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Export spillovers with Chinese characteristics

by

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Abstract

This paper investigates the impact of information spillovers on the export entry decision of Chinese manufacturers between 2000 and 2006 by using a combination of firm and transaction level data that allows to track the occurrence of individual export starts and captures the extent of local export agglomeration at a detailed geographical level. We examine if the presence of neighboring exporters involved in similar or different product and destination markets gives rise to knowledge transfers that facilitate a firm’s export entry and carefully consider how differences across starters, neighbors, geographical proximity, trade regimes and private networks influence the transmission of information between firms. Export starts are measured at the product level and related to a disaggregated set of spillover proxies via a linear probability model with fixed effects that accounts for a large set of unobserved firm, region, destination and product characteristics. Our results confirm the presence of export spillovers in China and show that they increase in spillover specificity, vary across different starters and neighbors, are subject to spatial decay, limited to ordinary traders and stronger within private networks. On the one hand, this corroborates the notion that information spillovers act as a catalyzing force for the extensive margin of trade, on the other it emphasizes that the transmission process relies on a conducive unity of its subparts and can be restricted by developmental features common to transition economies.

Keywords: export spillovers, agglomeration effects, China, international trade, transition economies

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1 Introduction

Many countries consistently seek to promote their exporting sector as a stronger integration in global markets is often associated with significant increases in economic growth. These can originate from scale effects that arise when accessing new markets, an alleviation of liquidity constraints by accumulating foreign exchange or a more efficient allocation of resources due to a higher degree of competitive pressure from abroad (Giles and Williams, 2000; Radelet, 1999). Despite the large potential these factors represent for a country’s economic development, only a fraction of firms across countries actually become exporters, leaving the extensive margin of trade (number of firms engaged) rather thin (Mayer and Ottaviano, 2008).

Economists typically relate this selective entry into foreign markets to the costs incurred when deciding to sell abroad. Before entering foreign markets, firms need to gather information on local market regulations and consumer preferences. These processes are often costly and a majority of the expenses non-retrievable (Choquette and Meinen, 2015). Consequently, a firm will only choose to become an exporter if its own productivity is sufficiently high to bear entry costs and still make profits from its export operations (Melitz, 2003). According to this logic, the interplay of firm productivity and fixed entry costs creates a natural threshold for export entry and guides the selection into exporters and non-exporters.

One factor that could influence this sorting of firms are spillover effects from neighboring companies. This form of externality dates back to Marshall (1920) who conceptualized how industrial and geographical agglomeration of manufacturing activity can give rise to scale effects by allowing firms to benefit from a specialized local labor pool, shared inputs and knowledge base within a specified region. Translated to modern studies related to the extensive margin of trade, scholars like Aitken et al. (1997) typically distinguish between three types of spillovers that affect export entry. A first spillover type are information transfers. Prospective entrants may learn about foreign preferences and regulations from experienced neighbors which reduces individual fixed costs and facilitates export entry (Koenig et al., 2010). Secondly, the presence of highly productive neighbors may raise competitive pressure in the region and force non-exporters to streamline their operations. Productivity gains created by local competition effects could therefore also boost chances of export entry (Greenaway et al., 2004). Thirdly, a geographical concentration of exporters can give rise to cost sharing devices as firms can bundle exports activities, mutualize variable transport costs and thereby lower the export entry threshold (Cassey and Schmeiser, 2013).

This study focuses on export spillovers in form of information transfers[1] and investigates their impact for the extensive margin of trade in China. The country represents an ideal basis for our purposes as despite its reputation as one of the prime engines of global trade has never been subject to an in-depth spillover analysis. We seek to close that gap, examine the relevance of export spillovers in China and carefully consider which underlying forces determine the outcome of that process. An important feature of our agenda is that we pay particular attention to learning differences across trade regimes and ownership types as these are directly related to key components of China's economic transition process and therefore may be of special interest to other developing countries. To address these questions, we rely on a matched panel of firm and transaction level data that uniquely combines customs and balance sheet information to provide a rich description of Chinese manufacturers' export behavior at the firm-destination-product level. We carefully differentiate between general, product, destination and product-destination specific export agglomeration at a detailed geographical level and separately estimate their impact on foreign market entry via a linear probability model with fixed effects that accounts for a plethora of unobserved time-invariant characteristics.

This approach relates our work to several theoretical and empirical accounts that also investigate the relevance of information spillovers for the extensive margin of trade. Two recent formal treatments of information externalities are Koenig (2009) and Krautheim (2012). Both extend previous heterogeneous firm models of Melitz (2003) and Chaney (2008) by introducing a spillover channel into the baseline trade models. Fixed costs incurred at export entry now depend on the number of nearby exporters. Following this approach, a larger number of neighbors exporting to country j decrease the fixed costs of exporting to that specific market and thus create a destination-specific spillover effect on the extensive margin of trade.

Empirical counterparts testing the relevance of this externality, however, are far from unanimous. While firms seem to benefit from export promoting local agglomeration effects in Mexico (Aitken et al., 1997), the UK (Greenaway et al., 2004; Greenaway and Kneller, 2008; Kneller and Pisu, 2007), France (Koenig et al., 2010; Koenig, 2009), Russia (Cassey and Schmeiser, 2013) and Denmark (Choquette and Meinen, 2015), opposing findings arise in Spain (Barrios et al., 2003; Requena-Silvente and Giménez, 2007) and no evidence for export spillovers is found in Indonesia (Sjöholm, 2003) and the US (Bernard and Jensen, 2004).

This lack of consistency across studies can partly be traced to the level of detail export spillovers are measured at (Koenig et al., 2010). Restricted by a lack of detailed firm level data, early analyses were

[1] As noted by Choquette and Meinen (2015), information spillovers could entail technological knowledge or destination-specific knowledge. While the former would boost a firm's productivity and thereby increases chances of exporting in general, the latter only facilitates entry to a particular market. Although we are unable to identify which kind of knowledge is ultimately exchanged between firms, our study pays respect to this distinction by differentiating between destination-specific and general agglomeration effects. Comparing economic and statistical significance across export spillovers thus also grants insights into which type of knowledge transfer has the strongest impact on export entry.

limited to the study of industrial agglomeration effects. Consequently, this approach only considers if a higher density of local exporters induces export entry of firms active in the same sector. This broad perspective bears two fundamental problems. Firstly, investigating export spillovers at the industrial level assumes that all information transfers within the sector are relevant for export entry. This is problematic as industrial sectors subsume a lot of different products into a single category and prospective exporters may not benefit from the experience of neighbors active in related but different product markets. Secondly, a solely industrial perspective abstracts from factors specific to the destination a firm starts exporting to and thus treats fixed entry costs as homogeneous across destination markets. This is highly unlikely as regulations related to market entry vary significantly across countries which is why fixed entry costs need to be treated as heterogenous (Koenig, 2009).

Recent papers avoid these aggregation problems by using more detailed datasets that allow to differentiate between general agglomeration effects and those pertaining to products, destination markets and combinations thereof (Cassey and Schmeiser, 2013; Choquette and Meinen, 2015; Koenig et al., 2010). Results within this small but detailed group of studies are more homogeneous and point towards the relevance of product and destination specific export spillovers.

Nevertheless, even within the group of papers promoting the existence of export spillovers, reported externalities are subject to additional sources of heterogeneity. Local agglomeration seems to vary across starters of different absorptive capacity (Poncet and Waldemar, 2015) and size (Koenig et al., 2010; Poncet and Mayneris, 2013), across neighbors of different experience (Greenaway and Kneller, 2008) and ownership forms (Aitken et al., 1997; Barrios et al., 2003; Greenaway et al., 2004; Sjöholm, 2003) and factors shaping the interaction between the two such as spatial proximity (Koenig et al., 2010) and quality of the signal travelling between neighbors and prospective exporters (Fernandes and Tang, 2014).

In summary, a more detailed level of analysis and careful consideration of heterogeneous spillover effects across firms seem key to resolve the conflicting evidence presented in earlier studies and may help to deliver a more comprehensive picture of information externalities for the extensive margin of trade.

This study follows both lines and hence contributes to the existing literature in two important ways. Firstly, it directly addresses the conflicting evidence presented in earlier studies by taking the spillover analysis to the firm-destination-product level. This informational detail allows us to investigate if export promoting agglomeration effects originate from general, product, destination or product-destination specific knowledge transfers between exporting neighbors and new starters. As described above, recent studies point towards the importance of specific spillovers which may be the key to explain inconsistencies in earlier accounts. Our approach broadens this narrow strand of the literature and helps to answer the question which type of export agglomeration has the highest potential to trigger export entry.

Secondly, we analyze the micro foundations of the spillover transmission process to understand which factors limit or facilitate the diffusion of knowledge within spillover categories. Unlike earlier studies which highlight the importance of individual factors, we address spillover heterogeneity in a more systematic manner by combining evidence from a broad range of papers to cover the whole spillover transmission process. This approach not only allows us to examine the relevance of traditional sources of spillover heterogeneity that have been covered in previous accounts but also motivates an investigation of two new sources that directly relate to China's economic transition process. As detailed in the next section, trade regimes and private networks may give rise to distinctively different learning patterns across firms and add another layer of complexity to the export spillover nexus that may be particularly important when studying export entry in transition economies.

Both extensions to the literature find support in our empirical application. The conducive impact of export spillovers in China increases in the specificity of local export agglomeration. This corroborates recent evidence from France (Koenig et al., 2010) and Denmark (Choquette and Meinen, 2015) and relates the disagreement in earlier studies to an insufficient distinction between different forms of export agglomeration. Moreover, our results reveal a considerable degree of heterogeneity within spillover categories. Traditional sources of spillover heterogeneity show that knowledge transmissions vary along different starter and neighbor characteristics and are subject to spatial decay. New sources indicate that export synergies are largely limited to ordinary traders and occur within private networks. Together, these findings suggest that export spillovers can lead to meaningful increases along the extensive margin of trade if two conditions are met. Firstly, prospective starters need to be surrounded by exporting neighbors that are engaged in similar product and destination markets as only they possess relevant information for foreign market entry. Secondly, forces underlying the transmission of spillovers need to form a conducive unity to allow information to flow from one party to the other. The rest of the paper obeys the following order:

Section 2 lays out the background of spillover transmissions and hypothesizes how differences across trade regimes and ownership forms can interfere with that process. Section 3 discusses our data sources and identification strategy on which we base our empirical results that are portrayed in section 4. Section 5 discusses our main findings and derives policy implications before section 6 concludes the analysis with some final remarks.

2 Export spillovers

2.1 A stylized model of spillover transmission

As mentioned in the section above, information spillovers can take a catalyzing role for the extensive margin of trade by using local knowledge about foreign regulations, tariffs, consumer preferences or competition to reduce fixed costs related to market entry (see Choquette and Meinen, 2015). Although this idea is appealing, its relevance will ultimately depend on a diverse set of factors facilitating or hampering the transmission of relevant information. To address these considerations systematically, it is useful to combine results from the large set of earlier studies into a single stylized model which divides the transmission process into three different stages as demonstrated in Figure 1. While market information continues to flow from neighbors to prospective exporters, its impact on a firm's entry decision will vary with qualities of the emitter, the receiver and the strength of the connection between the two.

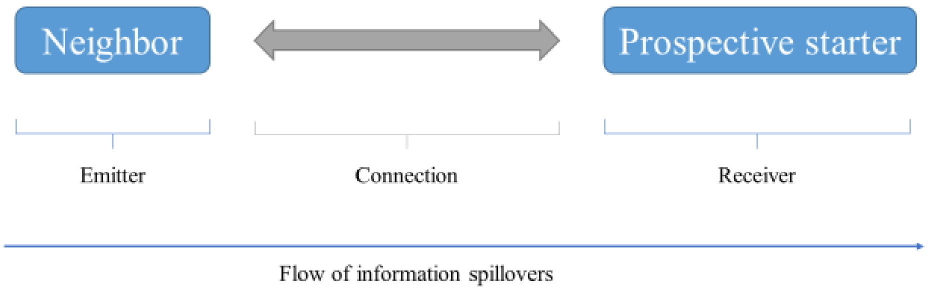


Figure 1: Spillover transmission

At the receiving end, this means that different starters will (ceteris paribus) show different reactions to the presence of nearby exporters. As shown by Poncet and Waldemar (2015), spillover diffusion is increased if starters have higher productivity levels. This highlights that information uptake is fueled by a higher absorptive capacity of the learner. Moreover, small firms seem to benefit disproportionately from export spillovers (Poncet and Mayneris, 2013) which could either be related to a lack of expertise in acquiring information themselves or a result of uneven governmental support programs that are geared towards the needs of larger firms.

