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Follow Thy Neighbor

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Follow Thy Neighbor: The Role of First Exporters*

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Abstract

Exporting to foreign markets offers new opportunities for growth and expansion, but also comes with inherent challenges and risks. To mitigate these uncertainties, firms often learn from neighboring firms that operate in similar markets and are geographically close (Koenig et al. 2010; Silvente and Giménez 2007). We adopt a research design from the peer effects literature that takes advantage of the spatial granularity in our data and present novel evidence of local export spillovers at narrowly defined spatial scales. Using transaction level Chinese customs data, we find that firms located in the same neighborhood (with a median area of 1 square mile) as a local first exporter that exports to a newly formed seller-market are 38% more likely to enter the same market the following year, compared to firms without a first exporter nearby. This effect is twice as large as export spillovers from later exporters in the same area, and gets stronger when the first exporter is a joint venture, both firms share the same ownership type or the export signal (measured by quantity or value) is strong. Our mechanism analysis suggests that the spillover effect is driven primarily by the flow of information, facilitated by close proximity.

Keywords: Learning, Spatial spillovers, Exports, Peer effects
JEL codes: F14, R32, D22, R12, L14

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1 Introduction

A growing literature sheds light on the informal trade barriers that hinder firms' access to foreign markets. Specific knowledge of factors, such as the tastes of foreign consumers, local legal and regulatory environment, logistics and distribution channels, country-specific demand, and the appeal of products specific to the target market, is crucial to establishing a productive export relationship (Rauch 1999; Lovely et al. 2005). To acquire such knowledge, potential exporters may learn from existing exporters that are geographically close. Silvente and Giménez (2007), Koenig et al. (2010), Fernandes and Tang (2014), Kamal and Sundaram (2016) and many others have documented firm-to-firm export spillovers at the city or commuting zone level. However, there is limited empirical evidence regarding the existence of geographical export spillovers at very local spatial scales within cities. Furthermore, little attention has been given to a special group of exporters that introduce a brand new exporting route for a specific product. These exporters tend to be more influential and can significantly impact the overall performance of exporting diffusion.[1]

This paper addresses the gaps in the literature by investigating the impact of first exporters in a local area that form a seller-destination-product route in facilitating a neighboring firm's first-time exporting of the same product to the same destination. We find strong evidence of positive and significant spillovers from first exporters to their neighboring firms at a small spatial scale, whereas the spillovers from later exporters at the same spatial scale are statistically smaller. The export spillovers, primarily driven by information transfer, are stronger when the first exporter is a joint venture, both firms share the same ownership type, or the export value or quantity of the first exporter is high. Our findings shed light on one concrete benefit of geographic agglomeration: facilitating the diffusion of information, which reduces informal trade barriers and promotes firms' exporting behavior. This study provides

[1]An extensive literature has documented the crucial role of first movers in a network in maximizing the diffusion of behavior. See, for example, Bjørnenak (1997), Rogers (2010), Banerjee et al. (2013) and Catalini and Tucker (2016).

novel empirical evidence of the importance of first exporters in influencing future exporting behavior, suggesting that export promotion policies specifically targeting first exporters, especially joint ventures, may be more effective than undirected export stimulating policies.

The use of a confidential transaction-level panel of all Chinese exporting firms is central to our analysis. China has experienced miraculous export growth in the past few decades, providing us with a well-suited environment to study the extent and impact of export spillovers. We use information on export value, quantity, product, destination country, trade regime (processing versus non-processing)[2], firm characteristics (e.g. ownership type), and firm addresses for 15,059 first exporters and 37,601 peer firms in nine major exporting Chinese cities from 2000 to 2006. The firms in our sample are large in size with an average annual export value of \$3.17 million for first exporters and \$1.5 million for peer firms.

To construct the sample, we match each first exporter of a product-destination route in a district (with a median area of 56 square miles) with all other exporting firms in the same district so that each observation has a pair of firms, first exporter and its peer. Firm-to-firm spillovers are measured in close spatial neighborhoods – spillovers occur if the first exporter and its peer are located in the same subdistrict (with a median area of 1 square mile). Our research design relies on a linear probability model to compare the export choices of firms that are located in the same neighborhood (defined as a subdistrict) as a first exporter with those that are in nearby neighborhoods. To estimate such spillovers, we face a key identification challenge: a first exporter and its neighbor's export choices may be correlated for reasons unrelated to geographic spillovers arising from firm interactions. For example, both firms may sort into a location due to preferential local trade policies that directly affects their export decisions (Wang, 2013; Chen and Moore, 2010).

We address the identification concern by adopting a research design from the peer effects literature into the context of firm interactions (Bayer et al. 2008). Our primary identifica-

[2]Processing trade refers to trade flows by Chinese firms importing raw materials or intermediate inputs from abroad, processing them locally and exporting the value-added goods. Non-processing (ordinary) trade includes all other trade flows.

tion strategy exploits the spatial granularity in our data and includes district fixed effects interacted with year. The main underlying assumption is that firm spillovers tend to occur at fine geographical levels (Arzaghi and Henderson 2008; Bisztray et al. 2018), whereas most location fundamentals, such as policy benefits and business environments, vary at larger geographical levels, such as district, city or state. In our preferred specification, we also add product-destination-year fixed effects to capture temporal trends specific to a product and a destination, such as destination country's product demand change due to consumer preferences, and peer firm fixed effects to account for firm-specific heterogeneity.

Our identification strategy relies on the absence of sorting into subdistricts within a district based on unobserved variables that are uncorrelated with peers' fixed attributes and annual trends in a specific product-destination route. Frictions in commercial real estate markets of the nine major cities in our sample support this assumption. Despite the relatively broad spatial scale of districts, firms located in these cities can only locate their offices in designated commercial use buildings which are typically dispersed across subdistricts. Given that different types of businesses have heterogeneous preferences for particular building attributes, the availability of a suitable space in a given subdistrict at a given time is constrained. This is corroborated by the low firm mobility rate (2%) in the nine cities during our study period. In addition, the large size of our exporting firms makes it more difficult for them to sort into the same small area of a subdistrict, especially when they have to purchase or rent an entire building. Similar strategies are employed by Bayer et al. (2008) and Schmutte (2015) in the context of residential housing markets and by Baum-Snow et al. (2020) to quantify local productivity spillovers across firms.

Our results indicate the existence of strong export spillovers at the subdistrict level. Our preferred estimate shows that the first exporter—the first firm to export to a new market (defined by product and destination country) within a district—increases the probability of exporting to the same market for an adjacent firm (located within the same subdistrict) by 0.014 percentage points, which is one third of the standard deviation of the outcome variable.

This effect is sizable: it is 38 percent of the mean propensity to export to the new market for enterprises without a nearby first exporter. Given the average number of exporting firms in a subdistrict, this estimate translates to approximately 4.3-percentage-point increase in the probability that at least one firm in the neighborhood start exporting to the market the following year. Furthermore, we show this estimate is not driven by significant export flows and twice as large as the influence from a later exporter in the same subdistrict.

We conduct a number of exercises to show that our results are robust, focusing on bias arsing from potential sorting within districts. First, we demonstrate that sorting on observables across subdistricts is mostly accounted for by district level unobservables. Next, to address the possibility of sorting on the basis of first exporter characteristics or temporal shocks specific to peers, we consider an alternative specification which contains district-product-destination fixed effects (equivalently, first exporter-year fixed effects) and peer-year fixed effects. This specification produces very similar results. Furthermore, we add to the main specification six pair level variables to take into account the possibility of sorting on pair level characteristics. These variables barely change the results.[3] Finally and maybe most convincingly, we perform a placebo test by taking advantage of the artificial spillovers that occur between relocated firms and their current neighbors in the period preceding the relocation, checking if "current" spillovers predict export decisions made prior to relocation using the same identification strategy. We show that the estimated placebo coefficient is very close to zero and lacks statistical significance. These validity checks lend credibility to our empirical strategy and the fact that our approach recovers a plausibly causal estimate that is close to the true spillover effect from local first exporters.

We explore the heterogeneity of this firm-to-firm spillover effect on a number of dimensions. Initially, we examine the magnitude of the spillover effect based on firm ownership type. We find that among peer firms (that are influenced by first exporters), the effect is

[3] The six pair-level controls are whether firms in the pair share the same ownership type, in the same industry, use the same main transportation or have the same trade mode (processing or non-processing), and whether the first exporter exports a larger number of products or has a larger number of destinations than its peer.

more salient for domestic (especially state-owned) than foreign owned. However, among first exporters, foreign firms exert greater influence on their peers than domestic enterprises. Further investigation of this finding indicates that the greater influence comes from joint ventures, rather than wholly foreign-owned firms. Additionally, we discover that export behavior diffuses more easily between firms of the same ownership type, revealing that positive sorting on ownership type can promote exporting. Moreover, the spillover effect varies with the size of the peer – larger firms are more likely impacted by first exporters, and with the export performance of the first exporter – larger export value or quantity sends a stronger signal and has a higher chance to facilitate peers' exporting. These findings uncover essential firm and export characteristics that could promote export spillovers. This information could help policymakers design targeted export-stimulating policies and initiatives. For instance, policymakers may boost export diffusion by encouraging joint ventures to export early or by supporting local first exporters in producing large volume or high value exports.

Last but not least, we shed light on the mechanisms through which the local export spillovers operate. When the first exporter enters a new foreign market, the costs of exporting to the market for neighboring firms may decrease due to the presence or higher presence of upstream specialized suppliers in the same neighborhood or sharing transportation with the first exporter. Other mechanisms we examine include labor pooling resulting from the new job opportunities created by the first exporters, technology transfer from first exporters that increases the productivity of nearby firms and foster exporting, and information spillovers presumably arising from planned or unplanned employer interactions facilitated by close proximity. Although we are unable to measure the four channels directly in the data, we employ the best possible proxies or infer the likelihood of a mechanism using heterogeneous results. Our analysis shows that even after conditioning on the first three mechanisms, our spillover effect is consistent with the main estimate, both qualitatively and quantitatively. The heterogeneous effect on product complexity indicates that our main estimate is driven by products subject to more information frictions (Rauch 1999), suggesting information transfer may be the primary mechanism.

The remainder of the paper is organized as follows. Section 2 summarizes related literature and discusses our contributions. Section 3 introduces the data source and variables used. Our empirical design and evidence supporting our identification strategy are presented in section 4. We report our findings in section 5 and conclude in section 6.

2 Related Literature

This study is part of a broader body of research on firm spillovers in trade, with a primary focus on geographical spillovers. Related theoretical research has argued that proximity to other exporters may reduce fixed costs (Krugman 1991, Foster and Rosenzweig 1995, Segura-Cayuela and Vilarrubia 2008 and Krautheim 2012) and thus promote exporting. Early studies in this literature focus on the spillover effects on the decision to export, with mixed empirical evidence on the existence of firm spillovers. For instance, Aitken et al. (1997), Barrios et al. (2003) and Bernard and Jensen (2004) find spatial spillovers play a negligible role in general export decisions, while Clerides et al. (1998), Greenaway et al. (2004), Kneller and Pisu (2007) and Greenaway and Kneller (2008) suggest positive spatial externalities from neighboring exporters. Empirical consensus has emerged in more recent studies where spillovers contain specific knowledge, such as export experience with a particular product and/or destination (e.g. Koenig 2009; Koenig et al. 2010; Mayneris and Poncet 2015; Kamal and Sundaram 2016; Bisztray et al. 2018).[4] For example, using Chinese customs data, Mayneris and Poncet (2015) documents product-country-specific export spillovers from neighboring foreign firms in the same province. Bisztray et al. (2018) find that the likelihood of starting to import from a country more than doubles with the existence of a peer who has previously imported from that country.

While there is a vast body of literature exploring geographical spillovers and trade activ-

[4] We only include a few studies as examples because of the extensive body of literature.

ity, it is challenging to disentangle geographic spillovers due to location-specific externalities, such as information sharing, from other local characteristics that attract firms to a specific location and affect their export behavior, such as localized productivity, infrastructure, or worker amenity shocks. This challenge has been a long standing issue in the peer effects literature (Manski 1993). The ideal solution is to take advantage of exogenous variations – usually via field experiments – that modulate tie formation (e.g. Sacerdote 2001), exposure to peer behaviors (e.g. Aral and Walker 2011), or shocks to peer behaviors (e.g. Banerjee et al. 2013). However, in many cases, exogenous variations are either not available[5] or unable to identify the effect of interest. For instance, variations due to shocks to peer behaviors through a specific channel (e.g. wind speed changes one's probability of posting surfing activities online as in Shriver et al. 2013) may only affect individuals whose behaviors can be altered through that channel, resulting in estimated effects only applicable to a limited population.

To the best of our knowledge, exogenous variations are rare in the trade literature related to this study, with Tian and Yu (2021) and Steinwender (2018) being notable exceptions. Tian and Yu (2021) exploit a quasi-experiment of high-speed rail expansion that dramatically reduces traveling time and increases geographic spillovers between cities, while Steinwender (2018) leverages the establishment of the transatlantic telegraph in 1866 to find average trade flow increases thereafter. In order to overcome the aforementioned challenge and address other identification concerns, we utilize a uniquely rich set of customs data and employ a research design commonly used in the peer effects literature. This design is explained in detail in section 4.

