3)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	-0.245	0.761***	2.532***
x high-tech	-0.628	-1.137**	-1.044
x low-tech	0.864*	-0.167	-1.725***
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$	-1.157***	-1.381***	-1.765***
x high-tech	-1.001	-0.355	1.635**
x low-tech	1.829***	0.956*	1.994***
$D_{z,t}$	0.356***	0.810**	0.760***
Industry & Year FE	Y	Y	Y
R-sqr	0.972	0.981	0.981
Obs	4200	4200	4200

Note: The granularity measures are interacted with a low tech and high-tech dummy, leaving mid-tech as the reference group. The dependent variable is industry exports. All models implement Poisson regression. Robust errors; * p<0.10, ** p<0.05, *** p<0.01.

namism and openness to competition, the interaction coefficient with FFF granularity is significantly positive, while that with DFF granularity is significantly negative. The same is true when interacting these terms with the proportion of state-owned firms within an industry. On the other hand, FFF granularity in industries already populated by many FFFs or industries with already high total factor productivity (TFP) [4] has a relatively negative association with industry exports.

The interpretation is that superstar FFFs are a mechanism of boosting industry export competitiveness in industries positioned for growth with many young firms or state firms that are ready to privatize, and is most beneficial in less mature industries with low levels of TFP and less existing FDI. In such cases, superstar FFFs are useful in paving the way for export-led growth. This positive granular residual tends to be mid-tech industries, as discussed above. Furthermore, there is a stronger granular FFF residual in industries with more significant real fixed assets, possibly due to a greater amount of absorptive capacity.

DFF granularity, on the other hand, induces a negative granular residual in industries primed for growth. This negative association with industry exports is also stroner in industries already populated by many FFFs, despite there being zero correlation of DFF granularity and the number of FFFs, even after controlling for industry and year fixed effects. This works against the concern that the negative association of DFF granularity and industry exports comes only because comparatively disadvantaged industries attract DFF granularity given that industries with more

[4] TFP is estimated following Wooldridge (2009) separately per industry and aggregated to the industry level following Olley and Pakes (1996).

FFFs are typically thought to be comparatively advantaged industries.

Granularity from DFFs has a relatively positive association with industry exports in industries experiencing high domestic market growth rates, and when taken with the above indicate that if the industry is healthy and well-developed in terms of mature firms that are non-state owned, then superstar DFFs no long have a clear negative granular residual. This is in line with the overall trend in the relationship of DFF granularity with industry exports approaching that of FFF granularity by the year 2007, as was shown in figure 5a.

4.6.3 Characteristics of Superstar Firms

The characteristics of the firms constituting the defined levels of granularity are diverse and can provide insights into what factors are important for strengthening an industry's granular residual. Table A14 in the appendix presents results of various interactions when considering details on the specific groups of granular firms.

Higher granularity from FFFs or DFFs with greater intermediate input to fixed asset ratios associates with higher industry exports, which could be due to spillovers from local input sourcing or processing trade.

Labor productivity and average real wages of granular firms is also important. This could reflect the influence of labor-intensive sectors where higher productivity allows granular firms to leverage economies of scale and pay higher wages. Efficient labor and resource allocation by these granular firms results in a relatively positive granular residual from both DFFs and FFFs.

Higher value-added to fixed assets ratios only result in a stronger granular residual for FFF granularity. This may again signify efficient resource allocation for the case of granular FFFs that results in higher industry exports, while there may be lingering constraints in the economy preventing such resource reallocation towards similarly productive DFFs.

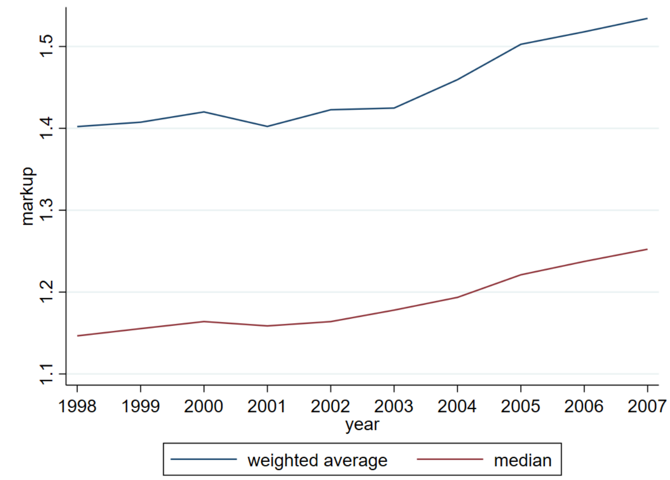
Conversely, granularity from firms with a high wage bill to fixed assets ratio negatively impacts exports for both FFFs and DFFs, suggesting possible inefficiencies in resource allocation where firm-level labor costs outweigh capital investment. This could imply that a granular firm's capital intensity is an important criteria from generating a positive granular residual.

To further explore the potential impact of granular firms on the outcomes of non-granular counterparts, the following section presents findings regarding the relationship between granularity and firm-level estimated markups.

5 Granularity and Pro-competitive effects

Atkeson and Burstein (2008) present a model of oligopolistic competition where firm markups increase with market share. Edmond et al. (2015) build on this by demonstrating that interna-

Figure 6: Markups



Note: Markups estimated as in De Loecker and Warzynski (2012) with Ackerberg et al. (2015) translog production function elasticities.

tional trade can lower markups if there is initial miss-allocation in the sense of markup dispersion and where domestic producers are put under more effective competitive pressure. In this section, I empirically examine how the presence of granularity from DFFs and granularity from FFFs in mainland China is related to firm-level markups of the non-granular firms. In essence, I test whether the insights of Edmond et al. (2015) transfer to the concept of granularity, and differentiate between the two sources of funding. The existence of strong pro-competitive effects from granular FFFs would imply the industry becoming more competitive, and thus provide a possible mechanism for FFF granularity increasing industry export competitiveness.

While foreign firms more generally are expected to decrease markup dispersion by intensifying competition, the influence of large, superstar firms is not as clear-cut. As a firm becomes larger relative to others, it takes their market share, and while this may result in higher markups for the large firm, it should also result in lower markups by all other firms if considering the linear relationship between market share and markups. However, if a larger firm displaces smaller firms entirely or causes inequality in the distribution of productivity then this effect may be reversed. Specifically, if granularity stems only from industry consolidation then granularity could correlate with higher markups across firms.

I estimate firm-level markups, $mu_{z,i,t}$, following De Loecker and Warzynski (2012) with Ackerberg et al. (2015) value-added translog production function elasticities. Control variables are taken from the literature include both firm-level controls as well as industry level controls, all varying with time. Figure 6 shows that there is much dispersion on average, with the weighted average of markups far above the median, and as mentioned in table 1, superstar DFFs have the highest markups, followed by Superstar FFFs.

The most important control variable in explaining firm-level markups is the firm's market share. Oligopoly models of competition suggest markups increase in market share. For export-intensive Chinese manufacturing it is sensible to proxy for this with $SS_{z,i,t} = ts_{z,i,t}/\sum_{i=1}^{N_z} ts_{z,i,t}$, the firms' total sales shares, where $ts_{z,i,t}$ comprises of both domestic sales and exports coming from firm's local operations.

Price of labor, $w_{z,i,t}$, is defined as total real wages over the number of workers (employment). A higher price of labor cuts negatively into markups as long as labor productivity is controlled for. At the same time, industry-level price of labor, $w_{z,t}$, or the logged ratio of total wages to total number of workers, should create barriers to entry, indicating tight labor supply for that sector, and thus raise markups. Labor productivity, $lp_{z,i,t}$, is defined as the logged ratio of real value added to the number of workers. Firms charge relatively higher markups when they are more productive as a result of lower unit costs.

More imports implies more competition for domestic market sales, thereby lowering markups of firms based in the country. Import penetration, $IP_{z,t}$, is calculated at the more aggregate ISIC revision 3 level in order to match with international datasets, with 111 industries. Higher export intensity at the firm level, $EI_{z,i,t}$, exposes the firm to more international competition causing markups to be lower (with productivity taken account for separately). A higher export intensity at the industry level, $EI_{z,t}$, implies that firms are more competitive in international markets, and thus may have higher markups.

Capital intensity, $ci_{z,i,t}$ is defined as the logged ratio of real fixed assets to the number of workers, and is expected to be positive with markups due to subsequently greater costs of capital accumulation. Capital intensity at the industry level, $ci_{z,t}$, is expect to associate positively with markups due to barriers of entry resulting from industry-level costs of capital.