Similarly, there are certain characteristics at the emitting end that influence which neighbors become sources of knowledge transfers for nearby export starters. Firstly, Greenaway and Kneller (2008) emphasize the role of a neighbor's export experience and find that especially an agglomeration of newly exporting neighbors induces export entry of others within the locality. This underlines that it may not be the accumulation of experience but rather the timely proximity of a neighbor's export decision that determines which neighbors are considered as relevant sources of learning. Secondly, Fernandes and Tang (2014) show that neighbors influence export spillovers by signaling business opportunity at foreign markets. The stronger and clearer the signal they emit, the larger the impact they have on the extensive margin of trade[2]. Thirdly, spillovers can vary depending on the ownership form taken by neighboring exporters. Scholars typically differentiate between the presence of domestic and foreign owned neighbors and argue that the latter's additional knowledge of foreign markets should lead to larger numbers of export entry for others located close-by (Greenaway et al., 2004). At the same time, critics stress that multinational enterprises often substitute dealings with local firms with their internal network which may limit the emission of information to others due to their weaker integration to the local economy (Poncet and Waldemar, 2015). This duality creates an additional source of spillover heterogeneity that is related to neighbor qualities and can produce mixed evidence across countries (Aitken et al., 1997; Kneller and Pisu, 2007; Poncet and Waldemar, 2015; Sjöholm, 2003).

Apart from the receiving and emitting end, the overall transmission of export spillovers also depends on factors influencing the connection between neighbors and prospective starters. Whereas heterogeneity at the end points of the transmission process stems from differences in information provision and uptake, this third stage is more concerned with forces gluing the two together as information needs to travel from neighbors to prospective starters. A first channel connecting teacher and learner are industrial linkages. The basic idea is that the incidence of spillovers is expected to be positively correlated with the frequency firms interact with each other. This relationship is typically proxied by the strength of sectoral entanglement[3] between neighbor and starter and empirical evidence does point towards a spillover conducive role of industrial linkages (Choquette and Meinen, 2015; Kneller and Pisu, 2007). Similarly, the chance of personal encounters between neighbors and prospective entrants depends on the spatial proximity of both parties. The larger the distance between the two, the more unlikely it becomes that valuable market information reaches prospective starters and facilitates market entry. Geographical distance can therefore limit the diffusion of information and induce a spatial decay of export spillovers (Koenig et al., 2010). A third connecting channel are inter-firm labor movements. In contrast to industrial linkages and spatial proximity, knowledge not only spills over to others as a result of frequent interactions with existing exporters, but also travels in form of human capital (Choquette and Meinen, 2015). Hence, differences in labor mobility across countries are also expected to impact the spillover transmission process.

In summary, each of the three stages can influence how smoothly information travels from exporting neighbors to prospective starters. This stylized view bears two important consequences. In retrospect, this systematic approach helps to explain why we observe heterogeneous spillover effects across countries. Some of the described factors may not be equally important in all settings which stresses the importance of considering local institutional structures when analyzing export spillovers. Secondly, the stylized model can also serve as a guideline for making predictions about the relevance of export

[2] Signal strength is proxied by export sales growth, clarity by the number of local exporters growing at similar rates.
[3] To measure how strongly two firms are connected to each other, researchers rely on intermediate consumption shares calculated from national input-output tables. For a more detailed explanation, we refer the interested reader to Choquette and Meinen (2015).

spillovers in a new environment. This can be achieved by integrating the local institutional setup into the transmission framework outlined above. The next part follows this idea and applies these considerations to the Chinese case. China's institutional landscape has experienced huge transformations in the past decades. We will focus on two key features of that process, explain how they relate to export spillovers and draw predictions about their expected manifestation in the Chinese economy.

2.2 Spillover transmission in China

For almost three decades, China has pursued an export-led growth strategy to alleviate poverty and transform itself into an economic powerhouse. An integral part of that strategy has been the establishment of special economic zones. These early instruments of industrial policy have to be understood as spatially confined areas that are governed by a distinct institutional environment (Radelet, 1999). Many are geared towards boosting processing exports, a specific kind of trade in which Chinese manufacturers assemble (foreign) inputs into final products that are destined to be exported to consumer markets abroad. This type of trade flourished under a set of preferential policies that allows registered processing traders to make use of duty-free input sourcing (Dai et al., 2016), a reduced income tax (Defever and Riano, 2016) and streamlined bureaucratic procedures related to their export regulations (Radelet, 1999). As a consequence, processing exports have become an important part of China's trade activity and account for a majority of export sales between 2000 and 2006 (see Fernandes and Tang, 2015). More importantly, they need to be separated from ordinary trade activities as the two types are expected to play very different roles in the transmission of export spillovers.

In terms of the stylized model described above, prospective processing starters face a very different initial situation than normal traders. They often do not make independent export decisions but rather respond to foreign orders. Therefore, they are less dependent on fixed entry costs as the analysis of consumer preferences and regulations in the destination market has already been made by the foreign partner (Fernandes and Tang, 2015). This leads to hypothesis A1:

Export spillovers play ceteris paribus a weaker role for the export entry of processing traders compared to ordinary traders.

Reversely, being surrounded by processing neighbors may prove to be less beneficial for any firm that requires local expertise to surpass its exporting threshold. If processors export according to foreign orders, they may possess less information about foreign markets and therefore become less valuable sources of learning for others (Wang and Yu, 2012). Moreover, processing firms often receive a considerable amount of their inputs directly from their foreign partners. This weakens their connection to the local economy as foreign inputs crowd out domestic sourcing and prevent the establishment of lasting industrial linkages (Poncet and Waldemar, 2015). Together, processing firms' lower accumulation of knowledge and their weaker integration to regional economic activity lead to hypothesis A2:

The presence of ordinary neighbors is ceteris paribus expected to create larger export spillovers than the presence of processing neighbors.

A second factor that requires special attention when conducting a spillover analysis in China are ownership forms. As explained above, most papers concerned with this factor focus on potential differences in learning between domestic and foreign firms. In the Chinese context, however, a separate differentiation between state and private ownership may be even more relevant. This is closely related to China's transition to a market economy which remains imperfect as the state retains a significant influence over key sectors of the economy. Consequently, private firms do not operate on a level playing field but are often discriminated against. They still suffer from limited access to finance (Poncet et al., 2010), are more subjected to red tape (McMillan and Woodruff, 2002) and only gained formal legal protection in 2004 - a time when they already accounted for 60% of the country's total industrial output (Li et al., 2008). To overcome inadequate formal institutional support, they formed private networks in which reputation mechanisms ensured informal norm compliance and allowed for inter-firm lending as well as independent supply and distribution channels (see Nee and Opper, 2012, chapter 6). As a result of this development, private firms predominantly interact with other private firms and conduct significantly less business with the state sector[4].

This has important implications for Chinese export spillovers. If institutional limitations force private firms to interact mostly with each other, learning should also follow along these lines as the transmission of information crucially depends on the frequency of interaction. We summarize these ideas in hypothesis B:

Export spillovers are expected to be stronger between private Chinese manufacturers than between private and state-owned manufacturers.

Both new sources of spillover heterogeneity will be formally tested in section 4. The next section describes the different data sources used to test the relevance of export spillovers in China and gives detailed accounts of the identification strategy in use.

[4] Nee and Opper (2012) present empirical evidence of this relationship in chapter 6. Their survey data of private firms in the Yangzi delta in 2006 shows that a majority of upstream suppliers and downstream customers are also private firms.

3 Datasets and identification strategy

3.1 Empirical strategy

To identify the impact of local agglomeration on Chinese export market entry, we closely follow the work of our predecessors (Choquette and Meinen, 2015; Koenig et al., 2010; Koenig, 2009) who assume that a firm will only enter a foreign market if the export profits generated in that process are larger than zero. On the one hand, export profitability is directly related to observable gravitational forces of international trade. These comprise both conducive elements such as a company's supply capacities (e.g. productivity, number of employees) and demand factors on foreign markets (e.g. foreign purchasing power) but also inhibitory ones like trade frictions (e.g. tariffs, physical distance). On the other hand, unobserved components related to firm, region or destination characteristics also play a role. This motivates the usage of fixed effects to control for profit related, time-invariant elements. The probability that firm i enters destination market d with product p at time t is thus

$$P(y_{idpt} = 1) = \alpha * spill_{idpt} + \boldsymbol{\beta} * \boldsymbol{X}_{idpt} + \delta_{idp} + \mu_t + \varepsilon_{idpt} \tag{1}$$

In this linear probability model with fixed effects (LPM-FE), y_{idpt} is an indicator variable denoting whether a firm already exports a specific product to a destination or not. We focus on export starters which means that we limit our attention to firm-destination-product pairs which experience at least one entry over the whole sample period[5]. Export entry is explained by a spillover proxy capturing the degree of regional agglomeration of exporters, a set of controls $\boldsymbol{X}_{idpt}$ which contain firm, destination and regional covariates. Firm-destination-product fixed effects δ_{idp} are included to control for unobservable time-invariant components such as culturally induced export market propensities or product properties that could complicate its transport over longer distances whereas time fixed effects μ_t are added to control for annual transitory shocks common to all firms. Robust standard errors ε_{idpt} are clustered at the regional level (see Moulton, 1990). Note that by using firm-destination-product fixed effects, individual and interacted controls of firms, regions, destinations and products are added implicitly[6]. This is crucial for a number of identification issues that are further detailed in section 3.3. Consequently, export entry is estimated on the time variation within firm-destination-product groups.

[5] In contrast to related studies that use fixed effect logit models (Logit-FE) which require within-group variation of y_{idpt} to estimate individual constant terms, LPM-FE models do not have this requirement (Greene, 2004a). Our focus on export starters is thus not governed by the properties of the underlying model, but due to endogeneity concerns. As mentioned by Koenig (2009), we are interested in a cost reducing spillover effect that potentially triggers export entry. This requires us to differentiate between real starters and continuing exporters. Using a selected sample to perform this differentiation is preferable to the alternative of using a firm's lagged export status, as this could give rise to serial correlation. The exact coding of our dependent variable is detailed in section 3.3.

[6] As we focus on firms that remain in the same locality over the period of the sample, controlling for firm fixed effects also controls for region fixed effects.

At this point, it is important to emphasize that a LPM-FE is not the only way to estimate this relationship. In fact, the closest predecessors Koenig et al. (2010) and Choquette and Meinen (2015) instead rely on a Logit-FE to analyze the impact of export spillovers on market entry. Compared to the LPM-FE, this approach has two advantages. Firstly, it models the relationship between explanatory variables and export entry nonlinearly. This means that an additional exporting neighbor in the region can now affect a prospective starter's probability to export differently, depending on the how many exporting neighbors already operate in the region. Moreover, the additional distributional assumption ensures that fitted probabilities are bounded between 0 and 1, a property that can be violated in the LPM-FE case for extreme observations.

However, these advantages come at a cost. If the number of fixed effects is large and the time dimension of the panel short, Logit-FE models can suffer from an incidental parameter problem that may lead to inconsistent estimates (Bastos and Silva, 2012; Greene, 2004b). Simply put, this problem arises from an inconsistent estimation of fixed (incidental) parameters due to an overly short panel structure which then also contaminates estimates for parameters of interest. As this analysis uses over 200 000 individual fixed effects for a period of 7 years, using a Logit-FE may be problematic. In contrast, the LPM-FE does not suffer from this property, allows a full usage of fixed effects and delivers reasonable estimates as long as we focus on average partial effects (Bernard and Jensen, 2004; Wooldridge, 2010). Therefore, we prefer the linear model and carefully consider the limitations this decision encompasses.