Existing literature has generally focused on cities or comparable big agglomerations as the geographical level at which spillovers occur, due to a lack of geographically precise data.[6] However, with access to firm addresses, we define the geographical scope at the

[5]For example, it may be infeasible or unethical to randomize tie formation or exposure to peer behaviors (Eckles and Bakshy 2021)

[6]As far as we know, Bisztray et al. (2018) is the only study in the trade literature exploring spatial spillovers at a smaller scale than ours. Their neighboring firms are defined as being located in the same

subdistrict level where the median area is 1 square mile. While there is extensive evidence on learning to export at broad regions, there is limited research on the magnitude and channels of export spillovers at the very local level within cities. The small spatial scale also enhances identification. It could avoid confounding variation from omitted spatially correlated variables (Arzaghi and Henderson 2008; Bisztray et al. 2018), lending credibility to our identification strategy that relies on the absence of firms sorting into the smaller geographical area (i.e. subdistrict) within the larger one (i.e. district).

The study also builds on a broad literature on the economics of networks. With the emergence of big data on social and economic networks, the study of behavior diffusion among individuals has grown rapidly (see the landmark papers of Brock and Durlauf 2001, Mas and Moretti 2009 and Jackson 2014). Only recently have economists started to pay more attention to networks involving firms (Bernard and Moxnes 2018; Bernard et al. 2022). Chaney (2014) and Cai and Szeidl (2018) show that personal contacts across firms can facilitate information diffusion. Baum-Snow et al. (2020) present evidence of revenue and productivity spillovers across firms at fine spatial scales. Inspired by the stream of studies that have highlighted the importance of first movers or early adopters in networks (Bjørnenak 1997; Rogers 2010; Banerjee et al. 2013; Catalini and Tucker 2016), this study focuses particularly on the network effects of the first exporter of a product-by-destination route in a fine geographical area.

This paper relates closely to Koenig (2009) and Koenig et al. (2010). Both studies investigate the presence of neighboring product and/or destination specific exporters on the export behavior of other exporters in the same commuting zone for workers (348 in France).[7] Using firm-level French customs data, export spillovers are identified via time variation within firm-country pairs (Koenig 2009) or firm-product-country triads (Koenig et al. 2010). Our work complements the two studies by examining the same phenomenon at a finer geograph-

building. They differ from this study by focusing on importing behavior and destination-specific spillovers.

[7]The average surface area of a commuting zone in France is 606 square miles (1570 square kilometers). Assuming that the areas are circular, the average radius is 14.3 miles (23 kilometers) (Koenig et al. 2010).

ical level and employing a different identification strategy which controls for localized time trends and time varying confounders specific to product and destination, in addition to unobservables at the firm level. Different from the two studies, we specifically focus on the spillovers from local first exporters who play a critical role in facilitating exporting relative to other exporters.

3 Data

3.1 Firm-Level Export Data: China Customs Records

This study uses the China Customs Records (CCR) as its primary data source, which covers the universe of exporting firms operating in China from 2000 to 2006. This confidential transaction-firm database is managed by the General Customs Administration of China. As one of the main sources of data for analysis of China's exports, it contains detailed export information for each transaction, including export value, export month and year, product category (at the eight-digit HS level)[8], destination country and adopted trade mode (processing or ordinary). The database also includes ownership information (e.g. domestic or foreign) and firm addresses detailed up to street number, which is critical for a much more precise definition of the spillover scale.[9] The CCR has been widely used to investigate spillovers, including by Fernandes and Tang (2014), Swenson and Chen (2014) and Mayneris and Poncet (2015). However, none of these previous studies have access to the level of detailed firm addresses that we utilize in this study, which is crucial for a more nuanced understanding of spillovers.[10]

[8]HS, also known as the Harmonized System, is a standardized international system to classify globally traded products. There are over 7000 HS 8-digit categories.

[9]Firm addresses in CCR are registered office or factory addresses. In the nine urban areas we consider in this paper, the addresses are unlikely for their factories.

[10]Spillovers are at the city level in Fernandes and Tang (2014) and Swenson and Chen (2014), and at the province level in Mayneris and Poncet (2015). Utilizing French data, Koenig (2009) and Koenig et al. (2010) observe firm addresses but their analyses are at the commuting zone level.

3.2 Firm Sample

Our analysis focuses on nine major Chinese prefecture-level cities that contain five of the ten largest ports (more than 100 million metric tons of cargo) in China.[11] Prefecture-level cities in China include an urban core, suburban and rural areas. The nine cities are Beijing, Fuzhou, Guangzhou, Hangzhou, Nanjing, Ningbo, Shanghai, Shenzhen and Tianjin. These cities are geographically large with the smallest being 790 square miles (about 1.5 times the area of Los Angeles). 35% of all exporting firms in China are located in the nine cities. We select the nine major cities because they have more precise and fewer missing firm addresses. The quality of address information for many firms in the non-major cities is significantly poorer, thus making it difficult to match with specific latitude-longitude coordinates.

We geo-code firm addresses using ArcGIS Pro and Google APIs and obtain their approximate latitudes and longitudes for 98% of the firms with a valid company name and/or address in the nine cities. We first utilize the ArcGIS World Geocoding Service to find latitude and longitude on the coordinate system, World Geodetic System 1984 (WGS-84). 70% of the firms are geo-coded this way. Then we use Google APIs to successfully geo-code 93% of the rest of the firms. Google APIs may not provide the most accurate coordinates based on WGS-84, because all map service providers in China including Google are required by the government to use a specific coordinate system that deliberately obfuscates WGS-84 coordinates with an unknown algorithm. However, as pointed out by Li et al. (2022a) that also geo-code Chinese firms, the distance bias caused by the obfuscation algorithm is often within the range of several hundred meters. After geo-coding, our sample covers 54,107 exporting firms in the chosen cities from 2000 to 2006. These firms have at least one export transaction between 2000 and 2006. Matching CCR with detailed geographical coordinates allows us to consider export spillovers in small geographical areas in which neighborhood characteristics are more homogeneous than in the aggregate comparisons in the literature.

[11] Ministry of Transportation of China provides cargo statistics for the 25 largest ports in China: https://www.mot.gov.cn

3.3 First Exporters

Koenig et al. (2010) find that export spillovers are magnified when they are product and destination specific, while Mayneris and Poncet (2015) show that foreign export spillovers are product-country specific. Inspired by the two studies, we explore product-destination-specific spillovers from local first exporters. To identify first exporters, we select the first firm in a district that exports a product of a two-digit HS category (thereafter, product) to a destination country between 2000 and 2006, except for those firms that began exporting in 2000, as their first exporting year cannot be confirmed due to lack of data.[12] To capture more broadly based spillovers, we use HS-2, which consists of 96 product categories, instead of HS-8, the most disaggregated category in CCR.[13] It is likely that exporting of umbrellas with a telescopic shaft excluding garden or similar umbrellas (HS-8: 66019100), for instance, would nudge the exporting of all umbrellas (HS-2: 66). Our sample consists of 15,059 first exporters, whose exporting products cover all 96 HS-2 categories. They export to all 232 destination countries in our database and are close to evenly distributed from 2001 to 2005. 85% of the first exporters are single establishments.[14] Number of first exporters by city is presented in the second column of Appendix Table A.1, with Shanghai having the largest number and Nanjing the lowest.

The first two columns in Table 1 present descriptive statistics on the first exporters' characteristics. All statistics are based on a sample at the firm-year level. The first group of firm characteristics pertains to export-related variables. On average, each first exporter exports

[12] As we have no data on firms' export history before 2000, we cannot rule out that firms classified as first exporters are not the actual "first" exporters. There may exist other firms who started a product-destination route as a classified first exporter before 2000 and stopped afterwards. We conduct a robustness check where the more recent first exporters, in 2004 and 2005, are used. The districts of these first exporters do not have recent unobserved actual "first" exporters. This exercise's result is very similar to the main result. It is available upon request.

[13] Examples of HS-2 products: 70 - glass and glassware; 29 - organic chemicals. Major export products from China include electrical machinery (HS-2: 85), furniture (HS-2: 94), chemicals (HS-2: 28 & 29), optical machinery (HS-2: 90), transportation (HS-2: 86 & 87), toys (HS-2: 95), and textiles (HS-2: 50-63). Detailed trade statistics are provided in the World Bank's China Trade Summary, 2007: https://wits.worldbank.org/CountryProfile/en/Country/CHN/Year/2007/Summarytext

[14] CCR does not have information on whether a firm is a multi-establishment. We identify them by examining company names, which may not be 100% accurate.

58 out of 6,986 HS-8 products to 21 destination countries. Their average export value is 21.7 million in 2006 RMB (about 3.13 million dollars based on 2006 exchange rates). The first four variables' wide standard deviations suggest significant variation in export performance across first exporters, with the majority (80%) of their products being transacted through ordinary trade. The second group consists of firm types which have two main categories, foreign (i.e. joint venture or wholly foreign owned) and domestic (i.e. state-owned, private, collective enterprises or other). The domestic category has slightly more first exporters, with state-owned and private firms making up the majority (92%). The firm's distances from the closest highway and subway are also included to capture the infrastructure benefits specific to its location.

We zoom in on first exporters as they have important policy implications. How to tailor export promotion policies so that they benefit firms and the overall economy to the largest extent is of great importance to policy makers. Theoretical and empirical results in the literature of economics of networks and marketing emphasize the role of first movers or early adopters in promoting diffusion. For instance, the selection of first movers may impact the ultimate reach of the diffusion process (Banerjee et al. 2013), and early adopters can determine the diffusion speed and the success of a new innovation (Von Hippel 1986; Mahajan et al. 1990). In light of the literature, we provide novel evidence in the exporting diffusion process on the unique role of local first exporters that disseminate new information to the local area. In particular, we estimate the magnitude of their spillovers, explore whether first exporters are more influential than later exporters, and characterize the type of first exporters policy makers should concentrate on to maximize externalities.

4 Empirical Design

We start with the identification challenges in this context, followed by the definition of neighborhoods (or spatial peers) and how we construct the estimation sample based on that.

At last, we discuss our identification strategy.

4.1 Identification Challenges

Our main threats to identification are similar to those in the peer effects literature: "reflection problem", "contextual effects" and "correlated effects" (Manski 1993; Sacerdote 2011). We use the three terms to highlight this parallel, even though it does not map one-to-one. "Reflection problem" occurs if a firm's outcome is a function of the outcome of its network connection, and vice versa. "Contextual effects" point to the issue that, for both the first exporter and the peer, background characteristics of the peer group (i.e. firms located in the same neighborhood) may affect the outcome variable. An example is when a firm's export outcome varies with the average productivity of nearby firms which is correlated with the exports of the nearby firms. Such background characteristics may also include firm type, size, registered capital and so forth.[15] In the empirical literature, most authors do not attempt to tackle the question, while some authors assume that peer background characteristics do not impact the outcome directly (e.g. Boozer and Cacciola 2001, Gaviria and Raphael 2001). The third candidate problem is "correlated effects" that occur when the first exporter and its peer are subject to unobserved characteristics or influences in common. An example is a common local policy shock that facilitates exporting for both firms sequentially. Without taking into consideration such positive common shocks, the spillover estimate will be biased upward.

In a spatial setting, sorting in particular is a fundamental challenge.[16] As has been well documented, firms tend to cluster in urban areas or industrial clusters. This is especially true for exporting firms. Spatially targeted programs, such as US Federal Empowerment

[15] There is a considerable amount of empirical challenges associated with separating "contextual effects" from "endogenous effects" in which a first exporter's outcome directly impacts other firm's outcome, especially in reduced form specifications (see Manski 1993 and Durlauf et al. 2010). This is partially due to a lack of guidance on the appropriate measures of contextual characteristics. To the best of our knowledge, credible identification of "endogenous" export spillovers in the literature is rare.

[16] Technically speaking, sorting belongs to the third problem, "correlated effects".

Zones and China's Special Economic Zones,[17] and regions with overall high productivity and well-developed infrastructure typically attract a large number of exporters (Wang 2013; Baum-Snow et al. 2020). The correlation between firm locations and both observable and unobservable neighborhood characteristics makes it difficult to identify export spillovers by simply comparing the export outcomes of firms with or without a neighboring first exporter. If the locations of firms correlate with some unobserved neighborhood fundamentals that affect exporting, the spillover estimate will be biased. Geographical evidence of sorting within cities for all nine cities is provide in Figure 1. The heat map in each panel shows the distribution of all exporting firms in our sample in the corresponding city. The density increases with color darkness. It is evident that each city has one or two hotspots, typically the urban core areas, where businesses are highly concentrated geographically.