Positive variation in TFP, $tfp_{z,i,t}$, should associate with higher markups, as a firm is able to produce more for less than its competitors. Conversely, positive variation in industry level TFP, $tfp_{z,t}$, means the industry becomes more competitive on average, which should lower markups. Finally, a larger number of firms, $obs_{z,t}$ in log, means more competition, and thus lower markups.

The variables of interests are the proxies for granularity from each the DFF and FFF groups. Here I use employment shares to build the granularity proxies, and maintain the notation $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$ and $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$, for each group respectively. The association of granularity with markups of any given firm within an industry will depend on how the granularity proxy interacts with key descriptors of the nature of competition facing the firms. Thus each of the industry level granularity proxies are interacted with the individual firm sales share, $SS_{z,i,t}$. A low $SS_{z,i,t}$ but high $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$ or $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$ should see firm i as having lower markups in the sense that the larger granular firms are taking sales share from the smaller firm i.

Lower markups of course may attract more market share, which is a channel of reverse causality

Table 8: Granularity and Pro-competitive effects

	(1)	(2)	(3)	(4)
$SS_{z,i,t-1}$; sales share		0.631***	1.577***	1.172***
		(0.06)	(0.11)	(0.11)
$\sum_{i=1}^{3} \widetilde{s}_{z,t-1}^{FFF}$	-0.060***		-0.072***	-0.056**
	(0.02)		(0.02)	(0.02)
$\sum_{i=1}^{3} \widetilde{s}_{z,t-1}^{DFF}$	0.033***		0.026***	-0.006
	(0.01)		(0.01)	(0.01)
$SS_{z,i,t-1} \times \sum_{i=1}^{3} \widetilde{s}_{z,t-1}^{FFF}$			-1.496***	-1.114***
			(0.35)	(0.33)
$SS_{z,i,t-1} \times \sum_{i=1}^{3} \widetilde{s}_{z,t-1}^{DFF}$			-2.085***	-1.467***
			(0.20)	(0.17)
$FDI_{z,t-1}$; firms that are FFFs				-0.005***
				(0.00)
Firm & Year FEs	Y	Y	Y	Y
All controls of equation 8	N	N	N	Y
Adjusted R_sq	0.861	0.861	0.861	0.862
Observations	1220553	1220553	1220553	1218377

Note: Dependant variable is log of estimated firm markup. Granularity proxy with $\widetilde{s}$ defined by employment only. All explanatory variables are lagged one year. Lowercase denotes log values. Column (4) implements the full markups regression of equation 8 with all 10 additional controls. Summary statistics in table A15 of the appendix. Industry×Year clustered errors; * p<0.10, ** p<0.05, *** p<0.01.

here for the term $SS_{z,i,t}$. Including firm-level fixed effects at least partially addresses this. Differentiated pricing or growth strategies, such as when a firm systematically undercuts its otherwise equal competitors in order to gain market share, will therefore be controlled for. Additionally, all variables are lagged one year in order to minimize endogeneity and reverse causality. The model estimated for all firms i not ranked in the top-3 of either DFFs or FFFs is then:

$$\begin{aligned} mu_{z,i,t+1} = \;& \alpha + SS_{z,i,t} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF} + SS_{z,i,t} * \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + SS_{z,i,t} * \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF} \\ & + lp_{z,i,t} + w_{z,i,t} + w_{z,t} + ci_{z,i,t} + ci_{z,t} + obs_{z,t} + EI_{z,i,t} + EI_{z,t} + IP_{z,t} + \delta_i + \delta_t + \varepsilon_{z,i,t}. \end{aligned} \tag{8}$$

and includes both year and firm fixed effects. All firms included in calculation of the granularity proxies are excluded. Firms-year observations that are outliers in either the computed firm-level markup or estimated firm-level TFP are also omitted, where outliers are identified under the strict criteria of being both more than three standard deviations from the mean as well as in the top or bottom 1 percent of observations in that industry-year.

Results are presented in table 8. Column (1) regresses firm-level markups on their the definitions of granularity by employment shares, with the two groups giving opposite signs. An additional 10 percent of total industry employment concentrating in the top-3 FFFs associates with a 0.6 percent decrease in markups of the non-granular firm, while the same reallocation of employment to the top-3 DFFs associates with a 0.33 percent increase in markups. This is robust to controlling for the non-granular firm's sales share and the interaction of the firm-level sales shares the the two definitions of industry granularity, as shown in column (3). The two interaction terms, however, are both negative, implying that there are strong pro-competitive effects from granular firms onto non-granular firms in their industry if those non-granular firms are also large (having a higher sales share).

Column (4) introduces all of the firm and industry-level controls of equation 8. The estimated partial effect of FFFs' granularity on a firms markup is $\partial E(mu_{z,i,t})/\partial worker\ share^{FFF}_{z,t-1} = -0.056 - 1.114 * SS_{z,i,t-1}$. The estimated partial effect of granularity from the group of DFFs on a firms markup is $\partial E(mu_{z,i,t})/\partial worker\ share^{DFF}_{z,t-1} = 0 - 1.467 * SS_{z,i,t-1}$. Thus, there is a pro-competitive effect in the sense that granularity form FFFs reduces markups of non-granular firms of any size, while the effect from granular DFFs only kicks in for larger firms described by a higher $SS_{z,i,t-1}$.

It should be noted that sales shares are quite low for a typical, non-granular firm. Among the firms included in the regressions for table 8 the mean sales share is 0.0038 across all industries and years with a standard deviation of 0.004. The broad pro-competitive effects from granular FFFs are therefore much more economically significant for a typical non-granular firm than is the effect from granular DFFs. Additionally, increases in FFF granularity associates with greater within firm reductions in total sales than does DFF granularity, but DFF granularity associates with greater reduction in the number of firms. I view this as in line with superstar FFFs putting firms under more effective competitive pressure, making the other firms feel their presence, but not to the point where they are driven out of business.

6 Granular FDI and Horizontal Spillovers

Horizontal productivity spillover effects from FDI on local Chinese firms in the same industry have been estimated to be zero or significantly negative. However, given the large gap between superstar FFFs and FFFs more generally, as discussed in section 3.3 and in particular with respect to labor productivity, it is worth investigating whether there are unique horizontal spillover effects coming from the granular component of FDI. Positive horizontal spillover effects would also provide further evidence of a granular mechanism at play in the Chinese economy.

While the spillover effects from FDI is a popular topic, it is one that is difficult to make progress on due to FDI being an endogenous decision, whereby firms may enter a developing country after observing or anticipating productivity growth among local firms. There is a source of exogenous variation in FFF granularity when China implemented reforms on the guidelines for FDI encouragement in late 2002, upon its accession to the WTO. This shock can be traced industry-by-industry by comparing the official 1997 Catalog of FDI Encouragement document to the 2002 update. These two documents provide lists of industries or areas of manufacturing that are divided into the three categories of "FDI Encouraged," "FDI Restricted," and "FDI Prohibited." A fourth category, "Permitted", therefore consists of all manufacturing items not listed in the catalog, where FDI is not given special treatment as in the "FDI Encouraged" category but not restricted either. Investment in items belonging to the encouraged category, for example, may be entitled to an "Import and Export Goods Tax Exemption Certificate" after submitting a request to a local Foreign Economic and Trade Commission.

There are 386 lines in the 1997 catalog and 449 lines in 2002 catalog, both including category headers, and with a majority, but not all, of the items relating to some manufacturing activity. The activities listed are sometimes specific and match to single 8-digit CIC codes, and sometime more broad, covering multiple 4-digit CIC codes. I proceed by manually mapping each year's catalog to Chinese Industry Codes by identifying which 8-digit product descriptions match the descriptions given in the catalogs. While this strategy is also used in Lu et al. (2017) when investigating general FDI spillovers, the constructed dataset is not publicly available and so I redo the matching for the current application.

The goal is to then identify which of the 420 4-digit CICs have a change to becoming more encouraging of FDI from 2002 compared to before 2002. To this aim, if at least one 8-digit CIC within a 4-digit industry experiences a move towards more encouragement of FDI while no 8-digit codes in that 4-digit industry experiences a lessening of encouragement, then that industry is marked as in the treatment group, receiving a positive shock on FDI encouragement. 4-digit industries that have no 8-digit codes that are affected by the catalog update are marked as the control group. All industries that experienced a worsening of FDI encouragement or a mixture of some 8-digit codes improving while some worsening are excluded.

In total, I identify 121 4-digit industries in the treatment group that experienced an improvement of FDI encouragement, and 283 industries in the control group that saw no change, meaning that out of the 420 industries in total, 16 saw either a mixed change or worsening of encouragement. 121 industries in the treatment group is slightly more than found in Lu et al. (2017). I view more industries in the treatment group as a relatively conservative approach that makes differences between the treatment group and the control group more difficult to detect.