3.2 Datasets

The detail of our spillover analysis naturally rests on the quality of the data at hand. In this study, we draw on two different Chinese data sets to construct our final sample. This allows us to combine informational detail of both sources but also raises some challenges, both of which are discussed below.

3.2.1 Firm-level data

The first source we employ are annual surveys of industrial firm activity that are compiled by the Chinese National Bureau of Statistics[7] (NBS). These record detailed firm-level data[8] of all Chinese companies with annual sales exceeding a minimum of around 0.6 million US Dollars per year (Manova and Yu, 2016) between 2000 and 2006. Surveys include information on financial indicators, detailed industrial and geographical codes and firm registration types[9]. These resources can not only be used to

[7] These are officially known as the "all state-owned and all above-scale non-state owned industrial enterprise data base" (Brandt et al., 2014).

[8] Subsidiaries can be defined as individual firms if they are legal entities with a distinct location and name, financially independent from the parent, create their own balance sheet and legally viable for their actions (Brandt et al., 2014). Subsidiaries which do not fulfill these requirements are reported as additional production sites. This could complicate the measurement of regional agglomeration if plants are located in different regions but only report the location of the headquarter. However, this concern is mitigated by the fact that only 10% of firms report having multiple plants.

[9] Firm ownership can directly be inferred from the recorded registration type of the entity. This study follows Brandt et al. (2012) and groups registration types into 5 different ownership groups: State-owned, hybrid, private, Hong Kong-Macao-

extract information on a firm's location and ownership form but also to construct detailed firm-level controls that are needed in the subsequent analysis. Non-manufacturing firms and irregular observations are excluded from the data to set a clear focus on manufacturing activity and limit distortions[10]. Moreover, we use concordance tables provided by Brandt et al. (2012) to accommodate a reclassification of industrial activity in 2002 and make industry codes comparable over the whole sample period. The unbalanced panel created from annual surveys[11] covers between 160 000 and 300 000 firms per year that are located in 31 Chinese provinces and operate in 424 different manufacturing industries. An important shortcoming of NBS surveys for the current analysis, however, is their limited coverage of a company's export behavior. While export sales can be used to generally differentiate between exporters and non-exporters, we do not know which products are sold to which destination. This gap is filled by our second data source which contains detailed transaction data of Chinese trade activity.

3.2.2 Transaction data

Specifically, we rely on Chinese Customs Trade Statistics (CCTS) which are compiled by the Chinese Customs Office and report monthly export transactions of Chinese firms at the 8-digit Harmonized Commodity Description and Coding System (HS). For each export entry, it reports the exporting company's name, product destination and trade regime the transaction adheres to. The latter is a unique feature of the data set and means that each product shipment leaving China is labeled as either processing or ordinary trade.

This differentiated classification relates to China's export promotion strategy described above. Firms that want to benefit from preferential policies (e.g. duty-free input sourcing) need to formally register as processing traders[12], adhere to different accounting standards and provide additional export documentation (Fernandes and Tang, 2014; Manova and Yu, 2016). Importantly, these legal requirements allow us to draw a clear dividing line between processing and ordinary traders which can be used to investigate how different trade regimes are related to export spillovers.

Further, our study follows Manova and Yu (2017) and uses annualized export transactions to reduce seasonality effects and aggregates products to the 4-digit HS level to curb the impact of outliers. Other

Taiwan owned (HMT) and other foreign ownership. Note that hybrid subsumes various mixed forms of state and private ownership to allow a clear distinction between the two.

[10] Manufacturing firms are identified by their 2-digit GBT industrial code and range from sectors 13 to 43. Irregular values of financial indicators include negative entries of output, sales, exports, capital, wages, intermediate inputs and investment which are dropped from the sample. Outliers are corrected for by winsorizing at the top and bottom percentile. Flaws in qualitative data such as miscoded industry classifications, zip codes and registration types are corrected for if possible and dropped otherwise.

[11] To create this panel, we use an adjusted version of the matching algorithm developed by Brandt et al. (2014). This program exploits different qualitative factors to trace firms across surveys. This becomes necessary, as the official firm identification number may change when a firm changes its legal form or merges with another company. The algorithm thus ensures that incumbents are not treated as new firms and thereby avoids unwanted fragmentation in the dataset.

[12] Fernandes and Tang (2014) emphasize that firms can follow both types of trade at the same time if they hold several export licenses. This reiterates the importance of working with transaction data to pay respect to the nuanced manifestations of international trade activity.

adjustments involve dropping pure trade intermediaries[13] which only serve as a bridge between domestic producers and foreign buyers and recode HS-codes to the 1992 standard to establish consistency of product classifications across years. The resulting panel covers the years 2000 to 2006 and includes between 1.3 and 4.4 million transactions of more than 1200 different products each year.

3.2.3 Matching firm and transaction data

As our analysis relies on a combination of firm and transaction level data, we need to find a common firm identifier to merge information from both sources. This proves to be very difficult. Although both sources individually include unique firm identifiers, they follow different coding systems and cannot be matched to each other. To solve this issue, we follow a method developed by Upward et al. (2013) who use company names to match the same Chinese transaction and firm level data[14].

Table 1: Matching rates of NBS and CCTS data

	NBS firms		CCTS firms	Matched firms		
year	all	exporters	all	exporters	as % of NBS exporters	as % of CCTS exporters
2000	162446	36696	61739	15853	43%	26%
2001	168567	39917	67247	18510	46%	28%
2002	181072	44802	74919	21496	48%	29%
2003	195721	50435	89569	25385	50%	28%
2004	275956	76362	118722	41485	54%	35%
2005	271312	74133	115616	40227	54%	35%
2006	301416	77944	161645	47439	61%	29%

Not surprisingly, our matching success rate is almost identical to their reported numbers. As shown in Figure 2, on average half of NBS exporters and 30% of CCTS exporters end up in the matched sample. Upward et al. (2013) relate these reduced numbers to different sampling requirements of the data sources and a supposedly high number of indirect traders in the NBS data[15]. More important than the absolute number of matched observations, however, is the question if the matching procedure significantly alters the distribution of exporters in terms of size, ownership and regional agglomeration. To address this issue, we compare unmatched and matched exporters across the three categories. Although this approach might be misleading if a considerable share of unmatched NBS exporters only engages in indirect trade, the comparison should help to evaluate the representativeness of our matched export sample.

[13] Ahn et al. (2011) describes a method to identify trade intermediaries by using key expressions in Chinese firm names that relate to sole import-export business activity.
[14] Matching via company names is by far the most efficient matching variable. Alternative procedures by Wang and Yu (2012) experiment with additional qualitative firm information such as phone numbers and zip codes. While these are not available in our transaction sample and therefore cannot be used to match the two data sets, direct comparisons between our and augmented matching procedures show that the latter on average would only have increased the number of matched firms by 5.7%.
[15] Recall that NBS surveys only include above-scale firms while CCTS also lists export activities of small enterprises. The term "indirect traders" refers to firms that rely on intermediaries to sell their products on foreign markets.

Similar to Upward et al. (2013), we find that matched exporters are slightly larger than unmatched ones. Specifically, matched exporters have 23% higher export sales, 7.3% more employees and achieve 6.6% higher total sales. We believe these numbers are within an acceptable range and relate differences to the presence of indirect traders in the NBS data. Secondly, the distribution of ownership types also differs slightly between the samples. As shown in Figure 3, private ownership is slightly more dominant in the matched sample[16]. While this will not affect general spillover tests, it may introduce a small bias when investigating private export entry. We take this fact into consideration and address it with additional robustness tests.

Table 2: Ownership distribution

	domestic exporters	
type	unmatched	matched
state owned	8.98%	12.12%
hybrid	21.34%	14.25%
private	69.68%	73.64%

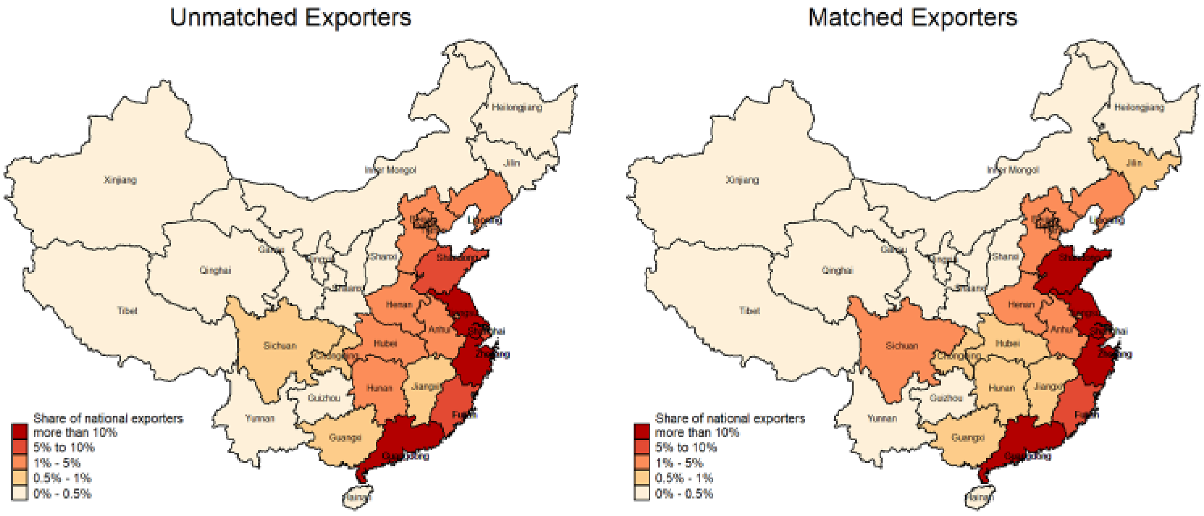


Figure 2: Geographical distribution of exporters

Finally, we look at the regional dispersion of exporters across samples. This comparison is by far the most important one, as matching-related changes in regional agglomeration affect all spillover measures. We plot the regional distribution of matched and unmatched exporters in Figure 2. While minor deviations can be observed, the overall pattern of strong concentration in coastal regions and decreasing exporter presence in inland provinces is common to both. We therefore infer that our matching procedure delivers a rather representative picture of China's exporting sector and move on to the description of relevant variables.

3.3 Variables and estimation issues

To investigate the impact of local agglomeration on the extensive margin of trade, we rely on the LPM described in equation 1. Our dependent variable export starts are modeled via a dummy variable. It takes

[16] The percentages are calculated as the average of annual ownership shares of matched and unmatched exporters.

the value 1 if firm i starts exporting product p to destination d in year t but has not done so during the two preceding years and 0 if it does not export. Restarts that do not follow at least two periods of exporting inactivity are coded as missing to ensure that the value of remaining experience from past exporting has decayed to a degree that necessitates a re-accumulation of relevant market information[17]. As stated above, we limit our attention to firm-destination-product combinations which experience at least one export start between 2000 and 2006 that fulfills these requirements. Non-starters, continuing exporters and exiting combinations are dropped from the sample. Our final sample includes more than 680 000 export starts of 1172 different products in 177 different countries.

The spillover variable we want to explain these entries with benefits substantially from the detailed geographical information provided in the matched sample. Specifically, we exploit the hierarchical structure of Chinese zip codes[18] and form spillover proxies by counting the number of neighboring exporters[19] at the provincial, municipal and county level. This fine regional disaggregation is crucial for our analysis as previous evidence from France suggests that export spillovers can be subject to spatial decay (Koenig et al., 2010). Therefore, we will focus on the most detailed geographical unit in our sample and measure export agglomeration at the county level. On average, there are 1151 different counties in our final sample and each is home to 188 different exporters. Next to this fine geographical disaggregation, we further divide our spillover proxies into four different categories to assess if export entry is facilitated by the general presence of exporters in the county, or by neighbors exporting to the same destination, shipping the same product (4-digit HS code) or do both. The four spillover proxies therefore separately measure the impact of general, destination, product and product-destination specific agglomeration on export entry.

