Essays in International Trade and Economic Geography

Sau Lai Book

Department of Economics

McGill University, Montreal

September, 2021

A thesis submitted to McGill University in partial filfillment of the requirements of the degree of Ph.D in Economics

Table of Contents

Table of Contents

Table of Contents

List of Figures

List of Tables

List of Tables

List of Tables

Thesis Abstract

The thesis consists of three chapters that study internal economic geography, spatial frictions, and firms' multiple dimensions of export behavior. They feature an explicit spatial structure within an exporting country and examine how the differences in geographical characteristics affect firms' extensive and intensive margins of trade activities, as well as price-setting behavior. The first chapter studies firms' learning from exporting peers in different spatial networks to reduce uncertainty in a foreign market's demand, formalizing the relationship between spatial frictions in learning and the extensive margin of trade activities. Evidence suggests that the learning effect is stronger when there are more geographically close neighbors to learn from, precision or the strength of the signal increases, and when the firm starts exporting to a market dissimilar from its previously served markets. The second chapter analyzes the role of internal distance, measured by geographical distance to the nearest port infrastructure, on shipment costs, volumes, and frequencies. It establishes the links between spatial heterogeneity in trade costs and the intensive margin of trade activities. A simple structural model is used to estimate shipment costs at the firm-product-destination level. Evidence reveals that shipment costs correlate positively with the internal distance, favouring large and infrequent shipments for geographically distant exporters. The third chapter examines the role of internal distance in quality differentiation and price-setting behavior of exporters. Empirical findings suggest that free-on-board export unit price decreases systematically with internal distance, and the effect is stronger in shipments of differentiated or knowledge-intensive products. It presents a theoretical framework that features quality differentiation across space to rationalize these empirical patterns.

Résumé

La thèse se compose de trois chapitres qui étudient la géographie économique interne, les frictions spatiales et les multiples dimensions du comportement d'exportation des entreprises. Ils présentent une structure spatiale explicite au sein d'un pays exportateur et examinent comment les différences de caractéristiques géographiques affectent les marges extensives et intensives des activités commerciales des entreprises, ainsi que le comportement de fixation des prix. Le premier chapitre étudie l'apprentissage des entreprises auprès de pairs exportateurs dans différents réseaux spatiaux pour réduire l'incertitude de la demande d'un marché étranger, formalisant la relation entre les frictions spatiales dans l'apprentissage et la marge extensive des activités commerciales. Les preuves suggèrent que l'effet d'apprentissage est plus fort lorsqu'il y a plus de voisins géographiquement proches à apprendre, la précision ou la force du signal augmente, et lorsque l'entreprise commence à exporter vers un marché différent de ses marchés précédemment desservis. Le deuxième chapitre analyse le rôle de la distance interne, mesurée par la distance géographique à l'infrastructure portuaire la plus proche, sur les coûts, les volumes et les fréquences d'expédition. Il établit les liens entre l'hétérogénéité spatiale des coûts commerciaux et la marge intensive des activités commerciales. Un modèle structurel simple est utilisé pour estimer les coûts d'expédition au niveau entreprise-produit-destination. Les preuves révèlent que les coûts d'expédition sont en corrélation positive avec la distance interne, favorisant les expéditions importantes et peu fréquentes pour les exportateurs géographiquement éloignés. Le troisième chapitre examine le rôle de la distance interne dans la différenciation de la qualité et le comportement de fixation des prix des exportateurs. Les résultats empiriques suggèrent que le prix unitaire d'exportation franco à bord diminue systématiquement avec la distance interne, et que l'effet est plus fort dans les expéditions de produits différenciés ou à forte intensité de savoir. Il présente un cadre théorique qui présente une différenciation de la qualité dans l'espace pour rationaliser ces modèles empiriques.

Acknowledgments

First, I am extremely grateful to my primary supervisor, Prof. Ngo Van Long, for his valuable advice, continuous support and incredible amount of time he spent in supervising this thesis. His extensive knowledge and experience have inspired me in all the time of my research. I am deeply indebted to him for his tremendous help he provided throughout my doctoral studies.

Besides my primary supervisor, I would like to thank my thesis committee members, Prof. John Galbraith and Prof. Francesco Amodio, for their insightful comments and valuable guidance. They have been generous with their knowledge and advice which greatly improved my thesis.