An FDI encouragement variable is constructed and the treatment group is assigned a value of 1 for years 2003 and later, and a value of 0.75 for 2002, as the 2002 catalogue was implemented 3 months into the year. The variable is zero for years before 2002 in the treatment group and for all observations of the control group.

This FDI encouragement shock can then be used as an IV for industry level granularity. As granularity is bounded on the interval zero to one with a mass closer to zero and with few values above 0.5 for FFFs domestic market granularity, it can be approximately described by an exponential Poisson distribution, which helps in more accurately determining which variables this shock is correlated with. I run the diff-in-diff style Poisson regression on all definitions of granularity and also a generic term for domestic market FDI penetration, as it may be expected that such an FDI encouragement shock affects all FDI equally, or perhaps even smaller firms more than larger ones. FDI domestic market penetration is defined as:

$$\sum_{i=1}^{N_z} domestic\ sales * FDI\ share\ of\ invested\ capital_{z,i,1998} \tag{9}$$

Table 9 presents results from regressing these variables on the corresponding $treatment_z \times post_t$ term. Year and industry fixed effects are also included. There is a dramatic estimated increase in FFF granularity for $\widetilde{s}$ defined by domestic sales. The coefficient of 0.199 in table 9 states that the WTO shock induced roughly 20 percent of the domestic market to reallocate to the top FFFs in impacted industries. There is no effect, however, on FFF granularity in terms of employment, or even exports, and also no effect for any form of DFF granularity (only DFF domestic sales granularity is shown but results are similar for DFF employment and exports granularity). This seems logical in that exports of foreign firms were already more liberally encouraged both generally from the existing 1997 catalogue and within numerous special economic zones, and China's WTO accession instead largely focused on improving domestic market access to foreign firms. Regardless, these results indicate that the WTO shock would make for a week IV for any variable other than FFF domestic market granularity.

Column (5) of table 9 then introduces the FDI domestic market penetration (FDI dom penetration). While its coefficient is significant at the 10% confidence level, it is half the magnitude as the granular component in column (1), and its significance as well as magnitude are lost when removing granular firms in column (6).

This indicates that the boost to FDI caused by this shock was only among granular firms serving the domestic market. That is, only firms positioned relatively well in the domestic market were able to benefit from the marginal changes in this shock[5]. Additionally, many of these regulation changes had clearly defined minimum scale requirements and were largely in marginal applications given that FDI was already quite established in China at that point.

As labor productivities and TFP of granular FFFs are the highest among all other groups, I proceed by regressing labor productivity and TFP of all DFFs on the granular proxy and a series

[5]The struggle of small firms to capitalize from the 2002 catalog change has been documented in case studies (http://www.cnfi.org.tw/cnfi/ssnb/155-428-20.htm)

of controls according to:

$$y_{z,i,t} = \alpha + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \mathbf{X}_{z,i,t} + \delta_i + \delta_t + \varepsilon_{z,i,t}, \tag{10}$$

with the first stage regression:

$$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} = \alpha + treatment_z \times post_t + \mathbf{X}_{z,i,t} + \delta_z + \delta_t + \varepsilon_{z,i,t}. \tag{11}$$

$y_{z,i,t}$ in equation 10 is firm level productivity, $\mathbf{X}_{z,i,t}$ is a series of firm-level and industry-level controls, to be discussed below, and $\widetilde{s}_{z,i,t}^{FFF}$ is FFF domestic market granularity.

Using the 1997 to 2002 catalogue change as an IV requires that it impacts productivity of domestic firms only through its effect on FDI, and not through other channels, such as tariffs. In terms of types of FDI, the previous paragraph establishes that the IV is most relevant for the specific type of FFFs granular in domestic sales. As Lu et al. (2017) mention, concerns on the exclusion restriction are partially alleviated in that the FDI deregulation in 2002 came after a very lengthy and process leading up to China's accession to the WTO, described by much uncertainty and thus the specifics of the changes were not anticipated. Additionally, these catalogue changes are not particularly correlated with changes in tariffs, and by 2007 there was indeed little variation left in China's weighted import and export tariffs as mentioned by Brandt et al. (2017).

To further alleviate concerns coming from tariff policy, I include in $\mathbf{X}_{z,i,t}$ the 1998 level of import and export tariffs obtained from the World Integrated Trade Solution (WITS) website at the ISIC Revision-3 product code-level, and interact it with year dummies to control for WTO induced variation. I also tested the non-time varying tariff levels in 2001 as well as the time and industry varying tariff levels with no interaction. The results on the variables of interest are not affected by the chosen strategy, but any significance on estimated coefficients for the tariff variables in explaining firm-level productivity is only found when taking the 1998 values and interacting with year dummies, with the expected estimations of tariff reductions being positively correlated with firm-level productivity. Utilizing WITS trade data, I additionally control for China's domestic market import penetration in a similar manner.

An additional concern for the exclusion restriction is China's privatization of state-owned firms at the same time of China's WTO accession which may then bias results. I therefore also include in $\mathbf{X}_{z,i,t}$ the 1998 total share of industry sales owing to state-owned firms, interacted with year dummies to allow for each industry's own time-evolution. To control for non-FDI granularity, I also include the 1998 values of DFF domestic market granularity interacted with year dummies. Additionally, 1998 FDI domestic sales penetration interacted with year dummies is included to control for direct effects of FDI more generally.

Table 9: China's WTO accession effect on industry granularity and FDI

	(1) FFF dom granularity	(2) FFF emp granularity	(3) FFF exp granularity	(4) DFF dom granularity	(5) FDI dom penetration	(6) non-granular FDI dom pen.
FDI encouragement	0.199**	0.131	.003	0.030	0.087*	-0.033
	(0.083)	(0.093)	(0.083)	(0.051)	(0.050)	(0.056)
Industry & Year FEs	Y	Y	Y	Y	Y	Y
Pseudo R-sqr	0.115	0.111	0.099	0.097	0.108	0.113
Observations	4040	4040	3990	4040	4040	4020

Note: Industry-level Poisson regressions. The DV for columns (1) - (3) are different measures of FFF granularity. Column (4) repeats column (1) for DFFs, while the repetition of columns (2) and (3) for DFFs is excluded (similar insignificant result). Column (5) is the FDI weighted share of domestic sales. Column (6) repeats column (5) but excludes granular FFFs. Industry clustered errors; * p<0.10, ** p<0.05, *** p<0.01

There are then other identified determinants of FDI. Following Lu et al. (2017), I control for new product intensity, export intensity, number of firms, and average age of firms, all by interacting the 1998 industry level values with year dummies. With respect to China's special economic zones, as also noted by Lu et al. (2017), there were no changes regarding the regional aspects of FDI entry regulations, and a 1997 law forbid further location discretion. Finally, the time-varying firm-level controls of logged output, logged capital-labor ratio, a state firm dummy, and an exporter dummy are also included in $\mathbf{X}_{z,i,t}$.

Table 10 presents results using the FDI encouragement shock as an IV for FFF domestic sales granularity, with both first and second stage regressions for the entire set of DFFs. Note that column (1) is the firm-level equivalent of column (6) in table 9, and continues to show that the FDI encouragement shock did not enable market gains for non-granular FDI. Column (2) then shows the firm-level equivalent of column (1) in table 9, and indicates that industries in the treatment group saw an additional 1% of domestic market sales concentrated in the top-3 FFFs. Taking account of all the controls, industries in the treatment group saw an increase in average concentration among top-3 domestic market FFFs from 0.113 to 0.123, or from of 11.3% to 12.3% of total domestic market sales belonging to all firms located in China.

Second stage results in column (3) shows that an additional 1% of domestic sales by firms in China concentrating in the top-3 FFFs per industry induces a gain in TFP for DFFs of 3.57%. Column (4) changes the dependant variable to labor productivity and gives a surprisingly similar coefficient. The IV passes relevant weak instrument testing, and gives coefficients much higher than the OLS regression shown in columns (5) and (6). While the coefficients in columns (3) and (4) may look large compared to the OLS coefficients, the first-stage estimate that 1% of domestic sales in affected industries became concentrated in the top-3 FFFs as a result of this regulation

Table 10: Granular FDI and Horizontal Spillovers

	1st stage		IV		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	FDI dom penetration	FFF dom granularity	ln TFP	ln labor productivity	ln TFP	ln labor productivity
$treatment_z \times post_t$	-0.001	0.010***				
	(0.006)	(0.003)				
$\sum_{i=1}^{3} \widetilde{s}_{k,i,t}^{FFF}$ (FFF dom granularity)			3.570*	3.697*	-0.012	0.154***
			(2.089)	(2.065)	(0.064)	(0.040)
Kleibergen-Paap Wald rk F statistic			12.34	12.34		
Anderson-Rubin Wald test			4.95**	5.13**		
Firm & Year FEs	Y	Y	Y	Y	Y	Y
Industry controls × year dummies	Y	Y	Y	Y	Y	Y
Time-varying firm controls	Y	Y	Y	Y	Y	Y
Observations	1200640	1200640	1200640	1200640	1200640	1200640

Note: Column (2) shows the first stage estimation of equation 11 for the IV regressions of equation 10 presented in column (3) for TFP and column (4) for labor productivity. $\widetilde{s}$ is defined by domestic sales. Control variables are listed in the text. Robust standard errors clustered at the CIC industry level shown in parenthesis; * p<0.10, ** p<0.05, *** p<0.01.

change leads to an end result that is quite modest, and thus it seems it is the OLS coefficients that are likely underestimated due to endogeneity.