Apart from local agglomeration effects, export market entry is also driven by firm, destination and region characteristics which need to be accounted for. At the firm level, previous theoretical and empirical work has shown that a company's productivity, size and wage structure are strong predictors of the decision to enter foreign markets (Bernard and Jensen, 1999; Melitz, 2003). Further, Melitz and Ottaviano (2008) emphasize that selection into densely populated areas may also be driven by

[17] If companies still hold information that can help them to (re)enter foreign markets, they are less dependent on export spillovers and expected to behave differently from real starters. Note that this restriction also excludes all fresh starters that enter before 2002 as the time frame of the panel does not suffice to ensure the two period non-exporting requirement.

[18] Chinese zip codes consist of 6 digits of which the first two refer to provinces, the third to the municipality and the forth the county the postal station is located in. To establish consistency over time, we compared zip code entries in our database with official recordings listed on the China Post website. While this procedure accommodates several zip code changes that happened due to mergers of multiple regions into one or the creation of new areas, we acknowledge that there may still be changes that remain unaccounted for.

[19] While most studies proxy export spillovers by counting the number of exporting neighbors in each region, other approaches to capture local agglomeration do exist. The most prominent alternative uses the local workforce employed in exporting companies (Henderson, 2003). This measure gives greater weight to the presence of larger neighbors instead of weighting all of them equally. While it might have been interesting to compare findings from different spillover proxies, the alternative is not feasible with the data sources at hand. While the number of exporting neighbors can directly be inferred from the CCTS data, the alternative measure would require employment data for all CCTS exporters. As we can only match a fraction of them to the NBS panel, employment-based spillover proxies may not be representative. To avoid this additional burden, we rely on simple neighbor counts.

productivity. Not controlling for this fact could bias our spillover estimates if export entry in dense areas is accounted to local agglomeration but ultimately driven by competitive pressure exerted by highly productive neighbors (Choquette and Meinen, 2015). We employ a value-added production function approach to estimate firm productivity as described by Levinsohn and Petrin (2003)[20]. This procedure accounts for additional sources of endogeneity that often contaminate productivity estimates based on ordinary least squares (OLS) approaches[21]. Firm size and wages, on the other hand, are proxied by the number of employees and the company's average labor expenses.

Furthermore, we add regional controls to our estimation which serves two purposes. Firstly, our firm-destination-product fixed effect triad does not control for time variant forces that may be related to export entry. Instead, these influences need to be captured separately which is why we include county population[22] as an additional control. Secondly, regional controls help to filter out other agglomeration effects that may arise at the same time but are not related to the information spillovers. Examples are regional competition and urbanization effects. While both could increase export entry by forcing prospective starters to become more productive, they are less related to the information transfers this study focuses on (Choquette and Meinen, 2015). Therefore, we control for regional competition by the total number of firms operating in the county and use an industrial agglomeration proxy suggested by (Aitken et al., 1997) to separate urbanization effects[23] from information related export spillovers.

Moreover, we include two destination controls to capture changes in foreign demand and purchasing power that may induce prospective starters to sell to these markets. An increase in foreign demand gives rise to opposing effects for export entry. It either represents higher market opportunity and is thus conducive to entry or discourages firms from entering as higher market potential also attracts a larger number of competitors which drives down mark-ups and limits export profitability (Melitz and Ottaviano, 2008). We use the BACI dataset compiled by Gaulier and Zignago (2010) to proxy destination-specific export demand at the 4-digit HS product level. Purchasing power, on the other, is included to control for changes in comparative advantage (Choquette and Meinen, 2015) and proxied

[20] We draw on the full NBS panel and follow Brandt et al. (2014) to construct the components needed to estimate firm productivity. This includes an alternative measure of value added, a corrected real capital stock and detailed industry and investment deflators, all of which are developed by the same authors. For details on this procedure we refer to their original paper and programs provided in their online appendix.

[21] The baseline approach to estimate firm productivity is to regress output on capital, labor and intermediate inputs via OLS and use the residual as an estimate of productivity. One main identification issue of this approach is that firms can react to unobserved productivity shocks by adjusting their input usage which is not observed by the econometrician and results in a violation of the exogeneity assumption imposed by the OLS procedure (Griliches and Mairesse, 1995). The method developed by Levinsohn and Petrin (2003) avoids this simultaneity bias and is therefore expected to deliver more reliable estimates than simple OLS calculations.

[22] We use the full NBS panel to proxy regional population by calculating the total number of employees at the county level.

[23] Urbanization effects relate to synergetic forces that may arise in industrial clusters and increase the productivity of firms operating within them. Examples are scale effects, input sharing or a specialized labor pool. The industrial agglomeration proxy used to capture these factors is calculated as the region-industry (2-digit GBT) share of total industrial output which is normalized by the regions total share of manufacturing output to account for the size of the region.

by exchange rate movements of Chinese Renminbi and destination currencies[24] which we take from the EQCHANGE database created by Couharde et al. (2017). Summary statistics of all variables used in the analysis are included at the end of this section.

We complement these control variables with a comprehensive set of fixed effects to account for time-invariant, unobserved factors that are related to export entry. As stated above, firm-destination-product fixed effect triads are crucial components of our identification strategy and subsume individual controls for unobserved firm, region, destination and product characteristics.

Firm fixed effects account for firm-specific time-invariant differences that enable them to enter foreign markets. This comprises both formal qualities related to a company's efficiency (e.g. experience of employees) or informal factors that grant them advantages compared to others[25]. Region fixed effects account for general differences in geography (e.g. topography, access to sea) and infrastructure across counties which otherwise drive the accumulation of exporters in certain areas. Moreover, they factor in time-invariant differences in regional policy (e.g. local export promotion programs) that may be responsible for export clustering in specific locations. Destination fixed effects account for trade related gravitational forces such as distance to the trading partner while product fixed effects consider differences in the ease of trade related to a good's size, weight or transport regulations. Notably, interacted fixed effects are also included in the triad. Examples are firm-destination fixed effects which control for factors granting a firm additional knowledge about a specific destination through a high share of foreign employment or direct investment from that country (Choquette and Meinen, 2015) and region-destination pairs which account for special trade connection between a county and foreign markets due to a shared border or historically developed trade relationship (Fernandes and Tang, 2014). Finally, we include time fixed effects to filter out broad shocks affecting all economic activity in China such as business cycle movements or upswings resulting from a deeper market liberalization.

While fixed effects are an important addition to our estimation that accounts for various sources of unobserved heterogeneity, we further need to address two central identification issues before proceeding to spillover measurements.

3.4 Identification issues

Firstly, our current specification (equation 1) may suffer from a reverse causality problem. As shown by Bernard and Jensen (1999), the firm controls we added earlier not only act as determinants of export entry but themselves change in reaction to the firm's export decision. This demonstrates that the causality can run in both directions if firm controls and the export indicator enter the estimation

[24] We calculate annual exchange rates as Chinese over foreign currency. Exchange rate increases thus represent a relative strengthening of foreign currency which is expected to induce more export entry.

[25] An example are personal relationships between company employees and custom officials. Companies with strong ties could for example be informed earlier about upcoming regulatory changes which grants them a natural advantage compared to unconnected competitors.

contemporaneously. Similarly, receivers of export spillovers in one period become emitters of information the moment they enter foreign markets. Hence, if our spillover proxy enters the estimation equation at the same time as the entry indicator, the causal relationship is again bidirectional (Koenig et al., 2010). Fortunately, these reverse causality concerns can easily be avoided if firm and spillover variables are lagged one period (Bernard and Jensen, 2004). This adjustment also helps to solve a simultaneity bias that arises from the interdependency of prospective starters and their neighbors. Both react to each other's export performance and are thus affected by the same unobserved supply and demand shocks they encounter (Koenig et al., 2010).

We incorporate these corrections in estimation equation 2 and lag all spillover proxies and firm controls by one period. Further, we follow earlier studies and transform some continuous variables into logarithms to establish comparability and facilitate the interpretation of partial effects[26]. The final estimation equation used in the subsequent regression analysis is thus

$$\begin{aligned} P(y_{idpt}=1) = \quad & \alpha * spill_{idpt-1} + \beta_1 * \log TFP_{idpt-1} + \beta_2 * \log employment_{idpt-1} + \beta_3 \log wages_{idpt-1} \\ & + \beta_4 * regional\ firms_{idpt} + \beta_5 * industrial\ agglomeration_{idpt} + \beta_6 * \log population_{idpt} \\ & + \beta_7 * \log foreign\ demand_{idpt} + \ \beta_8 * exchange\ rate_{idpt} + \delta_{idp} + \mu_t + \varepsilon_{idpt} \end{aligned} \tag{2}$$

3.5 Descriptive statistics

Before turning to our results, we present summary statistics of all variables used in the analysis in Table 3 and take a closer look at the distribution of export starts and spillover proxies. As depicted in Figure 3, foreign market entry of Chinese products is clearly driven by gravitational forces of international trade. New destinations are predominantly located in high income economies whose large market size attracts international trade flows or neighboring markets which promise an increased customer base at moderate transportation costs. The largest product groups shipped to new destinations are textiles and electrical machinery and equipment.

The regional dispersion of export transactions in China, on the other hand, closely resembles the overall distribution of exporters. As seen in Figure 4, most product starts occur in coastal regions while central and western provinces experience fewer international product entries. Interestingly, a comparison of total and domestic export entry reveals that export starts are slightly less concentrated among native companies. This fact may be related to the historical agglomeration of foreign companies in coastal regions and would explain the disproportionate share of foreign product starts in these areas. Our study

[26] As done by Koenig et al. (2010) and Choquette and Meinen (2015), we use logarithms of firm productivity, size, wages, regional population and foreign demand.

will focus on domestic export entrants and therefore rely on a more evenly distributed group of transactions portrayed on the right panel[27].

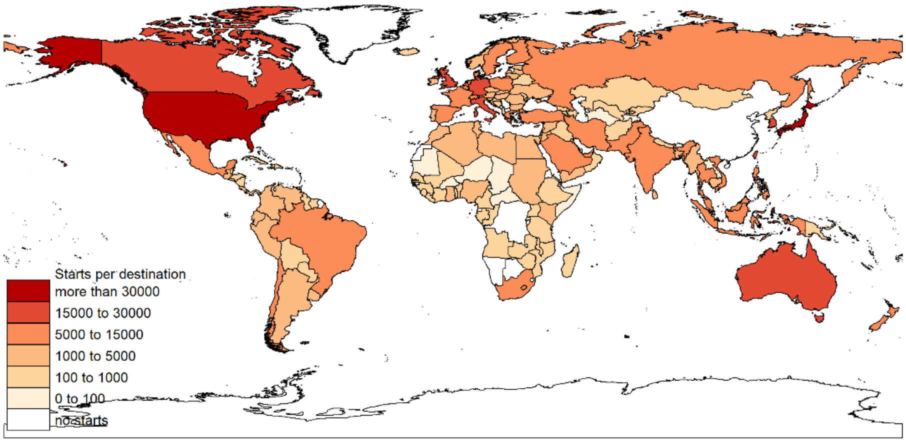
Turning to the distribution of spillover variables depicted in Table 4, a couple of interesting observations emerge. At the low end, the chance of having no exporting neighbors operating within the same county increases in the specificity of the spillover proxy. Absence of general export agglomeration in the region only applies to 0.8% of observations while product-destination specific neighbors are non-existent in 75.9% of the cases. Reversely, the likelihood of being subject to strong export agglomeration (more than 20 exporting neighbors) decreases in neighbor specificity. At both extremes, these observations create an ordering of spillover proxies from common to rare, with agglomeration decreasing from general to destination, product and product-destination specific spillovers.

Table 3: Summary statistics

	Number of observations	Mean	SD	Min	Max
Spillover variables (t-1)					
General	2,187,970	187.22	187.10	0	1490.00
Destination-specific	2,187,970	45.96	77.11	0	1277.00
Product-specific	2,187,970	9.29	21.74	0	340.00
Product-destination specific	2,187,970	1.33	5.41	0	236.00
Firm controls (t-1)					
Total Factor Productivity (log)	2,187,970	6.03	1.07	0.03	11.62
Employment	2,187,970	752.95	1709.86	8	47114
Wages	2,187,970	15.33	15.11	1.00	1012.41
Regional controls					
Number of firms	2,187,970	781.24	669.34	1	3761.00
Industrial agglomeration	2,187,970	3.45	4.93	0	148.14
Population	2,187,970	190.26	200.59	0	1844
Destination controls					
Foreign demand	2,187,970	0.11	0.49	0	33.90
exchange rate	2,187,970	1.29	15.85	0	1618.80

Note: The statistics presented in this table are based on the benchmark estimates depicted in Table 5. Average wages are depicted in thousand CNY, regional population in thousand inhabitants and foreign demand in million US$.