4.2 Neighborhood Definition

Given the lack of knowledge or theoretical guidance regarding the geographical scale at which export spillovers occur, we need to make our own choice of an appropriate local geographic network and this choice is inseparable from the identification strategy. The likelihood of firms positively sorting into a neighborhood is high if we define neighborhood at a large spatial scale (such as a city or census tract), which will result in an estimate that is biased upward. In the absence of sorting, if the spillover range is defined too large, some actually untreated firms would be falsely considered as treated resulting in an underestimated spillover effect. Conversely, the identification issue caused by sorting might be alleviated if we focus our analysis on a smaller spatial scale. However, disadvantages arise if the treatment neighborhoods are defined too small. This may fail to account for spillovers at a broader region. On the one hand, the neglected spillovers may foster exporting for both the first exporter and its peer, overestimating the externalities in the small neighborhood; meanwhile,

[17] China's Special Economic Zones (SEZs) with varying scopes and functions aim to support free trade, facilitate technical innovation, and attract more productive talents and firms (Wang, 2013). In China, SEZ normally refers to seven specific zones: Shenzhen, Zhuhai, Shantou, Xiamen, Hainan, Shanghai Pudong New Area, and Tianjin Binhai New Area. These areas cover either an entire city or a sizable district of a city.

the spillover effect may be underestimated as the portion of the spillover outside the defined region is not considered. In addition, as neighborhoods get smaller, fewer and fewer firms are observed to be peers, leading to much noisier estimates.[18]

To balance the concerns discussed above, we proceed by defining firms located in the same subdistrict as (spatial) peers or neighbors. Namely, a neighborhood in each of the nine large cities is a subdistrict by our definition. In China, a subdistrict is the smallest administrative division.[19] In our sample, the median area of subdistricts is 1 square mile[20] and the median number of firms in a subdistrict is 129. This scale is much smaller than that of the cities in our sample, which have a median area of 3790 square miles and a median number of firms of 4552.[21] Among the nine cities, there are on average 124 subdistricts and 12 districts per city. The size of our neighborhood is consistent with the scale found in a recent study by Li et al. (2022a) where almost all agglomeration spillovers occur within this scale using the universe of Chinese manufacturing firms.

Figure 2 provides geographical evidence supporting our neighborhood choice by demonstrating a lack of sorting into subdistricts within districts. The figure displays firm locations as individual black dots in the most densely populated areas of Figure 1, using a unique color for each district and black lines to indicate subdistrict boundaries. Although only a few populous districts are shown for each city, some districts, such as Luohu (yellow) and Futian (light blue) in Shenzhen, clearly have more firms than others.[22] However, as shown in all panels, within the same district there is a great amount of independent variation in firm locations. This serves as the motivating evidence for choosing subdistricts as our

[18]Since precisely measured firm location data are scarce, extremely small spatial scale is also not the most applicable choice.

[19]The current Chinese division system mainly includes a four-level structure: provincial level, prefectural-city level, county level (i.e. district for large urban cities) and township level (i.e. subdistrict for large urban cities). There is a fifth level called community or village, which is usually referred as "basic level autonomy", not an administrative division.

[20]There are a few sizable and less populated subdistricts leading to a larger mean area (10 square miles) and a big standard deviation (15.9 square miles).

[21]The median area of districts is 56 square miles and the median number of firms in a district in our sample is 762.

[22]Sorting into districts is more salient if we zoom out the maps a little bit. Since sorting within cities has been shown in Figure 1, for the simplicity of illustration we do not present nine more panels here.

neighborhood unit.

Certainly, it is possible that firms with similar characteristics co-locate in the same subdistrict, though the distribution of firm locations seems even across subdistricts within the same district. If this is true, defining neighborhoods at the subdistrict level will create endogeneity when similar characteristics are correlated with export decisions and not carefully controlled for. To check whether firms sort into subdistricts on the basis of factors that impact their export decision, we rely on the testable implication: if firm sorting does not exist, observable characteristics should not be sorted on either.

Table 2 reports the extent of sorting on observables across subdistricts within districts in our sample. We first select one firm at random from each subdistrict and then we run two linear regressions for each characteristic in the table that predicts the characteristic of the randomly selected firm. Subdistricts with fewer than six firms are dropped, resulting in a sample of 734 subdistricts. Column 1 presents the R^2 from univariate regressions predicting a given characteristic using the average characteristic of other firms in the chosen firm's subdistrict. The results indicate the existence of sorting to varying extents on all characteristics but export value and quantity. Column 2 presents the within R^2 obtained after adding district fixed effects. In the absence of sorting, the distribution of any given firm characteristic in a district should be almost identical to that in each subdistrict within the district[23] and therefore the variation in a given characteristic within districts should not predict the characteristic of a random firm. As shown in column 2, sorting is heavily attenuated after district fixed effects are added. Similar to Bayer et al. (2008) and Schmutte (2015) that find residential sorting not identically zero, we find firm sorting into subdistricts also not zero, but only to a little extent. In section 4.4, we introduce other strategies to control for potential sorting within districts. Our robustness checks and the placebo test in section 5 suggest it is unlikely.

[23] Due to sampling noise, the subdistrict distributions may not be exactly the same as the district distribution.

4.3 Sample Construction

In this section, we discuss how the estimation sample is constructed utilizing our neighborhood definition. Different from the existing literature, our sample consists of pairs of firms (i.e. dyads).[24] In other words, we explore the geographical spillover from a local first exporter to a peer firm, instead of a group of peer firms. This setup allows us to establish the relevance of the dyad-specific component of the spillover effect and sheds light on the types of firms that policy makers should carefully target to better promote the diffusion of exporting.

To create pairs of firms, we match to the first exporter in a district of product p to destination country c every exporting firm located in the same district. The matched firms (henceforth, peers) have to locate in the district since $t-1$, the year the first exporter starts exporting p to destination c, and have not exported p to c before t. Figure 3 depicts our sample construction where j is the first exporter and paired with two firms, i and i' both of which are located in the same district as j. Firm i is in the same neighborhood (i.e. subdistrict) as j, so our variable of interest is one indicating the presence of spatial spillover. The variable is zero between i' and j because they are not located in the same subdistrict. We hypothesize that exporting requires destination- and product-specific knowledge, thus the outcome variable is whether the peer (i or i') in a dyad follows the first exporter j to export the same product to the same destination in the following year. To reduce noise resulting from infrequent trade patterns, we follow the literature and aggregate export activities to the year level.

The last two columns of Table 1 report descriptive statistics for peer firms in our sample. These firms, on average, export 10.2 million RMB (about 1.5 million USD) of value to the world and 1.1 million RMB (about 0.16 million USD) to each destination market. Of these firms, 86% operate as single establishments. Compared with the first exporters, the peer firms on average export fewer product categories (HS8) to fewer countries with lower

[24] For the rest of the paper, we use dyad interchangeably with pair of firms.

export quantities and values. In addition, peer firms are more commonly foreign-owned than domestic. For reference, Appendix Table A.2 presents summary statistics for all exporting firms in the nine cities. Notably, the peer firms in our sample share similarities with those firms regarding all variables in the table.

Table 3 displays descriptive statistics for our estimation sample, which comprises 55,175,656 observations and 7,763,766 pairs of firms. When the pair is not located in the same neighborhood, the probability of a peer firm starting to export the same product to the same destination as the matched first exporter is 0.037%. We use this value as a baseline probability to assess spillover magnitudes in the main results section. This probability increases by 54% to 0.057% when the pair is located in the same neighborhood. The entire sample covers 108 out of 113 established districts during the study period,[25] with 447 out of 1560 subdistricts not included due to lack of exporting firms in these subdistricts.[26] The average distance between firms in a dyad is 5.7 miles, with a median distance of 4.2 miles. In 61.5% of dyads, both firms belong to the same general category in terms of domestic versus foreign ownership. Among these dyads, both domestic and both foreign firms account for a similar proportion.

4.4 Empirical Strategy

Our primary analysis explores the likelihood of a firm following a first exporter to export the same product to the same destination country, comparing this likelihood for a pair that locates in the same subdistrict with that of a pair located in the same district but not the same subdistrict. The main estimation equation is

$$\text{export}_{i,p,c,t} = \beta \text{ same neighborhood}_{i,j_{p,c,t-1}} + \chi_{d,t} + \chi_{p,c,t} + \alpha_i + \varepsilon_{i,p,c,t} \tag{1}$$

[25] Five districts are not covered because there are no exporting firms in those districts.
[26] Almost all of the dropped subdistricts are located in areas far away from the city center.

where j is a first exporter in district d that first exports product p to destination country c in year $t-1$, and i is a firm located in the same district as j in $t-1$ that has not exported to country c before year t. Our variable of interest, same neighborhood$_{i,j_{p,c,t-1}}$ is 1 if i and j are also in the same subdistrict in $t-1$ and 0 otherwise. This variable is referred to as "neighbor" in the result tables. Our outcome, export$_{i,p,c,t}$ is a binary variable equals to 1 if firm i starts exporting product p to country c in year t. It measures entry into a foreign market (defined by product and country) following the first exporter j. $\chi_{d,t}$ is a district-year fixed effect that captures localized time varying confounders. α_i is a peer fixed effect and $\chi_{p,c,t}$ is a product-destination-year fixed effect capturing product-destination-specific secular trends. It is clear from equation (1) that our empirical design does not suffer from "reflection problem" because we focus on the effect of a first exporter's past export experience (in $t-1$) on its peer's current export decision (in t).

In section 4.1, we identify a major concern that firm location choices may be correlated with neighborhood-specific time-invariant and time-varying fundamentals that also affect export decisions, such as distance to coast and localized neighborhood trends in input price, labor supply and policy benefits. However, such confounders tend to vary little within a small spatial scale, making firm sorting into subdistricts based on them less likely. Section 4.2 provides geographic and empirical evidence that supports subdistricts as a good candidate for the spillover spatial scale in our context. Moverover, the existence of frictions in commercial real estate markets of the nine major cities corroborates this choice. Firms in these cities are only allowed to locate their offices in designated commercial use buildings which are typically scattered across subdistricts. Given that different types of businesses have heterogeneous preferences for particular building attributes, the availability of a suitable space in a given subdistrict at any given time is very limited. Our low mobility rate in the database further supports the sluggishness of the commercial real estate markets. Specifically, among all exporting firms with valid company names or addresses in the nine cities, only 2% moved during the time period from 2000 to 2006.[27]

In light of this, our primary identification strategy hinges on variation in exposure to market-specific spillovers by first exporters within districts across subdistricts. The key underlying assumption is thus the variation is not related to highly local trends in unobservables that drive the outcome, which plausibly holds based on the arguments above and the evidence in Section 4.2. This design is similar to the one employed by Bayer et al. (2008) and many other studies in the peer effects literature (e.g. Schmutte 2015). This method has the advantage of allowing us to recover export spillover at a relatively broad spatial scale and having enough variation in the data to explore mechanisms driving the results.

To implement our primary strategy, we include district-year fixed effects that account for all district-specific time-varying confounders. In addition to fixed district attributes and localized trends that attract firms to the district, the fixed effects also take care of "correlated effects" by accounting for district-level common shocks to both the first exporter and the peer firm that may result in sequential exporting accidentally, such as unobserved technology or infrastructure quality shocks and any supply shocks stemming from new government policies. Such shocks tend to occur at a broader level of spatial aggregation than a subdistrict and thus can be controlled for by district-year fixed effects.

Peer fixed effects α_i account for firm-specific heterogeneity. It allows us to deal with subdistrict sorting on the basis of peers' unobserved attributes. In particular, if a certain firm is more likely to export after a first exporter in their district for unobserved reasons (e.g. because they are both located very close to an export port) and they sort themselves into the same subdistrict, our estimate would misattribute their propensity to export together to the fact that they are located in the same subdistrict. It is possible for the bias to go in the opposite direction. For example, firms that tend not to export after the first exporter (e.g. because they are producing very different products) are more likely to sort into the same subdistrict (perhaps to avoid within-sector competition). Product-destination-year fixed

[27] The actual number may be slightly higher or lower than 2% due to potential measurement errors in firm addresses.

effects $\chi_{p,c,t}$ control for any aggregate market-specific shocks, such as time-varying demand due to business cycle fluctuations or changes in consumer preferences, and economic policies in the importing countries. These shocks are unlikely to differ across Chinese cities. For instance, if U.S. consumers begin preferring Chinese shoes, it is not likely that the preference shift is towards a particular Chinese city because U.S. consumers do not know which city the products are produced. Consequently, the product-destination-year fixed effects should be good enough to control for these shocks.

To further address the possibility of sorting within districts on the basis of first exporter characteristics or annual shocks specific to peer firms, we consider the following alternative specification:

$$\text{export}_{i,p,c,t} = \beta \text{ same neighborhood}_{i,j_{p,c,t-1}} + \chi_{d,p,c} + \alpha_{i,t} + \varepsilon_{i,p,c,t} \tag{2}$$

where $\chi_{d,p,c}$ represents district-product-destination fixed effects and $\alpha_{i,t}$ represents firm-year fixed effects for a peer firm. $\chi_{d,p,c}$ captures shocks at the district level that are specific to the product and destination, such as the availability of skilled labor that specializes in particular products based on the preference of a particular country's consumers. It also controls for changes in district-product-country or district-country economic agreements, local prices of product-specific inputs and the distance between the district where firms in the dyad are located and the destination country. We define first exporters as the unique exporter j in a given combination of district, product, and destination whose first export occurs at time $t-1$ (detailed in Section 3.3), which means that controlling for $\chi_{d,p,c}$ is equivalent to controlling for $\chi_{d,p,c,t-1}$, and is essentially the same as controlling for first-exporter-year fixed effects, $\chi_{j,t-1}$. $\chi_{j,t-1}$ together with $\alpha_{i,t}$ enables us to capture subdistrict sorting to a large extent. They account for not only technology, productivity or supply shocks that are firm specific, but also any time-variant unobservables varying at a higher level than the firm (i or j), such as local trends of productivity, infrastructure, work amenity and firm composition (e.g. foreign v.s. domestic; processing v.s. ordinary trade) in the corresponding firm's subdistrict.