In addition, I would like to thank Prof. Leonie Baumann, Prof. Saraswata Chaudhuri, Prof. Francisco Alvarez-Cuadrado, Prof. Paul Dickinson, Prof. Francisco Ruge-Murcia for their helpful comments and support during my studies and job market preparation. I thank my friends, Ying Tung Chan, Yin Chi Tam, Qian Sun, Bixi Jian, and many others, for their help and encouragement. I also thank the following for generous financial support throughout my doctoral studies: CIBC Fellowship, STP – Ruge-Murcia – SSHRC, Graduate Excellence Award, Brecher Fellowship in Economics, STP – Long – SSHRC, STP – Long – FQRSC, James McGill – Long – Graduate Award, and the Department of Economics, McGill University.

Last but not least, I would like to express my deep and sincere gratitude to my family for their unparalleled love and support. I am forever indebted to my parents for giving me the opportunities that have made me who I am. This journey would not have been possible without them.

Contribution to Original Knowledge

This thesis consists of three chapters. Each chapter contributes both theoretical developments and empirical evidence to existing literature on international trade and economic geography.

The first chapter contributes to the literature on spatial frictions, knowledge diffusion, and international trade. This chapter develops a new Bayesian learning model with two key ingredients: (i) an internal geography framework which indexes locations of exporting neighbors of a focal firm according to their geographical distance; and (ii) a selective perception assumption that firms value geographically close neighbors and their revealed signals more than the distant ones, in order to formalize the effects of spatial networks on heterogeneous learning effects among firms. This chapter improves identification by focusing on spatial neighborhoods at fine resolution, which addresses the concern of spatially correlated omitted variables in estimating the knowledge diffusion. The use of fine spatial neighborhoods also allows a close examination of how learning decays in space.

The second chapter contributes to the literature on trade barriers, shipment costs, and export behavior. Using a geospatial firm-transaction dataset of Chinese manufacturing exporters, this chapter structurally estimates the shipment costs at the firm-product-destination level, and studies its relationship with within-country trade frictions, measured by the geographical distance separating a firm and its nearest port infrastructure. This study also provides new empirical evidence on how the internal distance could serve as a source of firm heterogeneity in explaining patterns on firms' decisions on shipment frequencies and volumes.

The third chapter contributes to the literature on within-country trade frictions, spatial quality differentiation, and price-setting behavior of exporters. This chapter contributes new empirical evidence that export unit prices at the firm-product-destination level decrease systematically with the internal distance to the nearest port infrastructure. This effect is stronger in shipments of differentiated or knowledge-intensive products, and in non-core products of exporters. These results suggest substantial quality sorting across space associated with the geographic locations of firms within the exporting country. This chapter also presents a simple theoretical framework extending Melitz and Ottaviano (2008) that features spatial quality differentiation to rationalize these empirical patterns.

Contribution of Authors

This thesis consists of three chapters. I am the sole author of all three chapters.

Introduction

The literature in economic geography and international trade have widely discussed the heterogeneity of firms' behavior and economic activities across space. While economic geography is primarily concerned with geographical proximity between countries, internal geographical characteristics, including domestic spatial networks among firms and within-country geographical distance to the nearest trade infrastructure, often add complications to the existing theoretical models and empirical findings.

Consistent with the standard gravity model, there is overwhelming evidence that trade activities fall with increase in market size and decrease in geographical distance between two countries. However, a major limitation of gravity model is that, without considering an explicit domestic spatial structure, all firms within a country are essentially treated as being located at the same point in space, such that domestic geographical characteristics play no role in generating variations in a number of trade performance measures, including the likelihood of exporting to a foreign destination, export sales, shipment costs, volumes, and frequencies of shipments, as well as the prices charged across product-destinations. This assumption is unrealistic because, for example, firms within a small spatial neighborhood could facilitate knowledge diffusion and innovation among them, and geographical proximity to the nearest port could help firms save internal transportation costs and minimize time delays.

In consideration of the missing spatial structure and its implications on within-country spatial variations in firms' economic decisions, this thesis considers an internal geography setting in heterogeneous firm trade models to deliver rich theoretical predictions on multiple dimensions of export behavior. This modelling approach is a major departure from previous studies where within-country locations and their associated spatial frictions are absent. As a result, a firm is not only characterized by its own quality (e.g., productivity and firm size) and country of origin, but also by a precise location defined by geographic coordinates. This approach permits a close examination of the locational advantages in firms' knowledge acquisition based on their spatial networks, as well as location-specific heterogeneity in trade and innovation costs based on geographical proximity between firms and their nearest trade infrastructure.