These results are in stark contrast to the existing non-granular FDI literature on horizontal spillovers, which are typically estimated to be negative for the case of China, and suggests that granular FDI behaves differently from non-granular FDI. This may be due their better market position, more differentiated products, or general ability to bring new market activity and positive horizontal spillovers, further demonstrating the existance of a granular mechanism at play in China.

7 Conclusion

This paper examines the distinct impacts of the largest foreign and domestic firms on industry-level comparative advantage in China between 1998 and 2007, investigates pro-competitive effects resulting from superstar FDI compared to domestic superstars, and presentes casual evidence of positive horizontal spillovers from superstar FDI.

Granular firms in China over the years 1998 through 2007 associate with a negative granular residual on industry exports that is nearly the exact opposite of what Gaubert and Itskhoki (2021) find for France over a similar time-frame. This implies that these firms hinder industry exports, whereby the comparative advantage of industries with granular firms is dampened. There is, however, huge heterogeneity in the types of firms operating inside mainland China, and once treating granularity from domestically-funded Chinese firms (DFFs) separately from mainland China operations of foreign-funded-firms' (FFFs), there emerges signs that granularity among FFFs is a source of a positive granular residual on industry exports in China.

These results are robust to separating out state-owned firms from DFFs, as well as Poisson 2sls regression using capital shares as instrumental variables. However, there is evidence of a transition taking place. While FFF granularity in terms of employment started out in 1998 with a strong positive contribution to Granular Comparative Advantage (GCA) and the corresponding group of granular DFFs strongly negative, they have been converging over the years, with the coefficients on FFFs slowly moving down and that on DFFs more rapidly moving up to both being positive and indistinguishable from FFF granularity by 2007. This attests to developing countries being dynamic and unique, taking on completely different characteristics from developed countries in their early stages, but that they remain on a path of convergence.

The association of granularity with exports is heterogeneous according to a number of key channels. For example, granularity from FFFs boosts industry exports when there is a healthy startup environment that is not already dominated by many FFFs, and where firms can compete within a relatively lower initial industry-productivity level but high absorptive captivity. Granularity from DFFs tends to suppress industry exports and signs point to firms needing to develop in a more equitable manner than out-sized DFFs seem to allow.

Policy makers in developing countries may wish to determine what type of superstar firms they should encourage for a given industry. A positive granular residual on industry exports is more likely when the granular firms more intensively use intermediate inputs relative to fixed assets, have higher value added relative to fixed assets, pay higher average wages, or are less labor intensive.

Industry can granularity plays an important role in determining firm-level markups, which indicates potential welfare implications beyond variation in exports. The extent of this relationship depends on whether the source of granularity is from DFFs or FFFs and on the non-granular firm's size. Granularity may be beneficial in reducing markups in industries described by firms with higher market shares, or less firms overall. While granularity from both groups induces pro-competitive effects, granular DFFs only do so for other large but non-granular firms, while granular FFFs induce pro-competitive effects for non-granular firms of any size due to more effective competitive pressure.

Finally, the plausibly exogenous 2002 shock to FDI encouragement China allows testing new sources of horizontal spillover effects as new guidelines directly impacted domestic market granularity owing to FDI. Results show that an additional 1% of domestic sales by firms in China concentrating in the top-3 FFFs per industry induces a gain in TFP for DFFs of 3.57% and a gain in labor productivity of 3.70%, despite the existing literature on FDI in China generally finding negative results when focusing on more general definitions of FDI penetration. This creates a story that superstar foreign firms have been beneficial for China's industries in terms of both aggregate and micro-level outcomes.

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8 Appendix

A1 Accounting for FFFs and DFFs

The distinction of foreign funded firms and private or state Chinese funded firms is made primarily from firms' reported paid-in capital (shí shōu zīběn), and secondarily through their registration-type (dēngjì zhùcè lèixíng) for a small number of observations with missing paid-in capital data. There are then a small number of firms that do not report capital funding but ownership can be identified by the registration-type, including 0.8 percent of firms that are among the top-3 employers in their industry.

A firm is officially recognized as a Foreign Invested Enterprise (FIE) in China if its non-mainland China capital investments are 25% or more of total capital investments. This paper, however, mostly leaves the definition at 50%, as it is concerned with comparing the fundamental differences between foreign affiliates and local Chinese firms, and FFFs with FDI amounting to 25% to 50% of firm capital may behave more like DFFs rather than FFFs. This range of FDI capital also has a higher likelihood of owing only to "round-tripping," whereby local capital resources are rerouted through Hong Kong or other markets in order to benefit from tax incentives. Additionally, labeling FFFs as including those firms with FDI in the range of 25% to 50% would take away from the most productive DFFs, thus inflating the differences between FFFs and DFFs and may bias results for applications that rely on direct comparison between these two types of ownership. Regardless, the main results of this paper hold whether using the 50% definition or the 25% definition. Additionally, results hold if excluding FFFs that have more HKMT capital than non-HKMT capital. In other words, potential round-tripping through HKMT is not a concern; likely due to the fact that I focus only on granular FFFs and not the bulk of non-granular FFFs.

The first three columns of table A1 shows what percentage of all firms are FFFs versus DFFs, and how many firms fall into each of 4 categories - for the years 1998, 2007 and across the whole 10 years of the panel. FFFs made up 11.8% of firms in 1998 and 16.0% of firms in 2007. Also of note is the considerable reduction in the number of state-owned firms, which is discussed in further detail in the next subsection within the context of large granular firms. The right-4 columns of table A1 give a breakdown of total sales and exports according to funding-type for 1998 and 2007. FFFs of any origin saw a more than an 8-fold increase in total sales from a combined 1,138 billion RMB in 1998 to 9,454 billion RMB in 2007, corresponding to an increase from 20.0% to 27.4% of the annual aggregate total. Total sales here includes both production sold to the Chinese domestic market as well as exports. There is also an increase of FFFs' share of aggregate exports from 49.7% in 1998 to 61.4% in 2007.

The prevalence of FFFs in terms of employment and total wage bill (not shown in the table) also grew significantly over the period, employing 10.9% of workers in 1998 at 15.3% of the wage bill and 26.8% of workers in 2007 at 31.4% of the wage bill. Notably, by 2007 FFFs did not produce a disproportionate amount given their labor input relative to DFFs. Thus, the importance of FDI to emerging economies, in the sense of making up significant portions of aggregate values, is well demonstrated in China over the panel of consideration in this paper.

Table A1: Break-down of panel data according to dominate firm funding type

	# of firms in survey data			total sales, b. RMB		exports, b. RMB	
	1998	2007	Total	1998	2007	1998	2007
% FFFs	11.8%	16.0%	15.0%	20.0%	27.4%	49.7%	61.4%
Foreign FFFs	8,038	25,707	147,553	684	6,601	284	3,124
HKMT FFFs	9,348	24,036	157,647	454	2,853	236	1,344
% DFFs	88.2%	84.0%	85.0%	80.0%	72.6%	50.3%	38.6%
Private DFFs	40,751	241,678	1,234,208	1,475	20,163	201	2,332
State DFFs	89,433	19,988	493,489	3,083	4,893	326	482
Total	147,570	311,409	2,032,897	5,696	34,511	1,046	7,282

Note: Percentages compare all FFFs to all DFFs, which are each made up of two subgroups as shown. The first 3 columns count the number of firms, while the last 4 aggregate their total sales and exports (a subset of total sales) and are in current billions of RMB. Firms kept in dataset are in one of 420 industries included in the analysis, and for which dominant origin of firm funding (ownership) can be deduced either capital funding or registration.

A2 Changing composition and relative dominance of granular firms

Table A2 below shows how ranking firms separately per funding type identifies each groups' different patterns of granularity. In each year, the top DFF takes both a larger industry sales share and a larger export share on average across industries compared to the averages of the largest FFFs. This still holds when looking at groups of the top-3 firms per industry. The difference is less pronounced, however, in terms of export shares, and adding these two groups together accounts for over 50% of industry exports on average for each year in the sample.