The reason $\alpha_{i,t}$ can be included is that peer firms are matched with multiple first exporters that export to different product-destination markets in the same year.

While our current research design accounts for the most plausible confounding factors, the possibility of unobservable factors at the dyad level affecting both the firm network (i.e., the locations of both firms in a dyad) and the outcome remains a concern. To alleviate this concern, we consider a list of control variables at the dyad level on the basis of the characteristics in Table 2 with non-zero within-R^2. Details about these controls and the results are discussed in detail in Section 5.1.

An implicit assumption of our empirical design is that a significant portion of interactions between a first export and its neighbors are very local in nature, that is, occur among firms in the same subdistrict. A well-established literature in agglomeration economies documents the extent to which agglomeration spillovers are local in a geographic sense. Most relevantly to our study, Li et al. (2022a) use administrative firm-level data for all manufacturing Chinese firms to look at spatial attenuation of localization economies measured by industry employment. They find that by pooling all industries, agglomeration spillovers attenuate by about 90% on average from a 0-1 km (0-0.62 mile) concentric ring to a 1-5 km (0.62-3.11 mile) concentric ring. If the shape of a subdistrict were a circle, the median radius in our sample is 0.56 miles which is very close to 0.62 miles, the radius of the 0-1 km ring where almost all spillovers occur. Therefore, Li et al. (2022a) give us more confidence that our choice of neighborhood is plausibly proper.

To the extent that firms do have some interaction at a broader scale than a subdistrict, we control for bias due to spillovers from nearby districts by including in a robustness check specification number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district. As explained in Section 4.2, in the absence of bias, we may underestimate the strength of the overall export spillover provided that the spillover is significantly stronger at closer distances.[28] Another potential

[28]It has been well documented that agglomeration economies decay rapidly with distance. See for example Arzaghi and Henderson (2008), Bisztray et al. (2018), Rosenthal and Strange (2020) and Li et al. (2022a).

concern with the current design is that market-specific competition effect could potentially weaken any positive spillover effect. Because we focus on exporting after the first exporter, it is less likely that the entire foreign market is taken immediately upon the entries of first exporters. Thus, the competition effect may not be as significant of a concern as in other studies in the literature.

5 Results

5.1 Main results and robustness

Table 4 presents our main estimation results. All the coefficients are multiplied by 100 for readability. Standard errors are clustered at the district level. In column (1), we estimate equation (1). The estimate shows that a local first exporter to a new foreign market (defined by HS-2 product and destination country) increases the probability of adjacent firms (within the same subdistrict) exporting to the same market by 0.014 percentage points, which is one third of the standard deviation of the outcome variable (0.00043). This result is coherent with the previous finding that export decisions are influenced by the presence of nearby product and destination specific exporters (e.g. Koenig et al. 2010).

The estimated effect in column (1) is sizable: it is 38 percent of the baseline probability of exporting to the same market for a peer firm located in the same district but different subdistricts as its local first exporter (0.00037). To put this into context, we compare it to the closest estimates in the literature that also focus on very fine spatial networks. Bisztray et al. (2018) find that the spillover effects of having a same-building peer and a neighbor-building peer with country-specific export experience on a firm's entry into exporting to the country are 76% and 19% of their baseline probability separately (the magnitudes are 0.16 and 0.04 percentage points). If the shares of exporters with same-building and neighbor-building peers are equal, their weighted overall spillover effect is 47% of the baseline. Our estimate is slightly lower, which is expected given that our spatial networks extend beyond neighboring buildings (which are, on average, 28.1 meters apart), and spatial decay of export spillovers is prevalent (Koenig et al. 2010; Mayneris and Poncet 2015; Bisztray et al. 2018).

An increased probability of exporting for a given neighboring firm implies a much larger probability for at least one neighboring firm in the subdistrict to export. With an average number of 359 exporting firms in a subdistrict across the nine cities, an estimated spillover effect of 0.014 percentage points translates to approximately 4.3-percentage-point increase in the probability that at least one firm in the neighborhood will start exporting to the market the following year.[29]

Column (3) of Table 4 presents the result of the alternative specification in equation (2). Controlling for first exporter heterogeneity and peer-specific time-varying shocks produces a very modest positive effect on the estimated export spillover. Moreover, the estimate in column (3) is not statistically different from that in column (1). We take this result as a sign that our research design in equation (1) is fundamentally solid and controls effectively for subdistrict sorting on the basis of both observed and unobserved attributes.

As discussed in section 4.4, remaining endogeneity concerns mainly come from dyad level unobservables and unknown true spillover boundaries. To address these concerns, we conduct a robustness check by including seven control variables in columns (1) and (3). These variables are: the number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the dyad are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or has a larger number of destinations than its peer. The first variable controls for potential export spillovers from nearby districts, while the dyadic variables are based on the variables with non-zero within-R^2 in Table 2. Adding the seven controls slightly reduces our

[29]For computation ease, we treat the likelihood of a first exporter influencing each neighboring firm's decision as an independent event. The reported $0.043 = 1-(1-(0.00037+0.00014))^{359}-[1-(1-0.00037)^{359}]$, where 359 is the average number of firms in a subdistrict, 0.00037 is the baseline probability for firms in the same district to export the same product to the same destination as their local first exporters, and 0.00014 is the estimated spillover effect.

estimates in columns (1) and (3), but does not render them statistically different.[30]

A firm's decision to export to a destination country may also be correlated with its other destination-specific experience, such as having owners in that country and importing from it. To control for such experiences, we add peer-destination fixed effects to all specifications in Table 4 in Appendix Table A.3. These fixed effects also capture confounding factors varying at the firm's subdistrict by destination level, such as the number of other firms in the subdistrict that have exported other products to the same destination. The spillover coefficients are similar to those in Table 4. Moreover, to ensure that our estimates are driven by multi-establishments, we reproduce Table 4 without multi-establishment firms in Appendix Table A.4. The results barely change across all four specifications.

Taken together, the robust results discussed above validate our attempt to isolate spillover effects from sorting and other confounders via the main research design. For the rest of the paper, we take column (1) as our main result and equation (1) as our preferred specification.

Next, we restrict our attention to firms with prior product or destination specific export experience. In Table 5 we consider a sample with the same first exporters and a subset of the original peer firms that had exported the HS-2 product p to at least one destination other than c before the first exporter j entered the new market (defined by p and destination c). Unlike in our main estimation (Table 4), in which the first exporters may facilitate both the production and exporting of a product possibly through sharing product-specific input suppliers, a similar labor market pool and/or market information, in Table 5 the spillover to firms that have produced and exported the product must be destination-related. This may occur through sharing information about import subsidy, product demand and consumer tastes in the destination country. Unsurprisingly, the magnitude of this spillover is larger than the main estimate, as these firms have already paid the sunk costs and started exporting (i.e., in our preferred specification, 0.062 percentage-points in Table 5, compared to 0.014 percentage-points in the main estimate). Nevertheless, the larger estimated coefficients

[30]Columns (2) and (4) of Table 4 drop a few observations from columns (1) and (3) respectively, due to missing values in the dyadic control variables.

represent smaller percentage changes over the baseline probability of this sample (about half of the percentage change for the main estimate).[31] Despite this percentage change decrease in effect, the fact that local first exporters are still influential in this case confirms the importance of the spillover's destination specificity. Similarly, in Table 6, we focus on a subset of the original peer firms that had exported a different product to destination c before the first exporter j entered the new market. The results have a similar pattern as Table 5, suggesting that destination-related and product-related spillovers are equally important in facilitating a peer firm to enter a new market.

5.2 Alternative samples

We explore a variety of alternative samples to further validate the robustness of our main analysis and shed light on the decay of export spillovers over time.

First, we perform additional robustness checks to show that our main result is not driven by observations corresponding to significant export flows. Column (1) of Table 7 restricts the sample to export intensive peer firms whose export values are at top 5% among all exporting firms in the CCR database. There are 3,259 such firms in our sample. In column (2), we focus on significant exported products, defined as HS-2 products whose average annual export value is above the median of all products in the CCR database. There are 49 such HS-2 products in our sample. To make sure our results are not driven by the clothing, textile, and footwear sectors that benefited substantially from trade liberalization over our study period, in column (3) we remove these sectors from our main sample. Finally, column (4) excludes three high export volume destinations, Hong Kong, Macao, and Taiwan, to account for round-tripping. We estimate our preferred specification, i.e. equation (1), for all subsamples in Table 7. The estimated spillover magnitudes are fairly similar to the main result except for column (1) whose sample size is much smaller than the main sample. To

[31]The baseline probability in the sample used for Table 5 is larger than that in the main sample because firms that are already in the industry with export experience of the product are more likely to export to a new destination on average.

make a better comparison, in each column we calculate the percentage effect over the baseline probability of the corresponding subsample. These effects corroborate the main finding that firms witnessing a nearby first exporter penetrating a new market are nearly 40 percent more likely to export to this new market.

Next, we investigate first exporter spillovers on continuous exporting. Due to the volatility of export market entry decisions, where firms may rapidly expand or retreat, this exercise allows us to explore whether there are important dynamic effects depending on the length of export years. In Table 8, the outcome is 1 if the spillover lasts for two consecutive years (column 1) or three consecutive years (column 2), and zero if the firm does not enter the market in year t. In the sample for column 1, we remove observations with only one year of exporting to ensure that when the outcome is zero it shares the same meaning as in the main estimation. Similary, we remove observations with one or two years of exporting in the sample for column 2. The results provide evidence that the spillovers are much smaller in magnitude when facilitating continuous exporting – 0.007 percentage points for two years (half of the main estimate) and 0.003 percentage points for three years (one fifth of the main estimate). However, if we compare the effects with their mean propensities of continuous exporting without the presence of a local first exporter (i.e. the baseline probabilities of the two samples), they turn out to be equivalently sizable (59% for two years and 57% for three years), suggesting that first exporter spillovers may be more powerful if the goal is to improve continuous exporting.

5.3 Placebo test: relocated firms

To further confirm our main assumption that there is no sorting within districts, we conduct a placebo test by exploiting firms that changed locations during our study period. Specifically, we create placebo export spillovers between the relocated firms and their current neighbors in the subdistricts of their new locations for the time periods before the moves. Then we estimate the spillovers using the same identification strategy as in equation (1) with relocated firms taking the role of first exporters. If the estimated placebo effect is significantly positive, it's evidence that firms sort into their current subdistricts as they behave similarly even in the absence of geographic spillovers during the time they are not neighbors. On the other hand, if the placebo estimate is close to zero and insignificant, it suggests that the relocations are not likely driven by sorting across subdistricts within a district on the basis of firm attributes.

In our main estimation sample, there are 1251 firms that changed addresses between 2001 and 2006, all of which only moved once.[32] We focus on 634 of them as they moved to a different subdistrict. To create dyads in the placebo sample, we match the 634 firms to all other exporting firms located in their relocated districts that never move in our entire study period. As in the main estimation, when firms in a dyad are in the same subdistrict, the variable of interest is one and otherwise zero. Utilizing the same specification as equation (1), we investigate the fake spillover effect of a relocated firm's product-destination-specific exporting in year $t-1$ on their current neighbor's decision to enter the same market in year t where t is the year before the move.[33] As in equation (1), we control for localized time-varying confounders, export market trends and peer-specific shocks. Ideally, we would like to restrict to relocated first exporters and the spillover of their product-destination-specific first exporting experience. However, this would largely reduce our sample size making it lack of power in the placebo estimation.

To ensure that the placebo estimation is reasonable and matches the sample selection criteria in the main estimation, we first exclude the cases where the peer firm's subdistrict is the same as the relocated firm's previous subdistrict to avoid contaminating the placebo effect. This leads to the exclusion of 730 peer firms. Second, we drop peer firms that do not exist in our database in the year before a matched relocated firm's move, i.e. those firms did not export at all in that year. Third, we restrict our analysis to peer firms that have never exported product p to the destination country c as of year t. As a consequence, we are left

[32] Our estimation results stay the same dropping these relocated firms from the main sample.

[33] Note that since the majority of the relocated firms are not local first exporters, the spillover of their produce-destination-specific experience is mostly not related to starting a new exporting route.

with 24,209 peers in 875 subdistricts of 87 districts.

The placebo estimates are presented in Table 9. Column (1) reports the naive OLS estimation without any fixed effects. The large, positive and statistically significant estimate indicates firm sorting across subdistricts. However, after including district-year, product-destination-year, and peer fixed effects, the same set of fixed effects used in our preferred specification, the coefficient becomes very close to zero at 0.0006 percentage points, and is statistically insignificant. This suggests that sorting within districts is minimal or non-existent, confirming the effectiveness of our identification strategy in controlling for bias arsing from sorting and other confounders. While we are not able to focus on first exporters and their placebo spillovers of initiating a new route due to the majority of relocated firms not being first exporters, the placebo test sheds light on the likelihood of sorting within districts in our context and provides important support to our main identifying assumption and therefore to our estimates of export spillovers.