[27] Within the group of domestic firms, processing export starts are more concentrated in coastal regions than ordinary trade activity (see appendix A1). This could be related to their lower profitability (Dai et al., 2016) which forces them to reduce variable trade costs and locate closer to transportation hubs.



Largest destinations	
Japan	8.07%
United States	6.99%
Hong Kong	4.86%
South Korea	4.36%
Taiwan	4.00%
Germany	3.60%
United Kingdom	2.82%
Australia	2.51%
Canada	2.49%
Italy	2.38%

Figure 3: Global distribution of export starts

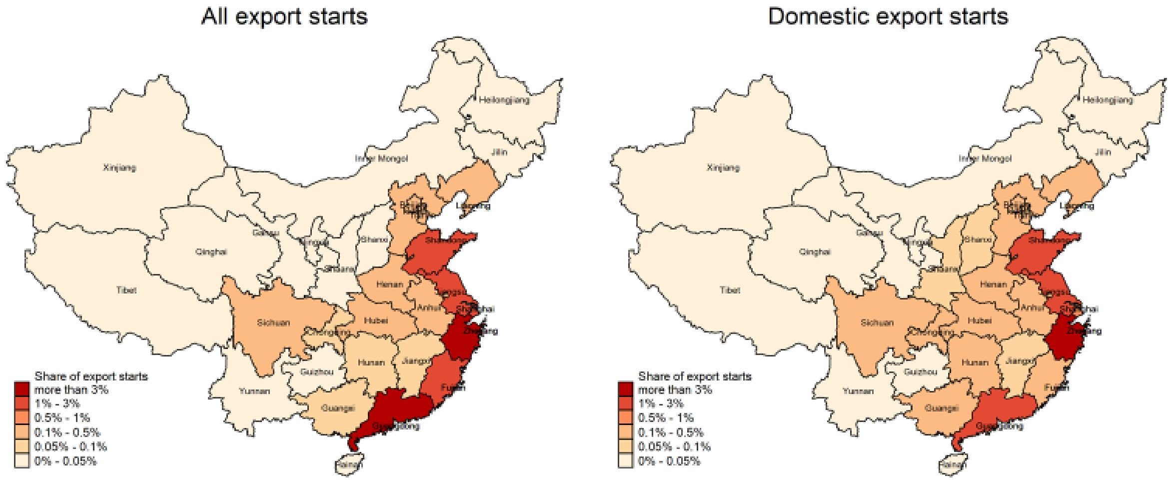


Figure 4: Regional distribution of export starts in China

Table 4: Distribution of spillover variables

	# of other exporters in county			
	all products - all destinations	all products - same destination	all destinations - same product	same destination - same product
0	0.8%	10.9%	32.4%	75.9%
1	0.7%	4.3%	11.5%	8.3%
2 - 5	2.2%	11.9%	21.8%	9.7%
6 - 10	2.3%	10.0%	12.0%	3.0%
10 - 20	4.3%	13.5%	10.6%	1.8%
> 20	89.7%	49.4%	11.7%	1.2%
observations:	2,187,970			

4 Results

As conceptualized by the stylized model in section 2, occurrence and relevance of export spillovers rest on the influence of starter characteristics, neighbor capacities and factors altering the connection between the two. Our regression analysis draws on this structure and is divided into three stages. Firstly, we are interested in the overall outcome of the transmission process and investigate the general presence of export spillovers in China. Secondly, we address the micro-foundations of the transmission process to examine if the relevance of spillovers is altered when looking at different starters, neighbors and forces tieing them together. Lastly, we address the China-specific influences of the transmission process and analyze the impact of trade regimes and ownership distortions for the extensive margin of trade.

4.1 Baseline estimation

To assess the general relevance of export spillovers in China, we first run the baseline model 2 on the full (columns 1-4) and domestic (columns 5-8) set of firm-destination-product combinations that experience at least one export start between 2000 and 2006. The results are presented in Table 5. Our main variables of interest are the four spillover proxies which pertain to different types of regional export agglomeration. Each of them enters the estimation equation individually to investigate if neighboring exporters indeed act as conduits of market related information transmission and which form of local exporting presence possesses the highest potential to induce others to export as well.

A first comparison of exporting proxies in columns 1-4 reveals an interesting pattern. On the one hand, general export agglomeration does not facilitate export entry but instead seems to impede firms from taking their product lines to global markets. On the other hand, neighboring exporters do seem to facilitate export entry the closer their export operations match those of prospective starters. In other words, export entry is only fueled by increases in specific export agglomeration at the county level. This sensitive ordering is magnified when looking at the subset of domestic export starters (columns 5-8) that we focus on in this study. The catalyzing character of neighboring export presence is statistically significant at the 1% level and strongest for product-destination specific spillovers. Having five (one standard deviation) additional neighbors that export the same product to the same destination market on average increases the probability of export entry by 1.6%. This impact is economically significant and underlines the relevance of export spillovers for the extensive margin of trade.

Further, the ordering of spillover coefficients suggests that this synergetic relationship rather works through a cost than a productivity channel[28]. This emphasizes the importance of a differentiated

[28] If technological spillovers drove export entry, we would expect a positive coefficient of general agglomeration proxies as the overall presence of highly productive exporting neighbors presents the largest source of learning. In contrast, the significance of product-destination proxies shows that only the presence of very similar neighbors induces entry which indicates that the conducive effect originates in market-specific information transfers rather than a general diffusion of technological knowledge.

Table 5: Baseline regression

	All starters				Domestic starters			
	General	*Destination - specific*	*Product - specific*	*Destination - product - specific*	*General*	*Destination - specific*	*Product - specific*	*Destination - product - specific*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products - all destinations	-0.000107***				-1.78e-05			
	(4.10e-05)				(4.07e-05)			
all products - same destination		8.99e-05				7.22e-05		
		(0.000197)				(0.000159)		
same product - all destination			0.000294				0.000753***	
			(0.000316)				(0.000212)	
same product - same destinations				0.00244***				0.00325***
				(0.000644)				(0.000666)
Firm controls (t-1)								
Log TFP	0.00738***	0.00735***	0.00733***	0.00737***	0.00761	0.00767*	0.00763	0.00773*
	(0.00224)	(0.00224)	(0.00223)	(0.00224)	(0.00466)	(0.00466)	(0.00466)	(0.00466)
Log employment	0.0188***	0.0185***	0.0184***	0.0186***	0.0228***	0.0227***	0.0227***	0.0231***
	(0.00407)	(0.00409)	(0.00410)	(0.00411)	(0.00609)	(0.00608)	(0.00605)	(0.00605)
Log wages	0.0174***	0.0173***	0.0173***	0.0173***	0.0179***	0.0179***	0.0179***	0.0180***
	(0.00325)	(0.00327)	(0.00326)	(0.00326)	(0.00546)	(0.00543)	(0.00541)	(0.00541)
Regional controls								
firms in region	3.05e-05*	1.76e-05	1.83e-05	1.82e-05	1.98e-05	1.64e-05	1.08e-05	1.40e-05
	(1.59e-05)	(1.74e-05)	(1.50e-05)	(1.45e-05)	(1.45e-05)	(1.47e-05)	(1.42e-05)	(1.45e-05)
industrial agglomeration	0.000348	0.000337	0.000301	0.000274	-0.00162	-0.00163	-0.00175	-0.00174
	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00256)	(0.00256)	(0.00254)	(0.00255)
Log population	-0.00233	-0.00508	-0.00502	-0.00492	-0.0801**	-0.0808**	-0.0812**	-0.0805**
	(0.0202)	(0.0204)	(0.0205)	(0.0205)	(0.0340)	(0.0340)	(0.0339)	(0.0339)
Destination controls								
Log foreign demand	0.00597***	0.00610***	0.00597***	0.00615***	0.00380**	0.00385**	0.00384**	0.00406**
	(0.00111)	(0.00112)	(0.00109)	(0.00109)	(0.00175)	(0.00173)	(0.00173)	(0.00173)
Exchange rate	0.000106***	0.000105***	0.000107***	0.000105***	9.82e-05***	9.76e-05***	9.95e-05***	9.66e-05***
	(2.48e-05)	(2.37e-05)	(2.49e-05)	(2.46e-05)	(3.26e-05)	(3.18e-05)	(3.29e-05)	(3.25e-05)
Observations	2,187,970	2,187,970	2,187,970	2,187,970	823,126	823,126	823,126	823,126
R-squared	0.616	0.616	0.616	0.616	0.631	0.631	0.631	0.631
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm-destination-product and year fixed effects and follow variants of the baseline equation (2).

treatment of local agglomeration effects. Disagreement in earlier studies may result from an aggregation of opposing influences of general and specific spillover effects if data sources did not allow a separation of the two. The picture we observe in China seems to support the relevance of product-destination specific export spillovers and reaffirms similar evidence of recent studies at the transaction level (Koenig et al., 2010; Poncet and Mayneris, 2013).

Although export spillovers do seem to play a role for the extensive margin of trade, firm indicators still account for a much larger share of entry variation and retain a dominant role in predicting export entry.

Regional controls, on the other hand, only have a limited impact[29] on the decision to sell abroad once time-invariant regional influences are accounted for by fixed effects. This is not the case for destination controls. Despite controlling for destination fixed effects, both increases in foreign import demand and foreign currency strength raise the probability of selling to these markets significantly. Accounting for time-variant influences on foreign product demand therefore appears to be a crucial component of our estimation procedure.

4.1.1 Baseline robustness

To test the robustness of our baseline findings, we explore three alternatives to the standard approach taken above which are portrayed in appendix B1. First, we use redefined spillover proxies that measure local export agglomeration at the (2-digit) industry level. Compared to our original variables, these alternatives take a much broader perspective and implicitly test if intra-sectoral information transfers can promote export entry of any product under the same industry label. As very different products might end up in the same sectoral classification, export spillovers are expected to be much weaker than our baseline estimates. The results depicted in columns 1-4 support that notion. While the general ordering from general to specific is preserved, destination-industry specific neighbor presence has a much weaker effect on export entry both economically and statistically when compared to the product counterpart. This emphasizes that entry conducive information transfers indeed need to be specific to the product in perspective for spillovers to become effective.

Next, we employ an alternative productivity measure developed by Ackerberg et al. (2015). Compared to the control used in the baseline model, their method additionally avoids a collinearity issue which could exacerbate the productivity identification approach taken by Levinsohn and Petrin (2003). While a re-estimation of the LPM shows that this alternative productivity measure is a significant determinant of domestic export entry, spillover proxies remain unchanged. Moreover, we exclude export starts to Hong Kong, Macao and Taiwan. These targets represent typical re-export locations from which products are ultimately shipped to other foreign markets. They may therefore rather serve as intermediary trade hubs than traditional sales markets and bias spillover estimates (Fernandes and Tang, 2014). Reassuringly, excluding these destinations does not alter spillover coefficients.

Lastly, we explore an alternative hypothesis that could also drive our observed findings. As explained by Choquette and Meinen (2015), the observed similarities in starter and neighbor export behavior may reflect a shared reaction to changes in local and foreign comparative advantage. While time-invariant factors of regions and destinations are already accounted for by our fixed effect triad, some areas might develop strong export promoting institutions over time or destination markets may lose or gain attraction

[29] As noted by Choquette and Meinen (2015), the impact of regional population on export entry is ambiguous. From a production perspective, a large local pool of qualified workers can help firms to build up the capacity to sell abroad. From a consumption side, having a larger local market makes exporting relatively less attractive. The negative net effect of regional population suggests that consumption effects dominate production effects in China.

for exporters dynamically. To control for these factors, we add linear time trends of regions and destinations. As seen in columns 13-16, our results remain unchanged when including these additional controls.