Table A3 shows how the top-6 firms from each of the 420 industries are distributed across the different funding-types and for 5 different methods of ranking firms. 32.1% of top-6 firms were FFFs in 2007 when ranking by total sales. When ranking by firm exports, 50.2% of top-6 firms were FFFs by 2007. However, in terms of sales to the domestic market, a much lower 24.3% of firms were FFFs.

For comparison, table A5 shows number of industries where FFFs take the number 1 spot by either total sales, exports, or sales to the domestic market. In 1998 112 out of the 420 were FFFs, increasing to 125 by 2007. A FFF was the top exporter in 190 industries in 1998, and 205 in 2007. FFFs are not only dominate at the industry level, but also take 299 places in the top-500 exporters in 1998, increasing to 336 places by 2007.

The dominance of FFFs as the largest firms grew within industries, although mostly through the foreign category, as the number of top-6 firms that are HKMT remained mostly unchanged from 1998 to 2007, both in terms of total production and exports. The number of top-6 firms that are private DFFs also grew in terms of all ranking methods, more than doubling their presence. What gave was the number of state-owned firms in a top-6 position, which from 1998 to 2007 declined from 1,226 spots to 319 spots in terms of total sales, or just 12.7%. Table A5 shows a similar decline in the number of industries where state-owned firms remained the largest. This is largely due to their privatization and also partly responsible for the increase in private DFF

Table A2: top-firms summary statistics - industry averages

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
# of firms	352	346	349	369	394	429	614	592	661	742
of which are FFFs	41	43	46	51	57	65	99	98	108	118
top firms SS	.143	.144	.147	.144	.14	.132	.117	.12	.118	.115
	(.131)	(.138)	(.140)	(.136)	(.124)	(.126)	(.108)	(.113)	(.116)	(.114)
top firms ES	.299	.295	.29	.285	.281	.262	.224	.235	.232	.232
	(.253)	(.236)	(.226)	(.226)	(.225)	(.218)	(.193)	(.188)	(.198)	(.201)
top FFFs SS	.064	.06	.064	.062	.064	.064	.061	.061	.057	.058
	(.089)	(.079)	(.078)	(.079)	(.079)	(.086)	(.074)	(.074)	(.072)	(.077)
top FFFs ES	.183	.18	.177	.166	.171	.164	.148	.147	.144	.139
	(.212)	(.189)	(.179)	(.171)	(.178)	(.172)	(.161)	(.152)	(.149)	(.149)
top DFFs SS	.122	.127	.128	.124	.118	.11	.096	.099	.098	.093
	(.121)	(.133)	(.135)	(.131)	(.117)	(.113)	(.101)	(.105)	(.108)	(.104)
top DFFs ES	.205	.208	.205	.205	.196	.183	.15	.161	.161	.166
	(.224)	(.221)	(.216)	(.219)	(.21)	(.199)	(.165)	(.172)	(.183)	(.187)
$\sum_{i=1}^{3} SS_{z,i,t}^{FFF}$	.11	.107	.114	.113	.114	.113	.11	.11	.105	.105
	(.12)	(.111)	(.114)	(.116)	(.116)	(.116)	(.11)	(.11)	(.109)	(.112)
$\sum_{i=1}^{3} ES_{z,i,t}^{FFF}$	.282	.288	.287	.275	.276	.269	.249	.248	.247	.245
	(.242)	(.229)	(.224)	(.223)	(.221)	(.216)	(.205)	(.203)	(.198)	(.203)
$\sum_{i=1}^{3} SS_{z,i,t}^{DFF}$	.231	.235	.236	.232	.223	.21	.184	.187	.184	.174
	(.185)	(.188)	(.192)	(.19)	(.177)	(.169)	(.15)	(.15)	(.152)	(.148)
$\sum_{i=1}^{3} ES_{z,i,t}^{DFF}$	.339	.34	.334	.337	.326	.305	.263	.273	.271	.277
	(.278)	(.279)	(.273)	(.275)	(.271)	(.251)	(.231)	(.237)	(.235)	(.241)

Note: SS denotes total sales shares, where total sales is the sum of exports and domestic sales. ES denotes export shares. Figures show industry-level data averaged across all 420 industries. Standard deviations are in parentheses. FFFs include those of both HKMT or foreign funding. DFFs include private as well as state-owned firms. The summation $\sum_{i=1}^{3}$ takes the top-3 firms according to SS or ES, per specified funding group.

firms, though those also grew in their own right. Table A4 shows how firms that made it into a top-6 position at least once over the 10 years changed their primary funding type. There were a total of 8,303 firms that made it to a top-6 position at least once in an industry. 2,160 of these firms changed to a new dominant ownership (funding) group either before, while, or after being in a top-6 position, with respect to the four funding-types. Large state-owed firms saw the most movement, with 1,118 being reclassified, 1,030 of which were to domestic private funding.

Table A3 shows 35.7% of top-6 firms in terms of ranking by wages paid out were FFFs in 2007, and 29.2% of top-6 firms were FFFs when ranking by number of employees; respectively 2.6% more and 2.9% less than when by total sales. Ranking by domestic sales on the other hand sees FFFs taking only 24.3% of the top-6 spots in 2007, or 7.8% less than by total sales.

Calculation of domestic sales shares cannot include imports at the 420-industry level. To match with imports data these must be aggregated up to 111 ISIC industries. Combined domestic sales of DFFs and FFFs make up between 77.8% to 84.1% of the entire domestic market in each year of the panel. The average 111-digit industry across all years sees the combined domestic sales of DFFs and FFFs taking 82.75% of the domestic market that includes imports.

There is a much different mix of firms in the top-6 spots when ranking by exports than when

Table A3: Break-down of top 6 firms by proxy shares

top 6 firm by:	total sales		exports		dom sales		wages		workers	
	1998	2007	1998	2007	1998	2007	1998	2007	1998	2007
% FFFs	25.5%	32.1%	41.8%	50.2%	18.1%	24.3%	20.9%	35.7%	13.3%	29.2%
Foreign FFFs	377	546	562	822	276	423	310	528	162	402
HKMT FFFs	262	263	418	418	178	188	214	371	171	335
% DFFs	74.5%	67.9%	58.2%	49.8%	81.9%	75.7%	79.1%	64.3%	86.7%	70.8%
Private DFFs	643	1,392	516	1,045	700	1,564	588	1,229	545	1,369
State DFFs	1,226	319	847	183	1,352	344	1,396	392	1,628	414
Total	2,508	2,520	2,343	2,468	2,506	2,519	2,508	2,520	2,506	2,520

Note: Funding types of the top-6 firms in each of the 420 industries. Percentage by main FFF or DFF group, and counts by further break-down into subgroups. In the main regressions, the top-3 firms from a funding group are used to build the granularity proxies, and may not match the overall top-6 firms described in this table.

ranking by one of the three granularity proxies of domestic sales, wages, or number of employees, with ranking by wages coming closest to that of by exports. Also, ranking by wage or employee shares means nearly every firm is ranked and every industry has at least 6 firms by 2007, to give a total of 2,520 top-6 firms across the 420 industries, while one industry is still a firm short in 2007 if looking only at domestic sales.

A3 Heterogeneity in firm size distributions

The Chinese data with 420 CIC codes can be aggregated up to 111 four-digit ISIC Revision 3 codes so to compare with international descriptions of industries. Aggregating the 111 matched four-digit ISIC industries further up to 22 two-digit industries allows for a clearer visualization of firm size distributions across the whole economy. Figure 7 shows estimated power-law exponents at this level of aggregation for DFFs and FFFs separately, in order to gain perspective on whether these two groups of firms systematically follow different parameters in their size distributions. There are 18 2-digit industries for which the power-law distribution describing the right tail for sales passes the goodness of fit test for both DFFs and FFFs. When comparing the estimated power law exponent for these 18 industries, FFFs have a higher alpha in 15, while DFFs have a higher alpha in the remaining 3. The pattern of lower alpha for DFFs may be an indicator that there is more inequality among DFFs than FFFs in a typical industry. These power-law estimates are only taken from a minimum threshold value of sales that is selected from a combination of criteria and tests. As the numerous smaller firms that fall below this minimum value are ignored in estimation, the differences in any sample selection bias between DFFs and FFFs according to how smaller firms enter the survey data is likely not a factor. This minimum threshold value also implies that the seemingly greater inequality among DFFs is actually inequality among the relatively large firms, rather than all the firms in general.