5.4 Are first exporters more influential than later exporters?

In this section, we show that local first exporters are more influential in promoting neighboring firms to start exporting than later exporters located in the same subdistricts. Specifically, focusing on subdistricts with at least one local first exporters in our main sample (940 subdistricts), we estimate the effect of an additional later exporter with a given product-destination experience on the entry decision to the market (defined by product and destination) the following year of a firm in the same subdistrict. The model is presented in equation (3), where firm i has not exported product p to destination c before year t and s represents the subdistrict firm i and its neighbors are located. Number of neighbors$_{s,p,c,t-1}$ is the number of firms in subdistrict s that export p to destination c in year $t-1$. Its mean is 1.4, with a median of 1. $t-1$ is at least one year after the initial exporter's first exporting year. We exploit the same markets as in the main sample and implement the same identification strategy as in the preferred specification to estimate the spillovers from later exporters. Although equations

(1) and (3) utilize different sources of variations, we choose to compare our main estimate with a specification whose key variable is the number of exporting neighbors because this variable has been widely used in the literature (e.g. Koenig et al. 2010, Fernandes and Tang 2014 and Hu and Tan 2016).

$$\text{export}_{i,p,c,t} = \beta \text{ number of neighbors}_{s,p,c,t-1} + \chi_{d,t} + \chi_{p,c,t} + \alpha_i + \varepsilon_{i,p,c,t} \quad (3)$$

To facilitate the comparison of our estimates, we normalize the outcomes in equations (1) and (3) by dividing them by their corresponding baseline probability, which is the probability of starting to export to the new market if the variable of interest is zero, and reestimate the two equations. Consequently, the interpretation of the coefficients is also relative to the baseline. We present the results in Table 10 where the first column presents the transformed estimate based on our preferred specification. The second column shows that one more neighboring firm exporting to a market increases the likelihood of entering the market for a firm located in the same subdistrict by 18.7%, which is half of the estimate in column (1). This smaller and statistically different estimate in column (2) supports our hypothesis that first exporters are more powerful in the diffusion of exporting behavior. Specifically, our results suggests that a first exporter is twice as influential as an additional later exporter.

5.5 Heterogeneous effects

The dyadic model offers a valuable advantage as it allows for a thorough examination of heterogeneity across a variety of characteristics, including firm characteristics (e.g. ownership type, diversity of exporting destinations and products, and major mode of trade), dyad characteristics (e.g. whether the pair of firms is in the same industry), and product characteristics (e.g. product complexity),[34] which can help identify potential benefits of targeted policies and clusters.

We begin by examining heterogeneous effects based on ownership type which consists

[34] These characteristics could lead to endogeneity issues, which have been discussed in Section 5.1.

of two main categories, domestic and foreign. We find that export spillovers tend to be more beneficial for domestic enterprises than foreign firms. This is because domestic firms are generally less informed about the new foreign markets ex ante and therefore rely more on information from their neighbors, such as distribution networks, consumer preferences, and regulatory frameworks. In contrast, foreign firms may have better contacts overseas and be more knowledgeable about foreign markets, making them less reliant on information from other exporters.. In Table 11, we interact the variable of interest, same neighborhood, with ownership indicators.[35] As expected, we find that local first exporters have a greater influence on domestic firms than foreign firms (column 1), while foreign first exporters are more likely to influence neighboring firms (column 3).

We further explores whether the spillover effect varies with subcategories of ownership types. In column (2), we focus on two subcategories of domestic firms, state owned and private, which accounts for 93% of all domestic firms in our sample. Not surprisingly, the results show that the spillover to domestic firms is dominated by state owned firms. These firms are typically sizable, enjoy easy access to loans and are protected by regulations that can limit competitions (Li et al. 2022a). Therefore, they are more likely to react to the spillover and get their products exported within a year. Private firms on the other hand are typically smaller than foreign-invested firms and state-owned firms, making them ineligible to directly export products to foreign markets in China until 2004.[36]. Additionally, private firms often face resource constraints. In column (4), we further examine the subcategories of foreign first exporters, distinguishing between joint ventures and wholly foreign-owned firms. The results show that the spillover from foreign firms is driven by joint ventures rather than wholly foreign owned firms.[37] This is consistent with the conjecture that wholly foreign owned firms are more attentive in restricting the leakage of trade secrets, and broadly

[35]The number of observations in Table 11 is smaller than that in Table 4 because a few firms do not have ownership type information.

[36]See appendix Table A.1 in Bai et al. (2017) for the details of the rules governing the ability of Chinese firms to trade directly.

[37]Joint ventures are a major vehicle by which foreign direct investment is conducted in China during our study period.

consistent with a recent finding that there is a larger industry spillover from joint ventures than from wholly foreign-owned firms in China (Jiang et al. 2018). These results add to the discussion on FDI externalities, supporting policies that attract foreign investors to partner up with domestic firms.

In the last two columns of Table 11, we demonstrate that export behavior diffuses easier between firms with the same ownership type (main category), which reveals that positive sorting on ownership type can also promote exporting. Specifically, the spillover effect increases by 0.011 percentage points (30% of baseline) if the pair of firms shares the same ownership type. Column (6) further suggests that the spillover is slightly stronger between domestic enterprises. To have a closer look at the heterogeneity on specific ownership types of the pair, we employ all dyadic combinations of ownership types and present their spillover effects in Appendix Table A.5. The results confirm the stronger spillovers between firms of the same type, reveal that joint ventures are the most influential first exporters, and are consistent with previous research that shows the export decisions of domestic firms are positively influenced by their foreign neighbors (Aitken et al. 1997; Kneller and Pisu 2007; Swenson and Chen 2014; Mayneris and Poncet 2015).

Next, we investigate the strength of the spillover effect along other dimensions of firm characteristics. To begin, we consider the diversity of export portfolios, measured by the number of exported products or served destinations in year $t-1$. These measures are also useful proxies for firm size.[38] We then create indicator variables (i.e. whether below median) to interact with the variable of interest, i.e. same neighborhood. The findings in columns (1) and (2) of Table 12 align with previous research, indicating that smaller firms (those with less than median number of products or destinations) are less likely to benefit from the export externalities and penetrate the new foreign market (Kamal and Sundaram 2016; Bisztray et al. 2018). This supports the idea of greater visibility or absorptive capacity of larger, multi-product and/or multi-destination exporters. This could also be because larger firms

[38] We observe firm employment data for only a small proportion of firms in our sample.

experience fewer trade frictions, for instance, they may possess better knowledge to predict market conditions and export revenues (Dickstein and Morales, 2018). The results regarding first exporters, however, are not the same. The close to zero and insignificant coefficients in columns (4) and (5) show that first exporter's size plays no role in strengthening the spillover, which implies that input sharing and labor pooling - both have a higher chance of being elicited by larger first exporters - are unlikely spillover channels. Similarly, competition generated by the first exporter becoming a specialized supplier and creating a barrier for other exporters to entry plausibly does not exist either, because such specialized suppliers are usually larger firms. Nonetheless, we observe no evidence of larger firms enhancing or weakening the spillover effect.

We also examine whether the spillover effect varies according to export heterogeneity, as measured by the percentage of ordinary trade. This is an important consideration for developing countries in the context of global production fragmentation. Firms engaged in assembly exports are likely to have access to more information, especially when the production is achieved through importing intermediate items (Goldberg et al. 2010), and do not need to search for foreign importers. Therefore, these firms are expected to benefit less from their neighboring first exporters, which is consistent with what we find in column (3) of Table 12. In contrast, the interaction between the percentage of ordinary trade of the first exporter and the spillover effect is not statistically significant.

Lastly, in Table 12 we present the heterogeneous effects on the basis of export performance of the first exporter, measured by export value or quantity to the new market. The two variables reveal critical information about market-specific demand. We include the interaction of the variable of interest with an indicator variable representing whether export value (column 7) or quantity (column 8) is above the median.[39] The idea is that the existence of a first exporter nearby may not encourage export entries, but the strength of the signal (measured by export sales or quantities) might (Fernandes and Tang, 2014). Our results

[39]Note that the observations are slightly fewer in column (8), because a few firms are missing export quantity information.

show that when the first exporter's transaction value or quantity is above the median, its impact increases by 24% (of the baseline). The statistically insignificant coefficient of the variable of interest in column (8) suggests that the spillover effect may be driven by the signal of a large quantity demanded in the new market.

Taken together, the results above suggest plausible heterogeneity in export diffusion: the effect is stronger when the peer firm is domestic or larger, when the first exporter is foreign, when the first exporter's export signal is strong, and when the pair of firms are similar in ownership type.

5.6 Mechanisms

We study four potential mechanisms of export spillovers, i.e. cost sharing, labor pooling, technology transfer and information spillovers.[40] Due to lack of data, we are not able to directly measure the four channels. Instead, we employ the best possible proxies given our data or infer the likelihood of a mechanism using heterogeneous results. Below, we discuss them one by one.

First, the increase in the likelihood of entering a brand new market could take place via the presence or higher presence of upstream specialized suppliers for the exporting product in the neighborhood, as a consequence of the first exporter's entry into the market. It reduces the cost for a local firm to search and find the best input supplier and the input transportation cost, increasing the propensity of entering the same market.[41] To check the possibility of this channel, we construct a variable measuring a subdistrict's yearly accessibility to upstream suppliers for each sector. The variable is defined as follows:

$$\sum_i \phi_i^j \, S_{i,s,t}$$

[40] The first three channels echo Marshall's theories about spatial clusters (Marshall, 1920), which have been studied by economists such as Krugman (1991) and Ellison et al. (2010).

[41] Bernard and Moxnes (2018) shows that improved accessibility to suppliers benefits a firm's export activity.

where ϕ_i^j is the input share from sector i for sector j and $S_{i,s,t}$ is the share of sector i firms located in subdistrict s in year t.[42] This measure increases if there is a higher presence of sector j's supplier sector in the subdistrict and when that supplier sector accounts for a higher input share in sector j.[43]

To construct this measure, we use China's national input-output table provided by the Asian Development Bank to calculate the input share ϕ_i^j, and the Annual Survey of Industrial Firms panel (ASIF) to calculate $S_{i,s,t}$. ASIF, maintained by China's National Bureau of Statistics, is an annual firm panel that covers private firms with annual sales of at least 5 million RMB (0.73 million USD) and all state-owned firms. Sixteen sectors in the input-output table are considered in the construction of this measure, all of which are successfully matched with the Chinese Industrial Classification (CIC) codes in ASIF that are used to define a firm's sector.[44] Each HS-2 category is assigned to one of the sixteen sectors, so for a given (HS-2) product in a subdistrict, we know its sector's annual accessibility to upstream suppliers in the subdistrict. $S_{i,s,t}$ is equal to year t's number of sector i firms in subdistrict s divided by number of all Chinese firms included in ASIF that are in sector i in the same year. Appendix Table A.1 presents the time trend of this measure averaged across all sectors and all subdistricts in our sample (solid line). Surprisingly, there is a decreasing overall trend from 2000 to 2006. Probably due to China's rapid development in infrastructure in early 2000s, especially the National Trunk Highway System, the importance of local accessibility to upstream suppliers is declining.

Next, we consider a different type of cost sharing, sharing transportation costs, which is a key component of trade costs. If a first exporter and its neighboring firm use the same main

[42]Alternatively, $S_{i,s,t}$ can be replaced with the share of sector i output produced in subdistrict s in year t, as in Tian and Yu (2021). However, we do not have subdistrict level output data by sector.

[43]Note that we only focus on domestic suppliers here.

[44]The sixteen sectors are mining and quarrying; food, beverages and tobacco; textiles and textile products; leather, leather products, and footwear; wood and products of wood and cork; pulp, paper, paper products, printing, and publishing; coke, refined petroleum, and nuclear fuel; chemicals and chemical products; rubber and plastics; other nonmetallic minerals; basic metals and fabricated metal; machinery, nec; electrical and optical equipment; transport equipment; manufacturing, nec; recycling; electricity, gas, and water supply. These sectors are more aggregated than HS-2 categories.

transportation mode (water, air or land), they are more likely to share transportation costs to the new destination.[45] Therefore, we interact the same main transportation indicator with our variable of interest. The results are presented in column (2) of Table 13. The small and statistically insignificant coefficient of the interaction implies sharing transportation may not be a potential channel. In fact, this finding aligns with the argument that the development of transportation technology and infrastructure has made cost sharing, especially transportation costs, associated with a large geographic scope (Li et al., 2022a).

Another potential channel through which the presence of a first exporter might stimulate export activity is by shifting the local labor market, bringing workers with specific skills to the area. However, this mechanism is likely to operate on a larger geographic scale than a subdistrict. For instance, the median commuting distance is 3.9 miles in Shanghai (Li et al., 2022b) and 5.5 miles in Nanjing (Sun et al., 2020), whereas the diameter of the median sized subdistrict in our sample (assuming it is a circle) is 1.12 miles. To confirm the argument above, we proxy for labor pooling specific to a given HS-2 category in each subdistrict. We measure this using the share of employers in the subdistrict who work for a firm in the HS-2 sector. We match the HS-2 categories in our sample with the CIC codes in ASIF that classify a firm's sector, and then construct this measure using data on the number of employers in a firm from ASIF. Appendix Table A.1 shows an overall upward trend in this measure (dashed line), which is averaged across all HS-2 categories and all subdistricts for illustration purposes.[46]

Technological knowledge spillovers have been well-documented in the literature, particularly among geographically proximate firms (e.g. Ellison et al. 2010, Bloom et al. 2013, Keller 2021). Such spillovers can increase the productivity of other firms that operate in the same industry and encourage exporting. In our context, however, we see little incentive for the first exporters, which are large firms, to share their technology with others in order

[45] A firm's main transportation in year t is defined as the transportation mode (water, air or land) that transports the largest proportion of products for the firm in year t.