Together, these tests confirm the qualitative picture drawn by our baseline estimation. Export spillovers do seem to induce export entry, provided local agglomeration structures match the specific product-destination mix of prospective starters. While this initial result is important, it only reflects the overall impact of export spillovers on Chinese export entry. It thus aggregates over various sources of spillover heterogeneity that arise at each stage of the transmission process. To see how these subchannels contribute to the overall results presented above, we follow the structure of our stylized model and examine how starters, neighbors and the connection between the two influence the spillover transmission in China.

4.2 Sources of spillover heterogeneity

4.2.1 Starter characteristics

To begin with, we rerun the analysis for different starter subgroups. Each of them highlights a particular channel that may facilitate or hamper the transmission of spillovers. To remain concise, we limit our focus to product-destination specific spillovers as these show the largest synergetic potential in our initial findings[30]. Results are depicted in Table 6.

The first channel we need to consider is a starter's previous export experience. Although our dependent variable ensures that firm-destination-product combinations have not been exported by a firm for at least 2 years, companies typically sell multiple products to foreign markets and may have accumulated relevant export knowledge from these activities. The more knowledge about destination markets or product regulations they already possess, the less they need to rely on their local export community.

We investigate this channel by looking at four different starter subsamples. In column 1 and 2, we limit attention to firm-destination-product (fdp) starts of entrants that have no export experience at the firm and product level whatsoever. As expected, export spillovers are larger than the benchmark estimate (Table 5, column 8) which suggests that unexperienced starters may benefit more from local knowledge than experienced ones. Explicitly controlling for previous product and destination experience of starters (columns 3 and 4) supports that claim. Having sold the same product to a different destination or having penetrated the foreign market with other products in the past increases the chances of export entry significantly[31] but leaves the impact of spillovers largely unchanged. Export experience is thus a

[30] More detailed tables including all spillover proxies can be found in appendix B2.
[31] Experience controls count the number of previous destinations (product experience) and products (destination experience) respectively.

Table 6: Starter characteristics

	Starter experience				Absorptive capacity	
	Fresh firm start	*Fresh product start*	*Product expertise*	*Destination expertise*	*low TFP*	*high TFP*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Spillover variables (t-1)						
same product - same destinations	0.00393***	0.00509***	0.00261***	0.00334***	0.00235**	0.00387***
	(0.000963)	(0.00114)	(0.000636)	(0.000655)	(0.000938)	(0.000925)
Experience controls (t-1)						
product experience			0.00890***			
			(0.000624)			
destination experience				0.0157***		
				(0.00201)		
Observations	138,789	331,275	823,126	823,126	326,545	404,128
R-squared	0.695	0.645	0.637	0.634	0.642	0.657
Control variables	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

cont. Table 6 : Starter characteristics

	Firm size		Export intensity		Multiproduct influence	
	< median employment	*>= median employment*	*< 5% exports*	*>= 5% exports*	*core product start*	*other product start*
	(7)	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Spillover variables (t-1)						
same product - same destinations	0.00235**	0.00376***	0.00269***	0.00438***	0.00267***	0.00446***
	(0.000938)	(0.000840)	(0.000489)	(0.000910)	(0.00101)	(0.000729)
Observations	326,545	439,855	98,145	475,762	224,372	582410
R-squared	0.642	0.606	0.662	0.636	0.645	0.638
Control variables	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

meaningful complement to our estimation without rendering the influence of local information transfers ineffective.

Next, we divide firms into above and below median productivity groups to proxy for the impact of absorptive capacity. As explained above, spillovers from highly productive exporting neighbors may be facilitated if the efficiency gap between receiver and emitter of information is narrow (Poncet and Waldemar, 2015). Our findings in columns 5 and 6 mirror this property but still attribute a sizeable influence of spillover effects to the low productivity group of starters.

Similar patterns can be observed when comparing firms of different size and export intensity (columns 7-10). Larger employers and export intensive companies[32] show slightly stronger responses to local agglomeration than the benchmark while their counterparts' reaction is weaker but still considerable.

Lastly, we compare how spillovers are affected by the products' relationship to the company's area of expertise. Firms that produce multiple different products at the same time are often better at producing some than others. Efficiently produced core products directly relate to the company's strengths while others do not (Eckel and Neary, 2010). This differentiation is important for spillovers. A company that wants to start exporting a core product will have a lot of expertise in that field which likely includes knowledge about foreign competition and markets. Core product launches should thus require less learning from neighbors than other product starts. We investigate this assertion by dividing fdp starts into core launches and other launches[33] and find that spillovers indeed appear to be more conducive for non-core launches. However, the facilitating character of local agglomeration for export entry is present in both cases.

In summary, starter heterogeneity does have the potential to mildly scale export spillovers up or down but does not seem to change the overall relevance of spillovers.

4.2.2 Neighbor characteristics

At the emitting end of the transmission process, we limit our attention to neighbors' export experience[34]. Neighbors are divided into new and experienced exporters for two purposes. From an empirical point of view, it is not clear which of the two groups is the more relevant information source for ongoing exporters. On the one hand, scholars like Greenaway and Kneller (2008) argue that entry related knowledge may decay over time and therefore stress the importance of newly exporting neighbors in the region. On the other, experienced exporters had more time to familiarize themselves with complex regulatory procedures of international trade and are thus more knowledgeable in absolute terms. A direct comparison of both groups therefore promises to shed some light on this empirical problem. Secondly, this separation addresses an important identification issue that could threaten the reliability of our spillover estimates. If export entry is solely driven by the presence of newly exporting neighbors, this could rather reflect the result of contemporaneous shocks in foreign demand or local policy than a transmission of relevant information (Greenaway and Kneller, 2008).

[32] Large employers are companies with above median employment numbers. Export intensity is defined according to Mayer and Ottaviano (2008). Firms which obtain a minimum of 5% from total sales from exporting are labeled as export intensive.

[33] We use concordance tables provided by Brandt et al. (2017) to translate HS4 product classifications into 4-digit GBT industrial codes. As industry codes are typically assigned according to the firm's main line of business, we assume that products that adhere to the company's industrial classification are core products.

[34] A differentiation of exporting neighbors along financial indicators is problematic, as our sample only provides detailed records for matched exporters. Other qualitative influences like trade type and ownership will be discussed in the third stage.

To answer both questions, we follow Choquette and Meinen (2015) and label firms which have been exporting for at least three consecutive periods as experienced, while those that started in the last or the current period as new[35]. The results are depicted in Table 7 and show that export spillovers from experienced neighbors are significantly stronger. This emphasizes that knowledge accumulation is much more important than the recency of emitted information and mitigates concerns that our results are driven by contemporaneous shocks.

Table 7: Neighbor characteristics

	experienced neighbors				*newly exporting neighbors*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products - all destinations	-3.67e-05 (9.44e-05)				-5.94e-05 (4.41e-05)			
all products - same destination		0.000376 (0.000294)				-9.65e-05 (0.000152)		
same product - all destination			0.00136*** (0.000179)				0.000533* (0.000311)	
same product - same destinations				0.00698*** (0.00102)				0.00216** (0.000882)
Observations	362,414	362,414	362,414	362,414	362,414	362,414	362,414	362,414
R-squared	0.727	0.727	0.727	0.727	0.727	0.727	0.727	0.727
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects as specified in our baseline model.

4.2.3 Connection influences

Apart from starter and neighbor characteristics, factors connecting emitters and receivers of information transfers also need to be considered. We focus on spatial proximity to evaluate if a smaller geographical distance to exporting neighbors indeed implies larger spillovers due to the increased interaction of both parties. While the exact distance between two firms is not easily available in our sample, we can exploit the hierarchical structure Chinese zip codes to differentiate between neighbors within the same province, municipality or county. We use this information to create two different spillover measures that account for exporter agglomeration at different geographical layers. In our first approach we simply repeat the standard spillover calculation, count the number of all exporting neighbors at each level and test which type of spatial agglomeration has the most conducive impact on export entry. We again limit our attention to product-destination specific spillovers, but report results for all spillover proxies in appendix B3.

[35] This implies that we only consider export starts that occur after 2002. To ensure that our sample includes experienced and new exporters, observations from 2000 and 2001 need to be dropped due to the time requirement of the experience label. Moreover, starts occurring in 2002 are dropped as spillover proxies are lagged one period.

Results for this initial regional disaggregation are reported in columns 1-3 of Table 8. A direct comparison of coefficients reveals that the influence of export agglomeration decreases in distance from the starter. The spillover effect from having an additional exporting neighbor with matching product and destination characteristics in the same county is roughly three times more effective than adding a similar neighbor somewhere in the province.

To further investigate this pattern, we repeat the analysis with a set of alternative spillover proxies. Whereas standard proxies of provincial, municipal and county agglomeration had to be tested individually to avoid double counting of neighbors in higher geographical categories, alternative measures avoid this issue by subtracting the number of exporters in the lower level. The resulting mutual exclusivity of proxies allows to include all geographical measures simultaneously. Estimates of this alternative approach also locate the largest spillover potential at the county level but in contrast to standard measures do not find any stimulating effect of agglomeration further away from the target. The impact of spillovers therefore not only depends on the specificity of the information contained or varies with different characteristics of actors involved in the process but is also subject to strong spatial decay.

Table 8: Spatial decay

	Same product - same destination (t-1)			
	normal spillover proxies			*alternative spillover proxies*
	(1)	*(2)*	*(3)*	*(4)*
Geographical level				
Province	0.00101***			0.000554
	(0.000185)			(0.000361)
Municipality		0.00209***		9.39e-05
		(0.000663)		(0.000721)
County			0.00325***	0.00292***
			(0.000666)	(0.000574)
Observations	823,126	823,126	823,126	823,126
R-squared	0.631	0.631	0.631	0.631
Control variables	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects and portray estimates of product-destination specific spillovers at different geographical levels. Regional controls and clustered standard errors in columns 1-3 adhere to the respective regional level in use. In column 4, alternatively specified spillovers are used which mutually exclude the lower or upper geographical levels and can therefore be used simultaneously.

4.3 Spillover transmission with Chinese characteristics

4.3.1 Trade regimes

Although the promotion of processing trade in China mainly intended to accelerate the country's integration into global value chains, the subsequent surge of processing activity also may have implications for inter-firm learning. Processing traders are distinctly less integrated in local economic structures than ordinary traders and their export behavior may largely depend on the strategy of their foreign partner (Fernandes and Tang, 2015). We test how these differences influence export spillovers by comparing ordinary and processing traders in their roles as receivers (starters) and emitters (neighbors) of market-specific information transfers.

To differentiate between trade regimes, we exploit detailed recordings in our sample and divide transactions into ordinary (OT), processing with imports (PI) and pure assembly (PA) trade. The latter two describe distinct forms of processors which operate at different modes of autonomy. While PI traders still make independent sourcing decisions and can choose where to import inputs from, PA traders receive all inputs from the foreign contractor and only assemble them into final products (Manova and Yu, 2016). Among processors, PI traders are thus expected to be slightly more receptive to export spillovers and represent larger sources of learning for others as their contact with foreign (input) markets should grant them additional absorptive capacity and experience.

To test for trade regime influences on spillover uptake and emission, we disaggregate starters and neighbors into OT, PI and PA traders. Each spillover proxy therefore has three versions which each account for the share of trade regime specific export agglomeration in the county. As before, we focus on product-destination specific spillovers (Table 9) but list the full set of proxies in Appendix B4. To address the concern that certain goods might be exclusively produced within one trade regime, we complement the disaggregated set of standard proxies (columns 1-3) with an alternative that focuses on fdp starts which have at least one matching neighbor in the same county that belongs to a different trade regime (columns 4-6).