The size distributions for DFFs and FFFs are generally different even at the disaggregated four-

Table A4: Number of top firms that change dominant ownership group

change from:	to new group by last year observed					
	Foreign	HKMT	Private	State	any group	totals
Foreign FFFs	-	178	98	17	293	1,414
HKMT FFFs	176	-	82	16	274	961
Private DFFs	105	79	-	291	475	3,527
State DFFs	56	32	1,030	-	1,118	2,401
any group	337	289	1,210	324	2,160	
totals	1,458	976	4,259	1,602		8,303

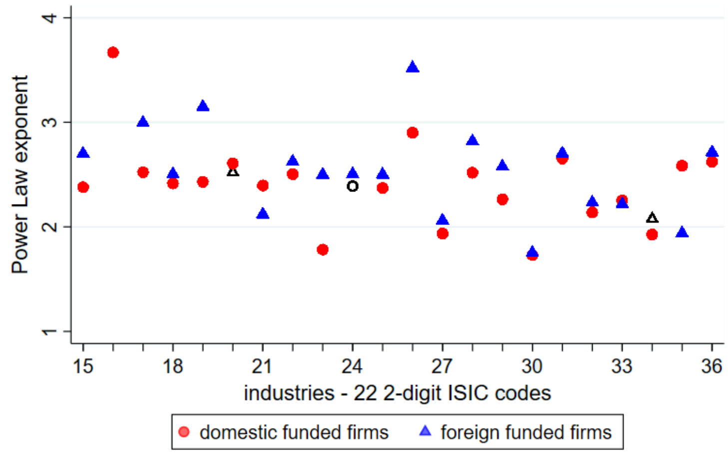
Note: There are a total of 8,303 firms that were a top-6 firm in terms of total sales for at least one year, i.e, only counting a firm once for the 10 years. of these 8,303 firms, 2,160 see a change in primary funding type. 1,030 initially state-owned firms became private DFFs, either in a year before, while, or after being a top-6 firm.

Table A5: Descriptive statistics of industry leaders

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
FFF is top sales	112	112	125	131	124	126	136	129	126	125
avg # of firms if FFF is top sales	385	403	377	377	392	363	526	445	525	644
portion FFFs	.15	.162	.169	.188	.187	.208	.216	.222	.24	.214
FFFs in top-500 sales	114	127	130	138	142	169	177	160	157	154
FFFs in top-500 sales, no state	278	255	253	230	229	243	241	211	201	198
avg # of exporters	83	82	88	96	107	120	182	177	186	187
portion FFFs	.323	.339	.342	.356	.35	.361	.389	.368	.375	.406
FFF is top exporter	190	195	201	195	213	202	221	210	213	205
avg # of firms if FFF is top exports	393	376	402	373	443	446	632	594	685	746
portion FFFs	.149	.167	.162	.164	.172	.169	.193	.197	.2	.203
FFFs in top-500 exports	299	309	316	309	321	325	352	355	341	336
FFFs in top-500 exports no state	397	386	379	370	368	370	391	380	369	368
FFF is top domestic sales	72	78	89	82	87	86	87	91	84	98
state firm is top sales	195	171	144	132	130	106	87	71	72	74
all state firms' sales share	.514	.452	.385	.319	.275	.224	.179	.135	.119	.101
state firm is top exports	133	109	98	89	79	65	47	45	44	46
all state firms' exports share	.359	.315	.27	.217	.189	.155	.114	.097	.089	.08

Note: Note: Other than top-500 figures, which are across all firms, figures show counts per industry or industry-level data averaged across either all 420 industries or the indicated subset. FFFs include those of both HKMT or foreign funding.

Figure 7: Power-law exponent estimates by firm funding type



Note: Goodness-of-fit p-value < 0.10 indicated by solid fill. Firms are aggregated up to 22 2-digit ISIC Revision 3 codes and split among DFFs and FFFs, resulting in 44 groups. Each group then has their power law exponent estimated separately. Note that DFFs generally result in lower power law estimates, implying more inequality in sales shares within industries compared to FFFs.

digit level. For each industry, the two categories of firms can be compared using the Kolmogorov-Smirnov test, where the null hypothesis is that the sales of DFFs and FFFs are drawn from the same distribution and with the same parameter values on this distribution. In order to guard against scale differences owing to superficial sampling reasons, the two sub datasets are first normalized at the aggregate level by taking $(sales - mean)/sd$ for FFFs and DFFs separately. This would dampen the ability to differentiate the distributions but provides additional robustness when stating that the distributions are different. Of the 420 industries in the year 2007, 268 have at least 30 FFFs and 30 DFFs. Among these 268 industries, 257 give Kolmogorov-Smirnov test p-values of less than 0.05, thereby rejecting the null that sales of DFFs and FFFs come from the same distribution. The null hypothesis is rejected for all industries with more than 63 FFFs. Where there is a small sample size of between 3 and 29 firms for one of the two groups, 62 additional industries exhibit significantly different distributions among DFFs and FFFs. All industries with more than 30 DFFs and 30 FFFs exporting have significantly different distributions of exports.

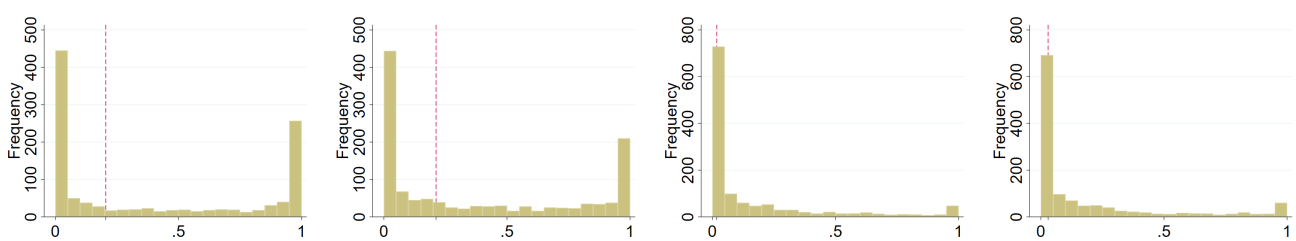
Finally, there are huge differences in export intensities of granular DFFs versus granular FFFs. This implies different exposures to trade and generally different business models that may logically translate into distinct channels of GCA, or lack thereof. Figure 8 displays histograms of all top-3 firms per group of DFFs and FFFs separately for the years 1998 and 2007. Notice the mass of export oriented firms shrinking slightly among top-3 FFFs, while it grows slightly among top-3 DFFs.

Table A6: Mean ranks of firms captured by definitions

	Top-3 dom sales		Top-3 wages		Top-3 workers	
	FFFs	DFFs	FFFs	DFFs	FFFs	DFFs
total sales rank	3.7	2.5	5.2	11.9	7.4	16.9
	(4.1)	(1.8)	(12.9)	(66.5)	(19.7)	(65.1)
exports rank	16.5	15.1	7.4	11.9	7.4	12.9
	(64.3)	(44.6)	(18.9)	(28.6)	(19.6)	(29.6)
dom sales rank			9.3	18.5	11.4	22.7
			(30.1)	(91.8)	(34.0)	(84.2)
Observations	11607	12586	11723	12573	11707	12528

Note: Mean coefficients; sd in parentheses. Groups of top-3 firms by wage bill shares and top-3 firms by employment shares have the same average exports rank of 7.4, but wage bill shares performs slightly better overall, lower average total sales ranks and lower average domestic sales rank.

Figure 8: export intensities of top-3 FFFs and DFFs by total sales



(a) top-3 FFFs in 1998 (b) top-3 FFFs in 2007 (c) top-3 DFFs in 1998 (d) top-3 DFFs in 2007

Note: Histograms show the heterogeneity in export intensities of granular firms. The red dashed line here indicates the median export intensity of all top-3 firms across industries separately for FFFs and DFFs and for years 1998 and 2007, according to the labels. Note the median export intensity of these groups of granular firms is near zero for DFFs (graph (c) and (d)), while there are masses of export-oriented granular firms pulling this median much further out for FFFs.

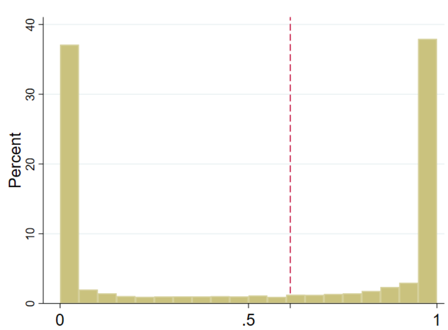
A4 Mapping employee and wage bill shares to horizontal and vertical FDI

Table A6 shows the mean total sales and export ranks of all firms identified by the three different granularity proxies. When grouping the largest 3 firms by domestic sales volume for each industry, separately for each category of FFFs and DFFs, the mean rank of total sales volume is 3.8 for FFFs, and 2.5 for DFFs, but a mean exporter rank of only 16.4 and 15.4, respectively, and thus, there is a bias towards granularity from domestic market-oriented firms. Sorting firms by wages or employment gives groups of top-3 FFFs that have an average export rank of 7.4, and each is also lower for DFFs than when sorting by domestic sales. Top-3 firms by employment, however, performs the least well in capturing firms ranked high in domestic and total sales, indicating it is the most export-biased method of grouping granular firms.