[46] The flat line between 2002 and 2003 is due to missing employer data in ASIF 2003. 2002's data are used as a proxy.

to compete in a newly established market. Furthermore, even if technology spillovers were to occur, it would be challenging for exporting firms to build or update production lines, manufacture products and begin exporting within a year. Due to the low firm match rate between CCR and ASIF (about 20%), we lack key variables for the majority of our firms to construct a common measure of technology spillovers, total factor productivity (TFP). Instead, we investigate this channel by looking at whether the spillover effect varies for dyads in the same industry, defined by producing the same main product (HS-2).[47] The rationale behind this is that technology spillovers are more likely to occur among firms in the same industry than among those in different industries.

The results, displayed in column (3) of Table 13, indicate that the interaction term is statistically insignificant (though the standard error is large). This implies that being in the same industry is unlikely to enhance the spillovers, although it should be noted that the findings may be influenced by the competition effect, which is more prevalent among firms in the same industry. It is possible that competition effect cancels out the technology spillover. However, competition between a first exporter and a neighboring firm may not be severe, if any, as the new market is less likely immediately saturated upon the entries of first exporters.

Considering the three channels discussed above, in column (1) of Table 13 we add the measures of cost sharing and labor pooling, and the same industry indicator to our preferred specification. To fully control for the impacts of cost sharing and labor pooling, for each channel we include three measures for the subdistrict of the peer firm, which are in the current year (t), the previous year ($t-1$) and the year before the first exporter exports ($t-2$). The contemporary and one year lagged measures can help us isolate the channels, while the measures at $t-2$ capture the potential endogeneity bias coming from common subdistrict shocks before the first exporter enters the market. The first take-away is that the estimated spillover effect barely changes compared to the main estimate in column (1)

[47] A firm's main product in year t is defined as the product that accounts for the largest export value for the firm in year t.

of Table 4, suggesting the three channels are unlikely the drivers of the export spillovers from local first exporters. The insignificant coefficients of supplier accessibility measures are consistent with the discussion above – local accessibility to upstream suppliers becomes increasingly less relevant in the study period. The significant coefficients of employer shares in t and $t-2$ confirm the importance of local labor pooling in a firm's export decision, though it is not driving the estimated spillover effect. The same argument also applies to the same industry indicator.

Last but not least, close proximity makes managers and workers easily move between firm locations, which facilitates planned or unplanned interactions (Jacobs, 1961). These interactions can lead to effective information diffusion about for instance, the existence of a new route, and the potential demand, distribution networks and consumer preferences in the foreign market. There is considerable evidence that closeness in geographical distance fosters productive interactions in residential neighborhoods (Bayer et al. 2008; Hellerstein et al. 2011; Hellerstein et al. 2014). Although the empirical evidence on information spillovers between employers is scarce, we believe it is a pivotal channel in the context of exporting diffusion from the first mover in local networks. If there had already been a number of exporters to the market in the neighborhood, the extra information obtained from an additional neighbor is likely low. Nonetheless, the other channels, such as cost sharing and labor pooling, have a higher chance to take place as the number of exporting neighbors rises. Another reason why information spillovers may be the main driver in our context is that planned and unplanned employer interactions tend to occur in a small geographical scale in nature, whereas cost sharing, labor pooling and technology transfer usually happen at a larger geographical scale, such as the metropolitan level (Rosenthal and Strange, 2020), in which case district by year fixed effects will shut down those channels.

We examine heterogeneous effects on product complexity to provide evidence on information spillovers. Rauch (1999) introduces the idea that complex goods are subject to more information frictions which dampen trade. Thus, complex goods should benefit more from export spillovers if information transfer is the main channel. We follow Rauch (1999) to group our products into two categories – complex and homogeneous. For example, carpets and other textile floor coverings (HS-2: 57) are classified as complex products, while cotton (HS-2: 52) is a homogeneous product. Then we interact the complex product indicator with the variable of interest.[48] As shown in column (4) of Table 13, the interaction is positive and statistically significant, confirming a stronger spillover for complex goods. Moreover, the insignificant coefficient of Neighbor in column (4) indicates that the estimated spillover effect is fully driven by complex products, further suggesting that information transfer is the main mechanism.

5.7 Spatial decay

To explore how the spillover effect varies with the geographical distance between firms in a dyad, we create six indicator variables. The first indicator equals one if the distance is within 1 mile, the second equals one if the distance is between 1 and 2 miles, the third equals one if the distance is between 2 and 3 miles, the fourth equals if the distance is between 3 and 4 miles, and the last indicator equals one if the distance is beyond 5 miles. Then we interact these indicators with the variable of interest, same neighborhood. The results are shown in Figure 4 where the black dots represent the estimated spillover effects for the corresponding distance range. Note that the effects in the vertical axis are not multiplied by 100 as in the other tables. As expected, the spillovers decrease with the dyadic distance. When the distance is larger than 2 miles, the effects are not statistically different from zero, while within 2 miles the spillovers are between 0.01 and 0.015 percentage points. The results confirm the spatial decay of export spillovers within major Chinese cities and provide insight into the geographical range of these spillovers. Additionally, the spatial decay results further support the argument that information sharing is the primary channel through which the spillover occurs, because the other potential channels, especially cost sharing, tend to take place at a

[48]Complex products account for 75% of our sample.

relatively larger distance than 2 miles (Combes and Gobillon 2015; Li et al. 2022a).

6 Conclusion

Early literature suggests that the process of entering foreign markets poses a variety of challenges, such as obtaining information about foreign tastes and establishing distribution channels. One obvious way for firms to learn about export markets is through neighboring exporters that have already acquired experience selling abroad.

Considerable evidence exists on the presence of export spillovers at the spatial scales of city or commuting zone level. This paper extends the existing literature by investigating the importance of geographic export spillovers from local first exporters at a much finer geographical scale. Using geo-coded China Customs Record database in top exporting Chinese cities, we show that first exporters act as export catalysts that foster the creation of new export transactions for neighboring exporting firms. In particular, the presence of an exporter serving a new market increases the probability of entering the same market for an adjacent firm (located within the same subdistrict) by 0.014 percentage points, representing a large change (38 percent) compared to the mean probability of exporting in the absence of the first exporter. This effect is robust to a variety of alternative specifications and samples. Exploiting artificial spillovers between relocated firms and their new neighbors during the time periods before the moves, we further confirm the credibility of our estimate.

Our analysis of the mechanisms behind the local export spillovers indicates that information flow plays a major role. Various heterogeneous effects suggest that export spillovers are stronger in the presence of a foreign first exporter, a large peer firm or a strong export signal, and exhibit complementaries in firm ownership type. Consistent with previous studies, we also find evidence of spatial decay, with the spillover effects disappearing beyond a distance of 2 miles from the first exporter.

Understanding empirically what facilitates entry into a new export market is a prerequisite to the design of adequate policies aimed at stimulating exports. Our analysis contributes to the literature by highlighting the important role played by first movers in local networks, whose impact is twice as large as that of later movers. Our results suggest that policy makers should consider to improve the connections between foreign firms and other types of firms, as well as encouraging the agglomeration of firms with similar ownership types within a relatively small geographical scope. More broadly, this study also adds to a growing literature on how firm networks shape economic outcomes.

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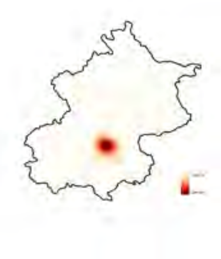
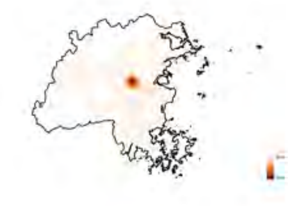
Tables and Figures

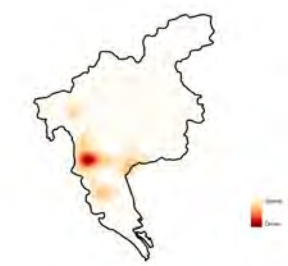
Figure 1: Heat Map of Firm Locations



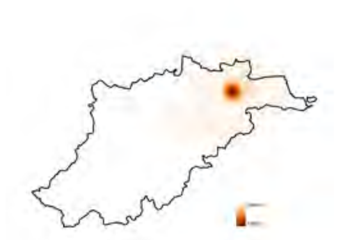
(a) Beijing



(b) Fuzhou

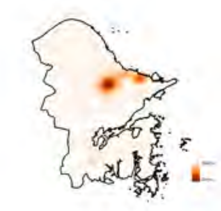


(c) Guangzhou



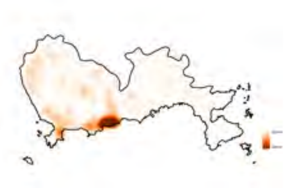
(d) Hangzhou

(e) Nanjing

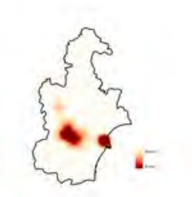


(f) Ningbo

(g) Shanghai



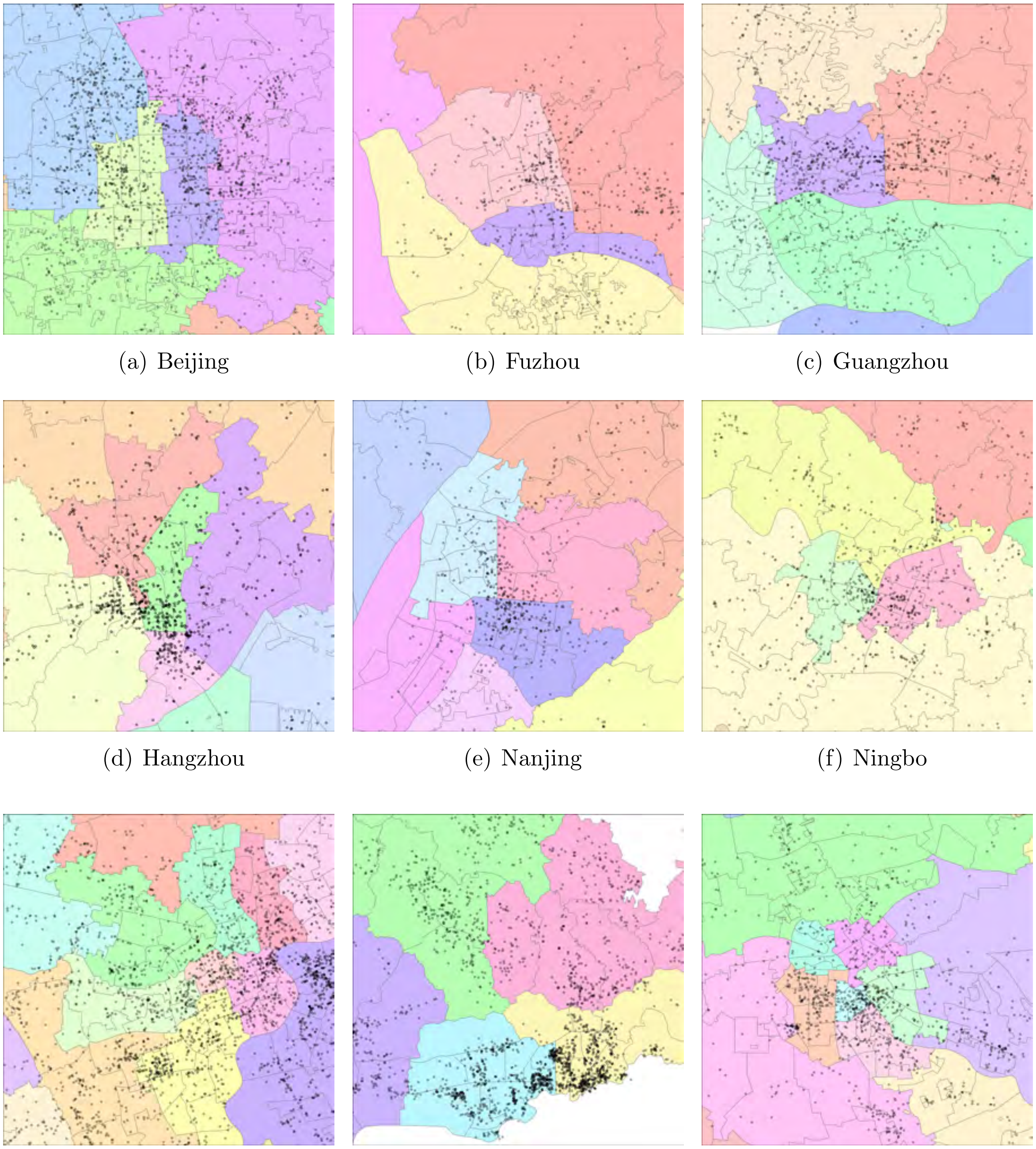
(h) Shenzhen



(i) Tianjin

Note: This figure reports the distributions of the firm locations in the nine cities. The density increases with color darkness.

Figure 2: Distribution of Firm Locations in Dense Areas



(a) Beijing (b) Fuzhou (c) Guangzhou

(d) Hangzhou (e) Nanjing (f) Ningbo

(g) Shanghai (h) Shenzhen (i) Tianjin

Note: This figure reports the distributions of the firms in areas with high firm density (mostly downtown areas). Firm locations are represented by black circles. In each city, different colors represent different districts. Subdistricts are marked by polygons with black boundaries.