We begin with a column-wise reading of Table 9 to compare the relevance of spillovers for different export starters. Among all entrants, OT and PI traders show the most consistent reaction to neighboring export agglomeration, followed by mild benefits for PI and hardly any for PA starters. As expected, the more independent the firm operates, the more it benefits from nearby sources of knowledge when deciding to sell abroad. Interestingly, this order changes when considering different neighbor types by reading the table row-wise. OT and PA neighbors seem to facilitate export entry while presence of PI traders impedes it. Whereas the conducive effect of OT neighbors is intuitive, we would have expected to see more spillovers from PI than PA presence. Nevertheless, this broad comparison of ordinary and processing trade regimes does lend support to our hypotheses A1 and A2. Overall, OT entrants do seem

Table 9: Trade regimes

	same product - same destiantion			>=1 product-destination specific neighbor of other trade regime in county		
Starter type	*ordinary*	*processing w. imp.*	*pure assembly*	*ordinary*	*processing w. imp.*	*pure assembly*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Neighbor type						
ordinary	0.00357***	0.0144***	-0.00227	0.00243***	0.00456	0.00625
	(0.000880)	(0.00401)	(0.00655)	(0.000580)	(0.00465)	(0.00615)
processing with imports	-0.00356***	-0.00438***	-0.0186***	-0.00204***	-0.00359***	0.00248
	(0.000663)	(0.00123)	(0.00615)	(0.000573)	(0.000928)	(0.00838)
pure assembly	0.00628	0.0300**	0.0228*	0.00959**	0.00961	0.0230**
	(0.00414)	(0.0131)	(0.0136)	(0.00478)	(0.0138)	(0.0115)
Observations	770,014	36,976	8,247	9,145	1,902	931
R-squared	0.634	0.621	0.649	0.762	0.772	0.702
Control variables	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm-destination-product and year fixed effects. Spillover variables are disaggregated into different trade regimes and count the number of exporting neighbors in the county that follow the respective trade type.

more receptive to export spillovers and become larger sources of spillover emission than most processing counterparts[36].

4.3.2 Ownership form

The second novel source of spillover heterogeneity we investigate are learning distortions between different forms of ownership. As explained above, we focus on the behavior of private firms to analyze if the informal networks they formed in response to economic discrimination have immediate consequences for who they learn from. Neighbors are thus disaggregated along lines of ownership to test which ownership-specific export agglomeration has the most conducive impact on private export entry. The results are depicted in Table 10 and provide several important insights.

As predicted, interaction among private firms appears to be the largest source of entry promoting information transfers. This points towards a strong disconnect to other neighbors of which only foreign ones show a mild potential for export spillovers in specific scenarios. To assess the validity of these findings, we need to address an important weakness of our matched sample. Whereas earlier spillover proxies solely rely on information available for all exporters in China, distributional statements regarding ownership types can only be made for matched exporters. Estimates of our disaggregated spillover proxies thus depend on the representativeness of our sample. We address this concern by limiting the sample to counties in which the distributional share of each ownership type lies at most one standard deviation above or below the respective share of the full NBS sample[37]. The results of this

[36] While this statement may seem disputable when only looking at product-destination specific evidence, a comparison of the impact of trade regimes on all spillover proxies (Appendix B4) clearly points in this direction.
[37] Specifically, we calculate the percentage difference of county ownership shares. As long as the absolute difference lies within a standard deviation of each individual NBS ownership share, the county qualifies for the robustness check. On average, this translates to a deviation of 56% from NBS county shares across ownership types. The requirement applies to all ownership shares simultaneously and reduces the number of counties from 1172 to 509.

Table 10: Private networks

	private enterprises			
	all products - all destinations (1)	*all products - same destination (2)*	*same product - all destinations (3)*	*same product - same destination (4)*
Ownership type				
state-owned	-0.00177	-0.00847***	-0.000223	0.0341
	(0.00323)	(0.00301)	(0.0162)	(0.0487)
hybrid	-0.00191	-0.00242	-0.000389	-0.0127
	(0.00125)	(0.00185)	(0.00476)	(0.00844)
private	0.000134	0.000885**	0.00187**	0.00667***
	(0.000167)	(0.000353)	(0.000745)	(0.00126)
HMT	-0.000253***	-0.000643***	-0.00219***	-0.00709***
	(7.00e-05)	(0.000116)	(0.000539)	(0.00150)
other foreign	-7.26e-05	5.78e-05	-0.000129	0.00370*
	(0.000200)	(0.000384)	(0.000794)	(0.00202)
Observations	544,037	544,037	544,033	544,009
R-squared	0.668	0.668	0.668	0.668
Control variables	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

robustness test are portrayed in Appendix B5 and reiterate the importance of private to private learning. Economic disparities across ownership types therefore clearly shape the relevance of export spillovers and along with trade regimes represent novel sources of spillover heterogeneity. We will discuss the implications of this and previous findings in the next section.

5 Policy implications for China and beyond

Our detailed analysis demonstrates that export spillovers play a decisive role for export entry in China. They increase in specificity, vary in size according to starter and neighbor characteristics, are subject to spatial decay and strongly shaped by key features of the country's economic transition process. These findings carry important implications for the ongoing discussion of spillover relevance and are of immediate interest to policy makers concerned with the extensive margin of trade.

With regards to the current disagreement in the spillover literature, we present comprehensive evidence that identifies a strong connection between local export agglomeration and increased export market entry. While this decidedly augments the recent pool of spillover supporting studies with new empirical evidence from one of the most dynamic economies on the planet, our main contribution to the ongoing debate is the structural identification of sources of spillover heterogeneity which may have caused conflicting evidence in the past. Two insights from our analysis become particularly relevant in this regard. Across spillover proxies, agglomerative forces mainly unfold the closer the match between neighbors and prospective entrants. The informational detail of underlying datasets therefore partly preconditions if researchers are able to pick up the highly specific transmissions of export knowledge. Secondly, even within the group of specific spillover proxies there remains a considerable degree of heterogeneity. Starters, neighbors and connecting forces individually facilitate or hamper the flow of information. As the overall manifestation of spillovers will depend on the sum of these subparts, different characteristics across countries may naturally give rise to opposing results. The discussion should therefore not circle around the question whether export spillovers exist but instead study the subchannels to identify which areas currently limit the transmission of information. Our structural approach can serve as a guideline for that process.

Similarly, the fact that we observe significant export spillovers in China also stems from a conducive unity of these subparts. This is especially true for traditional sources of spillover heterogeneity. Apart from minor variations across different starter and neighbor groups, spillovers retain their supportive character as long as export agglomeration is specific and in close proximity to prospective starters. Policy makers could therefore foster inter-firm learning in two distinct ways. Firstly, spillover specificity suggests that investing in broad communication platforms that target a plethora of different exporters may be less efficient than the establishment of smaller specialized communication hubs. At the same time, the geographical reach of these specialized platforms needs to be increased as spatial decay largely limits the diffusion of knowledge to the county level.

Although these suggestions represent meaningful adjustments to traditional sources of spillover heterogeneity in China, their effectiveness may be eroded by different learning patterns across trade regimes and ownership forms – two factors largely ignored by the spillover literature so far. Without considering the weaker responsiveness and emission potential of processing traders or the fact that private firms predominantly learn from each other, spillover promoting policies may end up connecting parties that have relatively little to offer for each other. These insights refine our understanding of spillover transmissions and should become an integral part of future analyses.

Apart from this imminent impact on the transmission of spillovers, inhibitory influences of trade regimes and ownership forms also become relevant in a broader context as they carry important feedback for the institutional factors they originate in. Firstly, promoting a processing trade regime may expedite the buildup a country's exporting sector in the short run but limit its growth in the long run by restricting its own synergetic potential. This is not only important for China but may be relevant on a global scale as many transition economies continue to use processing trade as an integral part of their trade strategy (Boyenge, 2007). Secondly, our results suggest that the cluster formation of China's private sector, in reaction to a discriminatory institutional environment, has led to a setting in which export related knowledge transfers are largely concentrated within private networks. Although private firms managed to become the vanguard of China's growing export industry[38] despite having to retreat to these social patterns, the apparent disconnect to traders of other ownership forms certainly leaves room for improvement. Especially the creation of a level playing field for all firms promises a wider diffusion of export related information beyond current borders and would allow all manufacturers to reap the full synergetic potential of the existing domestic knowledge pool.

6 Conclusion

This paper investigates the impact of information spillovers on the export decision of Chinese manufacturers between 2000 and 2006. Our analysis relies on a combination of detailed firm and transaction level data to deliver a rich description of Chinese export behavior at the firm-destination-product level and observe regional export agglomeration at highly disaggregated geographical units. This allows us to extend the literature in two important ways. Firstly, we directly address persistent disagreement regarding the relevance of export spillovers by differentiating between general and specific forms of local export agglomeration to identify which type of information facilitates export entry. We thereby expand a narrow strand of recent studies which emphasizes the importance spillover specificity to explain earlier inconsistencies across studies. Secondly, we combine previous evidence of spillover heterogeneity into a stylized model of information transmission and use this structural approach to not only corroborate the influence of known sources of spillover heterogeneity related to starters, neighbors and the connection between the two but also reveal the importance of trade regimes and private networks as new sources of heterogeneity.

Our findings strongly suggest the relevance of export spillovers in China which increase in spillover specificity, vary along starter and neighbor characteristics, experience considerable spatial decay, are largely absent for processing traders and from the perspective of private firms predominantly occur within social networks. These results contain two important messages. On the one hand, export spillovers appear to be an influential component of a country's further integration into global markets. On the other, the occurrence of learning crucially depends on the specificity of local export agglomeration as well as factors influencing the transmission of knowledge between parties.

Importantly, our study of the process' micro-foundations shows that the transmission of information is equally dependent on economic influences related to the qualities of agents involved in the process as well as key elements of the country's developmental strategy. How a country integrates into global markets and how evenly it treats market participants does shape the learning behavior between firms

[38] According to the fifth *Annual Report of Non-State-Owned Economy in China*, the private sector already accounted for a larger share of China's total trade volume than the state-owned sector in 2007.

and can limit the diffusion of knowledge. Policy makers in China and other transition economies that seek to expand the domestic exporting sector should bear in mind that a promotion of processing trade and an incomplete commitment to equal market opportunity may severely restrict the sector's own synergetic potential and slow down its growth in the long run.

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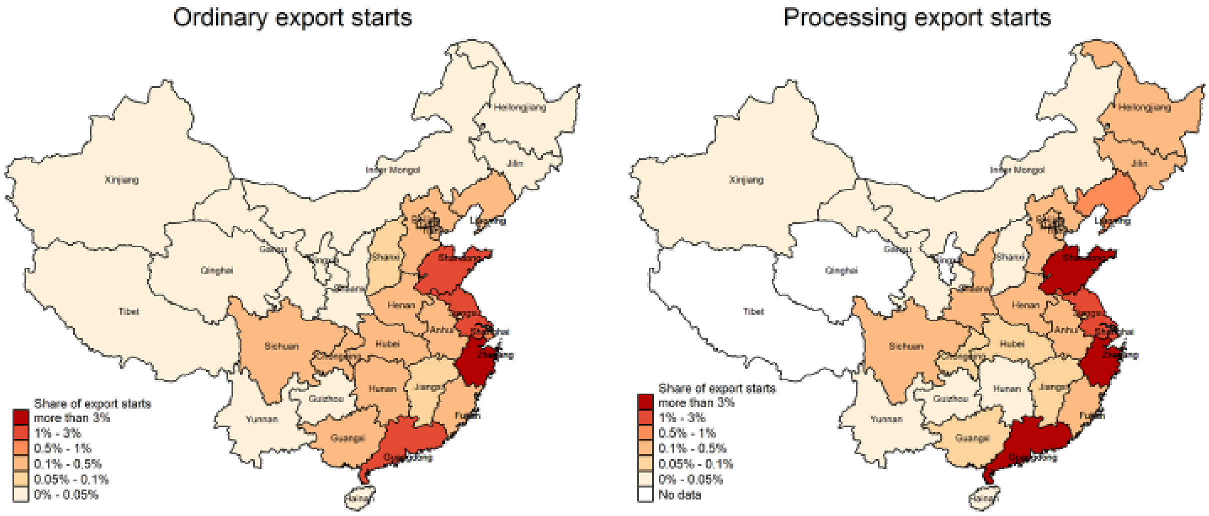
Appendix A