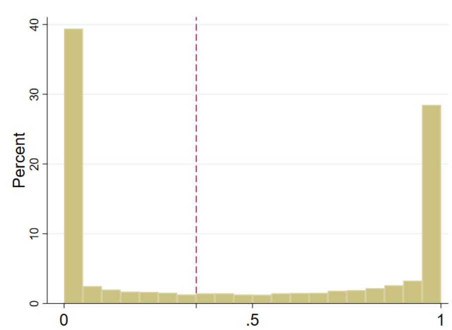
Export intensity has a low correlation with wage bill and employment shares of 0.0206 and 0.0636, respectively, among FFFs across the entire panel. In levels, wage bill, employment, log wage bill, and log employment correlate slightly more with export intensity at 0.0274, 0.1101, 0.134 and 0.257, respectively. In the following, I interpret export intensity as a spectrum mapping horizontally motivated FFFs on the left, towards an export intensity of 0, and vertically motivated FFFs on the right, towards an export intensity of 1. Figure 9 shows a histogram of FFFs' export intensities for the years 1998 and 2007. Notice the median export intensity, defined by exports over total sales, decreases from 0.61 in 1998 to 0.35 in 2007, indicating a shift of the typical FFF to focusing on the domestic market rather than on exports. With respect to the correlations, more employment should indicate a more rightward position on the spectrum, or a relatively more vertically motivated FFF, while this argument in terms of wages is much weaker.

To discuss the difference in what type of firms the similar granularity proxies of wage bill shares (WS) and employment shares (LS) tend to represent, table A7 associates export intensity with them and their log levels as controls, includes industry and year fixed effects, and clusters errors at the industry level. All models here are GLM with logit transformation, as export intensity lies between 0 and 1, with large concentrations around 0 and 1. Column (1) of table A7 includes only FFFs, giving 303,174 observations across the panel, and shows a strong negative coefficient on WS accompanied with a strong positive coefficient on LS. Thus, for a given LS, a higher industry WS is associated with firms more on the left of this horizontal-vertical spectrum. This pattern holds when including all DFFs and singling out FFFs with a dummy interaction term, denoted δ^{FFF}, in column (2). It similarly holds up with replacing shares with levels in column (3), and even when including shares and levels together as in columns (4) and (5).

Figure 9: export intensities of FFFs



(a) Export intensities in 1998



(b) Export intensities in 2007

Note: Red dashed line indicates median export intensity across all FFFs. The median was 0.61 in 1998 and decreased to 0.35 by 2007, indicating a greater proportion of FFFs' Chinese operations focusing relatively more on the domestic market rather than on exports.

Table A8 further shows firm-level regressions, still looking at all firms in the dataset, where the dependent variable is firm-level log exports or firm-level log domestic sales according to the label in the first row. The coefficient on wage bill share is twice as high in magnitude than that on total employment share in explaining exports of exporting DFFs in (1), while when interacting with δ^{FFF}, the FFF dummy, there is exactly the opposite relationship. The similarity of magnitudes on wage bill share for DFFs and FFFs but the much higher magnitude on employment share for

FFFs in explaining exports may point to FFFs' greater reliance on China's comparative advantage in labor intensive sectors for exports. The fact that the coefficient on the FFFs employment share interaction is so comparatively high attests to employment shares being a relatively vertical FDI biased proxy for sorting firms. An alternative interpretation is that foreign firms extract more productivity per additional worker, unconditional on their wage; but while this may explain why the coefficient is high for FFFs relative to DFFs, it does not explain why the coefficient is so much higher when explaining exports of FFFs compared to domestic sales of FFFs shown in column (2).

Table A7: Associating wages and worker shares with export intensity

	export int (1)	export int (2)	export int (3)	export int (4)	export int (5)
wages share	-13.364***	5.435***		-9.481***	-6.504***
x δ^{FFF}		-18.384***			-8.403***
worker share	48.926***	3.872***		9.684***	-3.416***
x δ^{FFF}		44.436***			23.202***
log wages			-0.092***	-0.061**	0.353***
x δ^{FFF}					-0.268***
log workers			0.442***	0.418***	0.078***
x δ^{FFF}					0.176***
δ^{FFF}		1.686***			2.737***
Industry & Year FE	Y	Y	Y	Y	Y
Observations	303174	1999201	302505	302505	1991085
deviance	263406	1005295	256080	255918	969208
deviance_p	18887608	30047303	225392	226655	1379778
chi2	69104	458223	73269	72841	466400

Note: Dependent variable is export intensity at the level of firm-industry-year. Exports are assumed not related to explanatory variables other than through their interaction with total sales (i.e. if multiplying both sides by the export intensity's denominator). This is plausible as the variation in exports is a subset of the variation in sales. If including log exports as an explanatory variable the estimated coefficient signs and significance levels do not change (not shown). All models are GLM with logit transformation. Industry-clustered robust errors; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

While the non-interacted-DFFs' coefficients maintain similar relative magnitudes in column (2) of table A8 as those in column (1), the FFFs' interaction terms see their relationship reversed compared to column (1), which are now more in line with the pattern for DFFs. This switch for the FFFs with the now much higher total magnitude on wage bill shares implies the relatively strong association of wages with horizontal FDI, which is manifested through more domestic sales. Including domestic sales shares along side wage bill shares and employment shares when explaining firm exports in column (3) hardly affects their coefficients compared with column (1), and domestic sales shares has a relatively low magnitude. In fact, if excluding DFFs from the regression (not shown), the coefficient is not statistically different from zero. Columns (5) and (6) each contain 3 regressions for each of the granularity shares separately, with the patterns just discussed still prevalent.

Table A8: Associating the granularity definitions with exports and domestic sales

	exports (1)	dom sales (2)	exports (3)	exports (4)	dom sales (5)
wage share	14.057***	21.126***	12.681***	19.594***	32.911***
x δ^{FFF}	-0.319	9.034**	0.768	13.472***	2.175
worker share	7.748***	15.652***	7.205***	22.354***	36.395***
x δ^{FFF}	26.876***	-4.744	27.538***	27.564***	11.773***
domestic sales share			2.447*	15.466***	
x δ^{FFF}			-1.885	1.731	
δ^{FFF}	0.576***	0.126***	0.576***		
R-sqr	0.169	0.186	0.169		
Obs	549458	1843091	549458		

Note: Dependent variable alternates from log exports to log domestic sales, both at the level of firm-industry-year. Columns (4) and (5) each include 3 separate regressions for each of the granularity proxies and their interaction with δ^{FFF} (δ^{FFF} also included separately in each but not shown). Industry and year fixed effects included. Industry-clustered robust errors; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Thus, I argue that ranking FFFs by domestics sales shares aligns almost entirely with ranking firms by horizontal FDI motives, employment shares best captures a ranking of vertical FDI motives, while wage bill shares, although likely more biased towards vertical FDI, is somewhere between the two. This is likely the reason wages in table A3 capture more foreign and HKMT FFFs in the top 6 industry rankings than do the relatively polarized rankings by domestic sales and employment.

Table A9: Extension of table A7: associating firm level wages and workers with export intensity

	exp int (1)	exp int (2)	exp int (3)	exp int (4)	exp int (5)	export int (6)	exp int (7)	(8)
wages share	8.544***				7.713***			
x δ^{FFF}					2.872***			
worker share		32.272***				9.200***		
x δ^{FFF}						22.830***		
log wages			0.247***				0.387***	
x δ^{FFF}							-0.122***	
log workers				0.359***				0.380***
x δ^{FFF}								-0.048***
δ^{FFF}					1.725***	1.686***	2.510***	1.893***
Obs	303174	303174	302700	302942	1999201	1999201	1991968	1997952
deviance	265001	263692	260069	256654	1007033	1005695	972794	978072
deviance_p	226131	1396983	225658	225812	1327423	6007398	1353413	1357232
chi2	67527	69146	70996	73240	458702	458598	468017	466281

Note: See table A7. Robust errors; *** $p < 0.001$.