Figure 3: Sample Construction

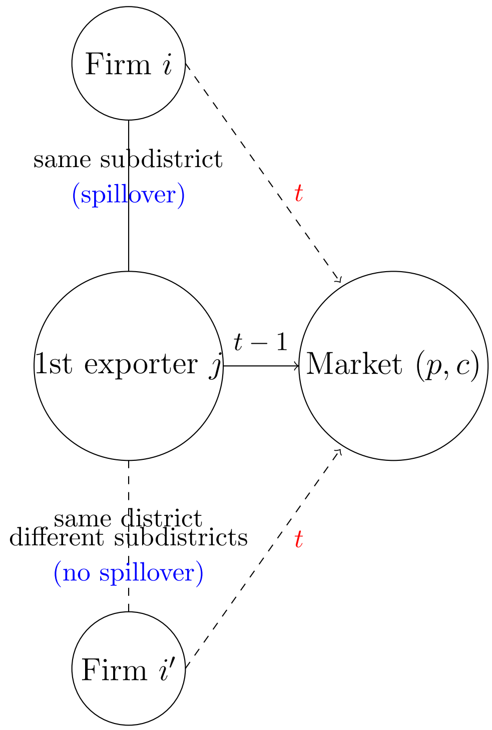
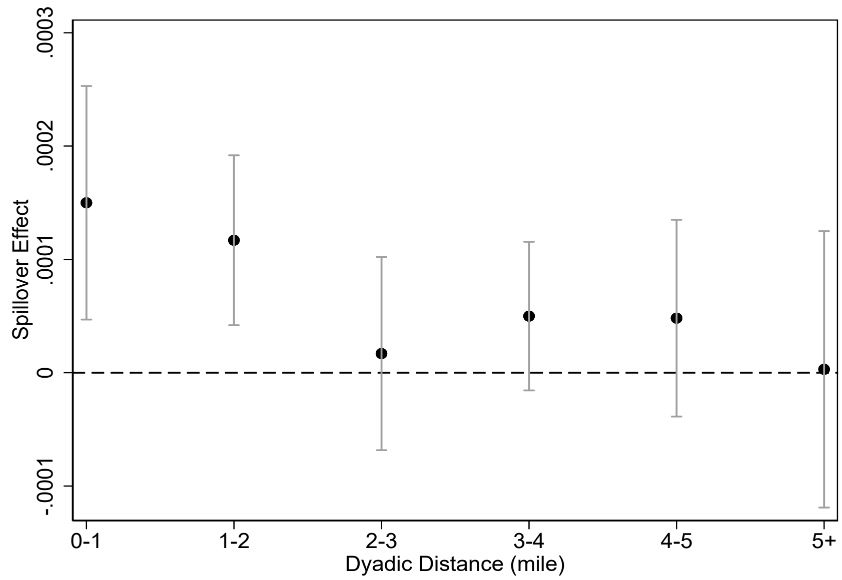


Figure 4: Spatial Decay – Export Spillovers



Note: The figure shows the estimated export spillover effects by the distance between the first exporter and its matched firm in the dyad (they may or may not be in the same subdistrict). 95% confidence intervals of these estimates are also presented. The horizontal axis labels indicate the distance range. For example, 0-1 means the dyadic distance is between 0 and 1 mile. Note that the effects in the vertical axis are not multiplied by 100 as in the other tables.

Table 1: Firm Descriptive Statistics

Firm-year level	First exporters		Peer firms	
	Mean	St.D	Mean	St.D
Number of products (HS-8)	57.785	124.427	22.135	71.090
Number of destination countries	20.867	21.966	9.113	14.651
Export quantity (in millions)	16.279	147.862	7.296	92.644
Export value (2006 RMB in millions)	21.723	377.997	10.247	223.362
Proportion of ordinary trade	0.795	0.354	0.652	0.445
Foreign	0.434	0.496	0.618	0.486
Joint venture	0.210	0.407	0.257	0.437
Wholly foreign owned	0.225	0.417	0.362	0.481
Domestic	0.556	0.497	0.368	0.482
State owned	0.289	0.453	0.146	0.354
Private	0.223	0.416	0.195	0.396
Collective enterprises	0.000	0.000	0.000	0.008
Other domestic	0.044	0.205	0.026	0.159
Distance to closest highway (miles)	1.055	1.335	0.938	1.113
Distance to closest subway (miles)	24.763	58.922	17.577	49.277
Number of firms	15,059		37,601	

Note: Summary statistics for the first exporters and their peer firms in our sample. All statistics are on the basis of the firm-year level sample. There are two trade modes in general: processing and ordinary. Processing trade refers to trade flows by Chinese firms importing raw materials or intermediate inputs from abroad, processing them locally and exporting the value-added goods. Ordinary trade includes all other trade flows. All firm ownership type variables are indicators and their summaries represent the fraction of the sample with the associated characteristic.

Table 2: Sorting within Districts, R^2 Method

	Raw	District FEs
Number of products (HS8)	0.024	0.012
Number of destinations	0.032	0.006
Export value	0.000	0.000
Export quantity	0.000	0.000
Domestic firm	0.104	0.029
Ordinary trade	0.197	0.024
Processing trade	0.223	0.021
Transportation: water	0.178	0.012
Transportation: land	0.476	0.006
Transportation: air	0.096	0.011

Note: This table reports sorting within districts on observables. The input dataset contains one randomly selected firm-level observation per subdistrict and the fraction of firms (excluding the firm) in the subdistrict who share the listed characteristic or its average. Each entry is the R^2 from a regression of the firm's characteristic on the subdistrict-level average. Columns 2 controls for district specific fixed effects and reports within R^2. The sample is restricted to subdistricts with more than six firms.

Table 3: Sample Descriptive Statistics

	Mean	St.D
Sample		
Export probability without 1st exporter†	0.00037	0.01919
Export probability with 1st exporter	0.00057	0.02379
Number of products (HS2)	96	
Number of destinations	232	
Number of districts	108	
Number of subdistricts	1113	
Number of observations	55,175,656	
Dyad level		
Distance to the first exporter (miles)	5.741	5.103
Same ownership type	0.61476	0.48665
Both domestics	0.32009	0.46651
Both foreign	0.29467	0.45589
Number of dyads	7,763,766	

Note: This table presents descriptive statistics for the main estimation sample. † indicates the baseline probability for the main sample. The variable, same ownership type, is in terms of the main categories of firm type, i.e. domestic and foreign.

Table 4: Effects of First Exporters

	(1)	(2)	(3)	(4)
Neighbor	0.014***	0.012***	0.017***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Percentage of baseline probability	38%	33%	46%	41%
R-squared	0.010	0.010	0.022	0.023
Observations	55,175,656	54,095,040	55,175,649	54,095,030
District by Year FEs	✓	✓	×	×
Product by Destination by Year FEs	✓	✓	×	×
Firm FEs	✓	✓	×	×
Firm by Year FEs	×	×	✓	✓
District by Product by Destination FEs	×	×	✓	✓
Additional controls	×	✓	×	✓

Note: The table reports our main estimation results. Coefficients and standard errors are multiplied by 100 for ease of readability. An observation is a pair of firms who are located in the same district. The first firm in the pair is a local (district) first exporter that exports HS-2 product p to destination c in year $t-1$. The second firm in the pair (peer) has not exported p to c by $t-1$. The dependent variable is whether the peer exports p to destination c in year t. The variable of interest is whether the first exporter and the peer are in the same subdistrict. Column (1) estimates equation (1) and column (3) estimates equation (2). Columns (2) and (4) add seven control variables to columns (1) and (3) respectively. They are number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the pair are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or have a larger number of destinations than its peer. A few observations are dropped in columns (2) and (4) due to missing values in the dyadic control variables. Standard errors in parentheses are clustered at the district level.

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Effects of First Exporters (Exported the Same Product Before)

	(1)	(2)	(3)	(4)
Neighbor	0.062***	0.054***	0.067***	0.060***
	(0.014)	(0.014)	(0.013)	(0.013)
Percentage of baseline probability	20%	17%	22%	19%
R-squared	0.044	0.045	0.115	0.116
Observations	6,735,086	6,639,268	6,723,287	6,627,315
District by Year FEs	✓	✓	×	×
Product by Destination by Year FEs	✓	✓	×	×
Firm FEs	✓	✓	×	×
Firm by Year FEs	×	×	✓	✓
District by Product by Destination FEs	×	×	✓	✓
Additional controls	×	✓	×	✓

Note: The table restricts the sample to peer firms with prior product-specific export experience. Coefficients and standard errors are multiplied by 100 for ease of readability. An observation is a pair of firms who are located in the same district. The first firm in the pair is a local (district) first exporter that exports HS-2 product p to destination c in year $t-1$. The second firm in the pair (peer) has not exported p to c by $t-1$ but has exported p to other destination(s). The dependent variable is whether the peer exports p to destination c in year t. The variable of interest is whether the first exporter and the peer are in the same subdistrict. Column (1) estimates equation (1) and column (3) estimates equation (2). Columns (2) and (4) add seven control variables to columns (1) and (3) respectively. They are number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the pair are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or have a larger number of destinations than its peer. A few observations are dropped in columns (2) and (4) due to missing values in the dyadic control variables. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Effects of First Exporters (Exported to the Same Destination Before)

	(1)	(2)	(3)	(4)
Neighbor	0.104***	0.091***	0.124***	0.111***
	(0.024)	(0.023)	(0.023)	(0.022)
Percentage of baseline probability	18%	16%	21%	19%
R-squared	0.047	0.048	0.106	0.107
Observations	5,828,971	5,742,771	5,819,092	5,732,856
District by Year FEs	✓	✓	×	×
Product by Destination by Year FEs	✓	✓	×	×
Firm FEs	✓	✓	×	×
Firm by Year FEs	×	×	✓	✓
District by Product by Destination FEs	×	×	✓	✓
Additional controls	×	✓	×	✓

Note: The table restricts the sample to peer firms with prior destination-specific export experience. Coefficients and standard errors are multiplied by 100 for ease of readability. An observation is a pair of firms who are located in the same district. The first firm in the pair is a local (district) first exporter that exports HS-2 product p to destination c in year $t-1$. The second firm in the pair (peer) has not exported p to c by $t-1$ but has exported other products to destination c. The dependent variable is whether the peer exports p to destination c in year t. The variable of interest is whether the first exporter and the peer are in the same subdistrict. Column (1) estimates equation (1) and column (3) estimates equation (2). Columns (2) and (4) add seven control variables to columns (1) and (3) respectively. They are number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the pair are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or have a larger number of destinations than its peer. A few observations are dropped in columns (2) and (4) due to missing values in the dyadic control variables. Standard errors in parentheses are clustered at the district level. * $p<.10$, ** $p<.05$, *** $p<.01$

Table 7: Alternative Samples

	(1)	(2)	(3)	(4)
Neighbor	0.048***	0.015***	0.013***	0.013***
	(0.015)	(0.003)	(0.003)	(0.003)
Percentage of baseline probability	40%	33%	35%	35%
R-squared	0.023	0.011	0.011	0.010
Observations	5,335,075	39,751,467	43,993,871	54,155,255

Note: The table reports the estimation results using different subsamples. Column (1) restricts to the sample of export extensive firms (export value at top 5% of all firms in CCR). Column (2) restricts to the sample of significant products (product annual export value above median of all products in CCR). Column (3) drops the clothing, textile and footwear sectors that benefited from dramatic trade liberalization over the study period. Column (4) excludes three destinations in the Greater China area, i.e. Hong Kong, Macao and Taiwan. Coefficients and standard errors are multiplied by 100 for ease of readability. All specifications use our preferred specification, i.e. equation (1). Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Continuous Exporting

	2 years	3 years
Neighbor	0.007***	0.003***
	(0.002)	(0.001)
Percentage of baseline probability	59%	57%
R-squared	0.006	0.005
Observations	55,158,915	55,154,916

Note: The table reports the spillover effects of a local first exporter's market-specific experience on a neighboring firm exporting to the same market for two consecutive years (column 1) or three consecutive years (column 2). Coefficients and standard errors are multiplied by 100 for ease of readability. Both columns are estimated using our preferred specification, i.e. equation (1). Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Placebo Test: Relocated Firms

	(1)	(2)
Neighbor	1.1008*	0.0006
	(0.5998)	(0.0208)
District by Year FEs	×	✓
Product by Destination by Year FEs	×	✓
Firm FEs	×	✓
Percentage of baseline probability	150%	0.08%
R-squared	0.002	0.089
Observations	34,097,865	34,097,865

Note: The table reports our placebo results using the relocated firms in our main sample. Coefficients and standard errors are multiplied by 100 for ease of readability. We create placebo export spillovers between relocated firms and their current neighbors in the subdistricts of their new locations for the time periods before the moves, and then estimate export spillover using the same identification strategy as in equation (1) with relocated firms taking the role of first exporters. Column (1) presents the raw estimate without any fixed effects. Column (2) uses the same set of fixed effects as our preferred specification. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Effect Comparison: First Exporters v.s. Later Exporters

	First exporters	Later exporters
Neighbor	0.376***	
	(0.083)	
Number of neighbors		0.187***
		(0.020)
R-squared	0.010	0.024
Observations	55,175,656	47,868,139
p-value of equal coefficient test	0.001	