A1: Distribution of domestic export starts



Appendix B

B1: Baseline robustness

Table B1: Baseline robustness check

	alternative spillover variable				alternative productivity control			
	General	*Destination - specific*	*Industry - specific*	*Destination - Industry - specific*	*General*	*Destination - specific*	*Product - specific*	*Destination - product - specific*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Alternative spillovers (t-1)								
all industries - all destinations	-1.78e-05 (4.07e-05)							
all industries - same destination		7.22e-05 (0.000159)						
same industry - all destination			0.000200*** (7.11e-05)					
same industry - same destinations				0.000560** (0.000227)				
Spillover variables (t-1)								
all products - all destinations					-1.72e-05 (4.06e-05)			
all products - same destination						7.28e-05 (0.000159)		
same product - all destination							0.000754*** (0.000212)	
same product - same destinations								0.00325*** (0.000665)
Alternative productivity								
Log ACF TFP					0.00783* (0.00460)	0.00787* (0.00460)	0.00779* (0.00459)	0.00790* (0.00460)
Observations	823,126	823,126	821,247	804,403	822,318	822,318	822,318	822,318
R-squared	0.631	0.631	0.632	0.633	0.631	0.631	0.631	0.631
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

	no HMT starts				alternative hypothesis			
	General	*Destination - specific*	*Industry - specific*	*Destination - Industry - specific*	*General*	*Destination - specific*	*Product - specific*	*Destination - product - specific*
	(9)	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
Spillover variables (t-1)								
all products - all destinations	-9.52e-06 (4.03e-05)				-4.528 (2,659)			
all products - same destination		0.000191 (0.000135)				-6.98e-05 (6.72e-05)		
same product - all destination			0.000789*** (0.000214)				0.00114*** (0.000391)	
same product - same destinations				0.00350*** (0.000802)				0.00318*** (0.000793)
Observations	782,826	782,826	782,826	782,826	822,567	822,567	822,567	822,567
R-squared	0.632	0.632	0.632	0.633	0.658	0.658	0.659	0.659
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Region & dest. time trend	NO	NO	NO	NO	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects and follow variants of the baseline equation (2).

B2: Starter characteristics

a) Starter experience

Table B2a: Starter experience

	Fresh firm start				Fresh product start			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products - all destinations	-5.34e-05				5.09e-05			
	(0.000146)				(7.41e-05)			
all products - same destination		7.10e-05				0.000153		
		(0.000288)				(0.000222)		
same product - all destination			0.00147**				0.00135**	
			(0.000617)				(0.000530)	
same product - same destinations				0.00393***				0.00509***
				(0.000963)				(0.00114)
Observations	138,789	138,789	138,789	138,789	331,275	331,275	331,275	331,275
R-squared	0.695	0.695	0.695	0.695	0.644	0.644	0.644	0.645
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

	Product expertise				Destination expertise			
	(9)	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
Spillover variables (t-1)								
all products - all destinations	-8.21e-05**				-2.49e-05			
	(4.14e-05)				(4.12e-05)			
all products - same destination		0.000251				1.90e-05		
		(0.000204)				(0.000143)		
same product - all destination			0.000260				0.000776***	
			(0.000158)				(0.000212)	
same product - same destinations				0.00261***				0.00334***
				(0.000636)				(0.000655)
Experience controls (t-1)								
product experience	0.00902***	0.00901***	0.00888***	0.00890***				
	(0.000607)	(0.000661)	(0.000616)	(0.000624)				
destination experience					0.0157***	0.0157***	0.0157***	0.0157***
					(0.00200)	(0.00200)	(0.00200)	(0.00201)
Observations	823,126	823,126	823,126	823,126	823,126	823,126	823,126	823,126
R-squared	0.637	0.637	0.637	0.637	0.634	0.634	0.634	0.634
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

b) Absorptive capacity

Table B2b : Absorptive capacity

	Below median TFP				Above median TFP			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products -	-7.61e-05				1.02e-05			
all destinations	(8.96e-05)				(3.71e-05)			
all products -		-0.000129				0.000218		
same destination		(0.000181)				(0.000194)		
same product -			0.000558				0.000714***	
all destination			(0.000393)				(0.000237)	
same product -				0.00235**				0.00387***
same destinations				(0.000938)				(0.000925)
Observations	326,545	326,545	326,545	326,545	404,128	404,128	404,128	404,128
R-squared	0.642	0.642	0.642	0.642	0.657	0.657	0.657	0.657
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

c) Firm size

Table B2c : Firm size

	Below median employment				Above median employment			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products -	-1.18e-05				-1.75e-05			
all destinations	(5.92e-05)				(4.49e-05)			
all products -		0.000221				4.36e-06		
same destination		(0.000174)				(0.000181)		
same product -			0.000628***				0.000811***	
all destination			(0.000158)				(0.000249)	
same product -				0.00241***				0.00376***
same destinations				(0.000449)				(0.000840)
Observations	343,737	343,737	343,737	343,737	439,855	439,855	439,855	439,855
R-squared	0.692	0.692	0.692	0.692	0.606	0.606	0.606	0.606
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

d) Export intensity

Table B2d: Export intensity

	< 5% export sales				>= 5% export sales			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products -	0.000194				-3.56e-06			
all destinations	(0.000133)				(5.83e-05)			
all products -		0.000331*				0.000132		
same destination		(0.000201)				(0.000200)		
same product -			0.00114***				0.000836***	
all destination			(0.000355)				(0.000240)	
same product -				0.00269***				0.00438***
same destinations				(0.000489)				(0.000910)
Observations	98,145	98,145	98,145	98,145	475,762	475,762	475,762	475,762
R-squared	0.662	0.662	0.662	0.662	0.635	0.635	0.635	0.636
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regionalr level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

e) Multiproduct influence

Table B2e : Multiproduct influence

	core product starts				non-core product starts			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Spillover variables (t-1)								
all products -	9.51e-05				-1.14e-05			
all destinations	(9.54e-05)				(4.40e-05)			
all products -		0.000568*				4.13e-05		
same destination		(0.000318)				(0.000159)		
same product -			0.000898***				0.000979***	
all destination			(0.000251)				(0.000249)	
same product -				0.00267***				0.00446***
same destinations				(0.00101)				(0.000729)
Observations	224,372	224,372	224,372	224,372	582410	582410	582410	582410
R-squared	0.645	0.645	0.645	0.645	0.638	0.638	0.638	0.638
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects.

B3: Connection influences

a) Standard spillover proxies

Table B3a : Spatial decay - normal spillover proxies

	All products - all destiantions			All products - same destination		
	Province	*Municipality*	*County*	*Province*	*Municipality*	*County*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Geographic level						
Province	2.57e-06			2.59e-05**		
	(4.19e-06)			(1.14e-05)		
Municipality		4.09e-07			6.10e-05*	
		(1.28e-05)			(3.38e-05)	
County			-1.78e-05			7.22e-05
			(4.07e-05)			(0.000159)
Observations	823,126	823,126	823,126	823,126	823,126	823,126
R-squared	0.631	0.631	0.631	0.631	0.631	0.631
Control variables	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

	Same product - all destinations			Same product - same destination		
	Province	*Municipality*	*County*	*Province*	*Municipality*	*County*
	(7)	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Geographic level						
Province	9.89e-05*			0.00101***		
	(5.31e-05)			(0.000185)		
Municipality		0.000227			0.00209***	
		(0.000207)			(0.000663)	
County			0.000753***			0.00325***
			(0.000212)			(0.000666)
Observations	823,126	823,126	823,126	823,126	823,126	823,126
R-squared	0.631	0.631	0.631	0.631	0.631	0.631
Control variables	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects. Regional controls and clustered standard errors adhere to the respective regional level in use.

b) Alternative spillover proxies

Table B3b: Spatial decay - alternative spillovers

	alternative spillover type			
	all products - all destinations (1)	*all products - same destination (2)*	*same product - all destinations (3)*	*same product - same destination (4)*
Geographical level				
Province	-7.07e-07	1.38e-05	1.43e-05	0.000554
	(5.35e-06)	(1.68e-05)	(3.72e-05)	(0.000361)
Municipality	6.09e-06	5.55e-05	-0.000224***	9.39e-05
	(1.25e-05)	(3.96e-05)	(8.14e-05)	(0.000721)
County	-1.83e-05	-3.15e-05	0.000785***	0.00292***
	(5.54e-05)	(0.000221)	(0.000136)	(0.000574)
Observations	823,126	823,126	823,126	823,126
R-squared	0.631	0.631	0.631	0.631
Control variables	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects. Regional controls and clustered standard errors use the county level. Alternative spillover proxies are mutually exclusive as export agglomeration at the upper and lower regional level is excluded.

B4) Trade regimes

Table B4 : Trade regimes

starter type	ordinary				processing with imports				pure assembly			
	General (1)	*Destination - specific (2)*	*Industry - specific (3)*	*Destination - Industry - specific (4)*	*General (5)*	*Destination - specific (6)*	*Product - specific (7)*	*Destination - product - specific (8)*	*General (9)*	*Destination - specific (10)*	*Product - specific (11)*	*Destination - product - specific (12)*
Neighbor type												
ordinary	1.74e-05	0.000383***	0.000956***	0.00357***	5.13e-06	0.00148**	0.000937	0.0144***	-0.000169	0.000811	0.00136	-0.00227
	(8.91e-05)	(0.000118)	(0.000344)	(0.000880)	(0.000233)	(0.000650)	(0.00114)	(0.00401)	(0.000561)	(0.00115)	(0.00240)	(0.00655)
processing with imports	-5.17e-05	-0.000453***	-0.000830***	-0.00356***	-0.000233***	-0.000774***	-0.00313***	-0.00438***	-0.00108***	-0.00133***	-0.00666	-0.0186***
	(3.84e-05)	(9.18e-05)	(0.000255)	(0.000663)	(6.56e-05)	(0.000151)	(0.000918)	(0.00123)	(0.000395)	(0.000437)	(0.00515)	(0.00615)
pure assembly	-2.16e-06	0.000184	0.000464	0.00628	-0.000260	0.000822	0.00496	0.0300**	-0.00267**	-0.00355**	0.00708	0.0228*
	(0.000477)	(0.000775)	(0.00179)	(0.00414)	(0.000883)	(0.00347)	(0.00712)	(0.0131)	(0.00120)	(0.00156)	(0.00621)	(0.0136)
Observations	770,014	770,014	770,014	770,014	36,976	36,976	36,976	36,976	8,247	8,247	8,247	8,247
R-squared	0.633	0.633	0.634	0.634	0.621	0.621	0.621	0.621	0.655	0.650	0.649	0.649
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm-destination-product and year fixed effects. Spillover variables are disaggregated into different trade regimes and count the number of exporting neighbors in the county that follow the respective trade type.

B5: Ownership robustness

Table B5 : Ownership robustness

	private enterprises in representative counties			
	all products - all destinations	*all products - same destination*	*same product - all destinations*	*same product - same destination*
	(1)	*(2)*	*(3)*	*(4)*
Ownership type				
state-owned	-0.000949	-0.00722**	-0.000629	0.0358
	(0.00335)	(0.00297)	(0.0164)	(0.0490)
hybrid	-0.00212*	-0.00276	-0.00117	-0.0139
	(0.00122)	(0.00185)	(0.00445)	(0.00870)
private	8.21e-06	0.000653*	0.00177**	0.00654***
	(0.000175)	(0.000333)	(0.000722)	(0.00127)
HMT	-0.000237***	-0.000684***	-0.00266***	-0.00792***
	(8.81e-05)	(0.000125)	(0.000643)	(0.00179)
other foreign	5.03e-05	0.000303	0.000352	0.00405**
	(0.000242)	(0.000406)	(0.000785)	(0.00205)
Observations	467,386	467,386	467,382	467,364
R-squared	0.665	0.665	0.666	0.666
Control variables	YES	YES	YES	YES
Firm-dest-prod FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Clustered standard errors at the regional level are reported in parentheses. Stars indicate statistical significance where ***, **, and * relate to the 1, 5 and 10 percent level respectively. All estimations include firm, regional and destination controls as well as firm-destination-product and year fixed effects. The sample is limited to counties in which the difference of each owernship type's share between the matched and the full NBS sample is at most one standard deviation.