A5 Additional Tables Referred to in the Text

Table A10: Poisson 2sls using invested capital shares as IVs

	Defining $\widetilde{s}$ as dom sales share			Defining $\widetilde{s}$ as employment share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-3.236**			-0.778			
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-4.874**			-1.337		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			-2.810			3.053*	3.002*
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-3.921**			-1.537	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$; private only							-1.531**
$D_{z,t}$	0.387***	0.393***	0.348**	0.753***	0.703***	0.698***	0.710***
s1 v	2.623*			1.007			
s1 v		4.344*			1.732		
FFFs s1 v			2.571			-1.668	-1.459
DFFs s1 v			3.050*			0.874	1.423*
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	4200	4200	4200	4200	4200	4200	4200

Note: Poisson IV version of table A10 with fixed effects procedure from Lin and Wooldridge (2017); estimates the reduced form (first stage) for endogenous variables and includes the residuals as controls (s1 v) in a Poisson regression. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

Table A11: 2sls using invested capital shares as IVs (Defining $\widetilde{s}$ as wage bill share)

	OLS IV			Poisson IV		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-0.666**			-2.363*		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-1.741***			-1.617	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			0.576			0.778
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-1.853***			-2.181**
$D_{z,t}$	0.985***	0.940***	0.959***	0.836***	0.814***	0.779***
s1 v				1.818		
s1 v					0.993	
FFFs s1 v						-0.911
DFFs s1 v						0.994
Industry & Year FE	Y	Y	Y	Y	Y	Y
LM-stat	830	599	729			
CD-F-stat	930	628	396			
Observations	4153	4153	4153	4200	4200	4200

Note: Repeats the 2SLS exercise of table 6 in columns (1) - (3) and table A10 in columns (4) - (6) defining $\widetilde{s}$ by wage bill for the granularity proxy, where now wage bill granularity is instrumented for with the corresponding capital shares. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

Table A12: Excluding the granular firms from industry exports

	Defining $\widetilde{s}$ by domestic sales			Defining $\widetilde{s}$ by employment		
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}$	-0.952***			-0.028		
	(0.241)			(0.289)		
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF} + \sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-0.953***			0.098	
		(0.229)			(0.270)	
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			-0.650*			1.352***
			(0.344)			(0.389)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-1.297***			-1.048***
			(0.297)			(0.390)
$D_{z,t}$	0.391***	0.378***	0.355***	0.817***	0.815***	0.746***
	(0.068)	(0.070)	(0.071)	(0.040)	(0.041)	(0.036)
Industry & Year FE	Y	Y	Y	Y	Y	Y
pseudo-R-sqr	0.968	0.968	0.968	0.978	0.978	0.980
Observations	4180	4180	4180	4190	4190	4190

Note: Repeats the Poisson regressions of columns (7) - (9) of table 2 and columns (4) - (6) of table 3, excluding the exports of granular firms from industry aggregates. Robust errors; * p<0.10, ** p<0.05, *** p<0.01.

Table A13: Interacting with various industry level controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	1.495***	1.284**	0.730*	4.189***	1.156***	6.205***	0.708	-7.302***	2.470**
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$	-0.807**	1.296**	0.974***	-1.694***	-0.832**	-4.704***	-2.706	5.366***	3.644***
$D_{z,t}$ (staff)	0.728***	0.765***	1.015***	0.788***	0.734***	0.681***	0.193***	0.559***	0.975***
ind. ratio < 5 yrs		1.399***						0.514**	0.681**
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$		2.892**						3.444**	1.938
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		-5.675***						-7.527***	-6.051***
ind. ratio state			-1.061***					-0.807***	-0.912***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			4.088***					1.293	1.045
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			-8.015***					-7.145***	-7.701***
ind. ratio FFFs				2.763***				1.514***	2.035***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$				-7.857***				-6.613***	-5.307***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$				4.104***				-2.877**	-2.306**
ind. dom. growth					-0.047			-0.073**	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$					0.009			-0.037	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$					0.135*			0.273***	
ind. TFP						0.417***		0.350***	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$						-0.822***		-0.782***	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$						0.526***		0.082	
ind. real FA (log)							0.660***	0.342***	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$							0.078	0.886***	
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$							0.134	-0.132	
Industry & Yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.980	0.982	0.984	0.982	0.982	0.983	0.983	0.989	0.986
Obs	4200	4200	4200	4200	3780	4168	4200	3751	4200

Note: Granularity proxy from $\widetilde{s}$ defined by employment only. All models implement Poisson regression. Column (1) reproduces column (6) of table 3 in the main text, with subsequent columns then interacting each of the two groups' granularity proxy with a specific industry level measure. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

Table A14: Interacting with various firm level controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D_{z,t}$ (staff)	0.731***	0.739***	0.853***	0.750***	0.753***	0.815***	1.002***
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	1.714***	1.657***	1.738***	2.479***	1.260***	0.126	0.095
$\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$	-1.326***	-1.514***	-4.907***	-0.872***	-2.217***	-3.785***	-2.487***
inputs/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$	-0.013					0.124***	0.163***
inputs/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$	0.155***					0.133***	0.118***
VA/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$		0.059*				0.124***	0.067*
VA/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$		0.483***				0.090	0.047
labor productivity x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$			0.232**			0.371***	0.438***
labor productivity x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$			1.065***			0.564***	0.335***
wages/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$				-1.014***		-2.178***	-1.525***
wages/assets x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$				0.480		-1.498***	-1.329***
wages/workers x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$					0.002	0.014***	0.015***
wages/workers x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$					0.039***	0.029***	0.018***
ind. ratio firms age < 5 yrs							-0.034***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$							0.062
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$							0.135**
ind. ratio firms state-owned							-0.807***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$							1.607
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$							-5.803***
ind. ratio FFFs							2.058***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{FFF}$							-7.021***
x $\sum_{i=1}^{3} \widetilde{s}_{z,i,t}^{DFF}$							-0.091
Industry & Year FE	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.980	0.981	0.981	0.981	0.982	0.983	0.987
Observations	4061	4061	3985	4060	4060	3984	3984

Note: DV is industry exports. Granularity proxy with $\widetilde{s}$ defined by employment only. The terms being interacted with each of the granularity proxies are computed from the corresponding group of top-3 FFFs or DFFs separately. For example, the inputs/assets ratio interacted with the proxy for granularity from FFFs sums inputs from these 3 FFFs only and divides by the sum of assets from the 3 FFFs only. All models implement Poisson regression. Robust errors; * p<0.10, ** p<0.05, *** p<0.01

Table A15: Markups regression summary stats

	mean	sd	min	max
$mu_{z,i,t}$; firm markup	.1653586	.2102257	-7.165493	4.521645
$SS_{z,i,t}$; firm sales share	.001493	.0037833	0	.1712571
$SS^2_{z,i,t}$	.0000165	.0001594	0	.029329
SS^{FFF}_{zt}; top-3 FFFs S	.0619915	.0641722	0	.876778
SS^{DFF}_{zt}; top-3 DFFs S	.1066401	.0881049	.0080249	.9919031
$SS^{FFF}_{zt} \times SS_{z,i,t}$	.0001357	.0006022	0	.058714
$SS^{DFF}_{zt} \times SS_{z,i,t}$	.0002509	.0011369	0	.1247247
mu^{FFF}_{zt}; top-3 FFFs markup avg	.2212758	.1297107	-1.511568	3.870852
mu^{DFF}_{zt}; top-3 DFFs markup avg	.2107103	.1005985	-.5063486	1.219947
$mu^{FFF}_{zt} \times SS^{FFF}_{zt}$	.0137781	.0196513	-.0855598	1.032074
$mu^{DFF}_{zt} \times SS^{DFF}_{zt}$	.0223764	.0241158	-.4259783	.4809249
$tfp_{z,i,t}$; TFP	4.847174	1.213008	-2.12472	10.6708
tfp_{zt}; ind TFP	5.92447	.8816606	.3063346	10.23052
$lp_{z,i,t}$; labor productivity	3.852993	1.161568	-5.925182	11.87841
$w_{z,i,t}$; price of labor	2.506345	.7647095	-7.81843	10.2643
w_{zt}; ind price of labor	2.710029	.4517251	1.244393	4.810623
$ci_{z,i,t}$; capital intensity	3.643026	1.248059	-7.046785	11.92603
ci_{zt}; ind capital intensity	93.63037	79.48284	9.431174	973.9621
obs_{zt}; number of firms	6.877505	1.121089	1.386294	9.540435
$EI_{z,i,t}$; export intensity	.173762	.3452372	0	1
EI_{zt}; ind export intensity	.2256916	.2036394	0	.9714133
IP_{zt}; import penetration	.5808644	.3376136	.0000563	.9998213
Observations	1824552			

Note: Summary statistics for observations included in regressions of table 8 over all years of the panel data, 1998 through 2007. Firm level TFP and markup outliers are excluded if both more than three standard deviations from the mean as well as in the top or bottom 1 percent of observations in that industry-year. Lowercase variables are in log. See text for variable descriptions.