Note: The table compares our main estimation result with the result using the number of neighbors with a market-specific experience as the variable of interest in the time period after the existence of local first exporters. To facilitate the comparison of our estimates, we normalize the outcomes in equations (1) and (3) by dividing them by their corresponding baseline probability, and reestimate the two equations. Consequently, the coefficients are interpreted as the effect over the baseline probability. Columns (1) and (2) present the transformed estimates based on our preferred specification and equation (3) respectively. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Heterogenous Results – Firm Ownership Type

	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor	0.008**	0.008**	0.012***	0.012***	0.010**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Domestic firm × Neighbor	0.015**					
	(0.007)					
State owned × Neighbor		0.019**				
		(0.009)				
Private × Neighbor		0.014				
		(0.010)				
Foreign firm$_{1st}$ × Neighbor			0.006*			
			(0.003)			
Joint venture$_{1st}$ × Neighbor				0.009**		
				(0.004)		
Wholly foreign owned$_{1st}$ × Neighbor				0.003		
				(0.004)		
Same ownership type × Neighbor					0.011***	
					(0.004)	
Both domestic × Neighbor						0.013*
						(0.007)
Both foreign × Neighbor						0.009***
						(0.003)
R-squared	0.010	0.010	0.010	0.010	0.010	0.010
Observations	54,279,112	54,279,112	54,279,112	54,279,112	54,279,112	54,279,112

Note: The table reports our heterogeneous results when the variable of interest is interacted with firm ownership type. Coefficients and standard errors are multiplied by 100 for ease of readability. District-year fixed effects, product-destination-year fixed effects and peer fixed effects are used in all columns. Only the coefficients of neighbor and the interaction terms are presented here. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Heterogenous Results - Firm Characteristics and Export Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neighbor	0.020***	0.023***	0.007*	0.013***	0.013***	0.016***	0.009***	0.005
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)
Firm characteristics								
Number of products (HS-8) (< median) × Neighbor	-0.011***							
	(0.003)							
Number of destinations (< median) × Neighbor		-0.018***						
		(0.004)						
Percentage of ordinary goods × Neighbor			0.011*					
			(0.006)					
(Number of products$_{1st}$ < median) × Neighbor				0.001				
				(0.003)				
(Number of destinations$_{1st}$ < median) × Neighbor					0.001			
					(0.004)			
Percentage of ordinary trade$_{1st}$ × Neighbor						-0.003		
						(0.005)		
Export performance								
Export value$_{1st}$ (> median) × Neighbor							0.009**	
							(0.003)	
Export quantity$_{1st}$ (> median) × Neighbor								0.009**
								(0.002)
R-squared	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Observations	55,175,656	55,175,656	55,175,656	55,175,656	55,175,656	55,175,656	55,175,656	55,043,274

Note: The table reports our heterogeneous results when the variable of interest, Neighbor, is interacted with various firm and export characteristics. Coefficients and standard errors are multiplied by 100 for ease of readability. District-year fixed effects, product-destination-year fixed effects and peer fixed effects are used in all specifications. Only the coefficients and standard errors of the variable of interest and the interaction terms are reported. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Alternative Mechanisms

	(1) All Controls	(2) Transportation	(3) Technology	(4) Information
Neighbor	0.012***	0.012***	0.012***	0.005
	(0.003)	(0.004)	(0.004)	(0.003)
Accessibility to suppliers (t-1)	1.214			
	(1.056)			
Accessibility to suppliers (t-2)	0.827			
	(1.020)			
Accessibility to suppliers	0.547			
	(1.057)			
Share employers in the HS-2 sector	0.112***			
	(0.023)			
Share employers in the HS-2 sector (t-1)	0.036			
	(0.024)			
Share employers in the HS-2 sector (t-2)	0.032*			
	(0.019)			
Same main transportation	-0.001	-0.000		
	(0.002)	(0.002)		
Same main transportation × Neighbor		0.003		
		(0.004)		
Same industry	0.152***		0.148***	
	(0.031)		(0.036)	
Same industry × Neighbor			0.016	
			(0.047)	
Complex product × Neighbor				0.012***
				(0.002)
R-squared	0.010	0.010	0.010	0.010
Observations	55,175,656	55,175,656	55,175,656	55,043,274

Note: The table presents the results in our mechanism analysis where we consider four potential mechanisms: cost sharing, labor pooling, technology spillovers and information transfer. Accessibility to suppliers and same main transportation are used to capture cost sharing. Share of employers in the HS-2 sector of the export product of the first exporter is used to measure labor pooling. Same industry indicator is one if the two firms in a dyad produce the same main product (HS-2). Complex product, defined as in Rauch (1999), is interacted with the variable of interest to check whether goods associated with more information frictions strengthen the effect. District-year fixed effects, product-destination-year fixed effects and peer fixed effects are used in all specifications. Standard errors in parentheses are clustered at the district level.

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix A Other Tables and Figures

Table A.1: Number of Firms by City

	Number of firms	Number of first exporters
Beijing	3891	2000
Tianjin	3478	1787
Shanghai	9571	3324
Shenzhen	9314	2230
Ningbo	2470	1199
Guangzhou	3942	1691
Hangzhou	1960	1067
Nanjing	1433	854
Fuzhou	1542	907

Note: This table includes firms in the main estimation sample.

Table A.2: Firm Descriptive Statistics

Firm-year level	All Firms	
	Mean	St.D
Number of products (HS8)	21.217	68.326
Number of destination countries	8.950	14.145
Export quantity (in millions)	7.563	106.610
Export value (2006 RMB in millions)	10.288	223.465
Proportion of ordinary trade	0.608	0.461
Foreign	0.626	0.484
Joint venture	0.243	0.429
Wholly foreign owned	0.383	0.486
Domestic	0.374	0.484
State owned	0.122	0.328
Private	0.221	0.415
Collective Enterprises	0.008	0.088
Other domestic	0.023	0.150
Distance to closest highway (miles)	1.107	1.961
Distance to closest subway (miles)	18.359	50.037
Number of firms	76,779	

Note: Summary statistics for all exporting firms in the nine cities in our database. All statistics are on the basis of the firm-year level sample. There are two trade modes in general: processing and ordinary. Processing trade refers to trade flows by Chinese firms importing raw materials or intermediate inputs from abroad, processing them locally and exporting the value-added goods. Ordinary trade includes all other trade flows. All firm ownership type variables are indicators and their summaries represent the fraction of the sample with the associated characteristic.

Table A.3: Additional Robustness Checks: Effects of First Exporters

	(1)	(2)	(3)	(4)
Neighbor	0.012***	0.011***	0.014***	0.013***
	(0.003)	(0.002)	(0.003)	(0.003)
R-squared	0.202	0.203	0.210	0.211
Observations	54,356,377	53,316,363	54,355,884	53,315,866
District by Year FEs	✓	✓	×	×
Product by Destination by Year FEs	✓	✓	×	×
Firm by Destination FEs	✓	✓	✓	✓
Firm by Year FEs	×	×	✓	✓
District by Product by Destination FEs	×	×	✓	✓
Additional controls	×	✓	×	✓

Note: Coefficients and standard errors are multiplied by 100 for ease of readability. An observation is a pair of firms that are located in the same district. The first firm in the pair is a local (district) first exporter that exports HS-2 product p to destination c in year $t-1$. The second firm in the pair (peer) has not exported p to c by $t-1$. The dependent variable is whether the peer exports p to destination c in year t. The variable of interest is whether the first exporter and the peer are in the same subdistrict. Columns (2) and (4) add seven control variables to columns (1) and (3) respectively. They are number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the pair are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or have a larger number of destinations than its peer. A few observations are dropped in columns (2) and (4) due to missing values in the dyadic control variables. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.4: Effects of First Exporters: Single Establishments

	(1)	(2)	(3)	(4)
Single establishment firms				
Neighbor	0.012***	0.011***	0.015***	0.014***
	(0.004)	(0.004)	(0.003)	(0.003)
R-squared	0.010	0.010	0.023	0.023
Observations	47,414,941	46,546,121	47,414,934	46,546,111
Single establishment first exporters				
Neighbor	0.013***	0.012***	0.017***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.011	0.011	0.024	0.025
Observations	44,658,288	43,806,366	44,658,276	43,806,351
District by Year FEs	✓	✓	×	×
Product by Destination by Year FEs	✓	✓	×	×
Firm FEs	✓	✓	×	×
Firm by Year FEs	×	×	✓	✓
District by Product by Destination FEs	×	×	✓	✓
Additional controls	×	✓	×	✓

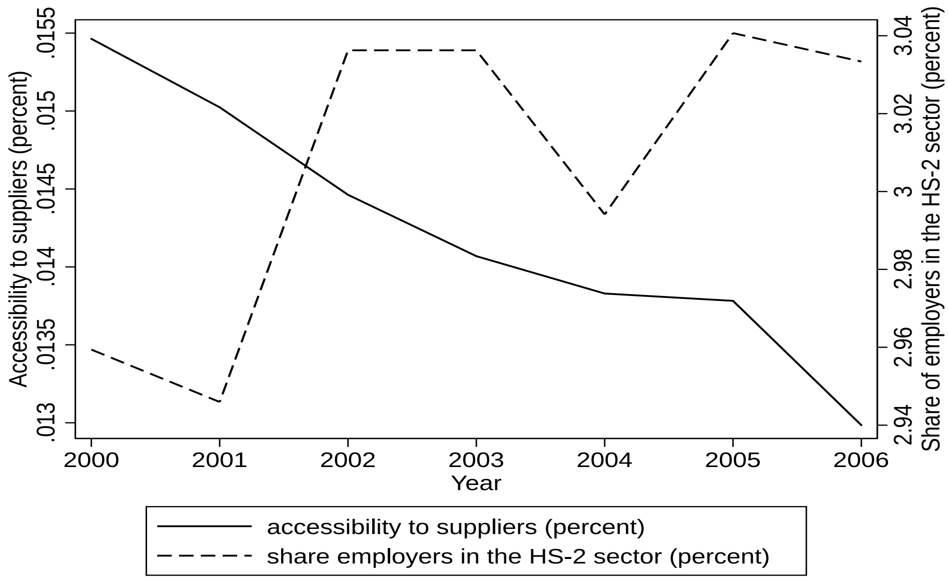
Note: The first panel reports the main estimation results when peer firms are single establishments and the second panel is when first exporters are single establishments. Coefficients and standard errors are multiplied by 100 for ease of readability. An observation is a pair of firms who are located in the same district. The first firm in the pair is a local (district) first exporter that exports HS-2 product p to destination c in year $t-1$. The second firm in the pair (peer) has not exported p to c by $t-1$. The dependent variable is whether the peer exports p to destination c in year t. The variable of interest is whether the first exporter and the peer are in the same subdistrict. Column (1) estimates equation (1) and column (3) estimates equation (2). Columns (2) and (4) add seven control variables to columns (1) and (3) respectively. They are number of exporters exporting the same product to the same destination as the first exporter by year $t-1$ in the nearest adjacent district, whether firms in the pair are of the same ownership type, in the same industry, use the same main transportation or have the same trade mode, and whether the first exporter exports a larger number of products or have a larger number of destinations than its peer. A few observations are dropped in columns (2) and (4) due to missing values in the dyadic control variables. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Table A.5: Heterogeneous Results - Firm Ownership (All Combinations)

	Spillover Effect	
	Primary Type	Secondary Type
Foreign × foreign$_{1st}$	0.017***	
	(0.004)	
Foreign × domestic$_{1st}$	0.003	
	(0.003)	
Domestic × foreign$_{1st}$	0.027***	
	(0.008)	
Domestic × domestic$_{1st}$	0.023***	
	(0.007)	
State owned × state owned$_{1st}$		0.031***
		(0.009)
State owned × private$_{1st}$		0.012
		(0.012)
State owned × joint venture$_{1st}$		0.029
		(0.020)
State owned × wholly foreign owned$_{1st}$		0.021
		(0.019)
Private × state owned$_{1st}$		0.020*
		(0.011)
Private × private$_{1st}$		0.024**
		(0.011)
Private × joint venture$_{1st}$		0.025*
		(0.014)
Private × wholly foreign owned$_{1st}$		-0.000
		(0.015)
Joint venture × state owned$_{1st}$		-0.001
		(0.004)
Joint venture × private$_{1st}$		0.014***
		(0.005)
Joint venture × joint venture$_{1st}$		0.033***
		(0.008)
Joint venture × wholly foreign owned$_{1st}$		0.001
		(0.004)
Wholly foreign owned × state owned$_{1st}$		-0.007*
		(0.004)
Wholly foreign owned × private$_{1st}$		0.003
		(0.005)
Wholly foreign owned × joint venture$_{1st}$		0.010**
		(0.005)
Wholly foreign owned × wholly foreign owned$_{1st}$		0.021***
		(0.005)
R-squared	0.010	0.010
Observations	54,279,112	50,985,420

Note: The table reports estimated spillover effects for all dyadic combinations of ownership types. Coefficients and standard errors are multiplied by 100 for ease of readability. District-year fixed effects, product-destination-year fixed effects and peer fixed effects are used in both columns. Standard errors in parentheses are clustered at the district level. * $p < .10$, ** $p < .05$, *** $p < .01$

Figure A.1: Supplier Accessibility and Specialized Workers



Note: The figure presents the time trend of accessibility to upstream suppliers averaged across all sectors and subdistricts (solid) and the time trend of average subdistrict level share of employers in the HS-2 sector of the export product (dashed). The definitions of the two measures are in Section 5.6.