Naturally, studying spatial networks and geographical proximity within a country requires precise geographic coordinates of locations such that computation of geographical distance between two units of observation is possible. The lack of precise geocoded data most often hinders the construction of geospatial firm-transaction level dataset, which causes difficulties in empirically testing the theoretical predictions in a spatial context. To address this issue, I exploit a large web mapping service application to accurately geocode firm addresses and major transportation infrastructure including ports and airports, which allows for construction of several key variables: the number and export performance of nearby firms in a highly localized definition of spatial neighborhood, as well as the distance to the nearest port as a measure of within-country trade frictions.

This thesis consists of three chapters which contribute both theoretical developments and empirical evidence using large geospatial firm-transaction data to the fields of economic geography and international trade. The three chapters are closely related to the role of spatial networks and frictions in shaping multiple dimensions of firms' export behavior. The first chapter formalizes the relationship between spatial frictions in firms' learning and extensive margin of trade: how firms respond to the number of exporting peers and their revealed information of varying geographical proximity, and how the learning from spatial networks contributes to reducing uncertainty about a foreign market's demand, which subsequently affects the likelihood of starting to export to a foreign destination and initial export sales via an update in entry threshold. The second chapter examines, conditional on exporting, the relationship between within-country spatial frictions and the intensive margin of trade: how firms adjust shipment frequencies and volumes given their locations, and how the shipment costs change with internal distance to the nearest port. Longer internal distance increases shipment costs associated with shipping delays and administrative barriers, favouring larger and infrequent shipments. This chapter also develops a simple structural model to estimate shipment costs for each firm-product-destination and documents its relationship with internal distance. The third chapter studies the relationship between spatial frictions, quality differentiation decisions and export prices at the firm-product-destination level. The geographical distance to the nearest port serves as a source of heterogeneity in firm-product level cost of quality upgrading. Firms that are geographically more distant from ports experience greater difficulties in acquiring technological knowledge, industrial equipment and imported raw materials, which translate into higher costs of innovation and quality upgrading. These spatial frictions, in combination with degree of differentiation and knowledge intensity of product, drive the scope for quality differentiation and optimal product quality chosen by a firm.

The goal of this thesis is to build a coherent and complete picture on how within-country spatial frictions could shape firms' export behavior. Taken as a whole, the three chapters formalize the presence of within-country spatial frictions and study how they affect firms' decisions along exporting activities. The theoretical developments and empirical findings contribute to a new line of research on how these spatial frictions interact with firms' learning, shipment considerations, and quality differentiation across firm-product-destinations. The following paragraphs will explain in greater detail the theoretical and empirical challenges in previous studies, and how each of the chapters addresses these important issues and makes novel contributions to knowledge.

The first chapter addresses two important issues in the literature: (a) most previous studies (e.g., Fernandes and Tang, 2014; Mayneris and Poncet, 2015, Kamal and Sundaram, 2016) define spatial neighborhoods as cities or similarly large agglomerations such that all firms are assumed to make equal contributions to the learning environment, regardless of their geographical proximity to a focal firm; and (b) the estimations of firm's learning effects are potentially biased by spatially correlated omitted variables. The paper incorporates an internal geography framework à la Coşar and Fajgelbaum (2016) and a selective perception assumption into a standard Bayesian learning model to allow for a close examination of firm networks in small spatial neighborhoods each separated by a 50-meter interval, as well as a realistic learning environment where firms value highly geographically close neighbors and their revealed signals. With this explicit spatial structure, a firm prioritizes information sources according to their geographical proximity to its own location, and updates entry productivity threshold which affects the likelihood of starting to export to a specific market.

In addition, endogenous peer groups and spatially correlated omitted variables are the main empirical challenges to tackle. Specifically, same-industry firms may co-locate, face correlated shocks, and make correlated export decisions. A spatial neighborhood could be better for exporting to a particular country because of unobservable links, and thus the surrounding neighborhoods are also more likely to enter the same country because of spatial correlations. The identification strategy of this chapter attempts to rule out these non-learning mechanisms in two ways. To begin with, this paper focuses on highly spatially localized spillovers within 500 meters of a focal firm, and further rules out any remaining omitted variables with placebo spatial groups, assuming that knowledge spillovers decay faster than the spatial correlation in that omitted variable. Next, this paper removes firms with ownership links and exploits variation in peer export experience across destination countries to limit confounding effects.

To build a spatial dataset of firm, a large web mapping service application is used to obtain precise geographic coordinates of firm locations. The dataset is also constructed using China's National Bureau of Statistics firm-level data and Customs Office transaction-level data. Both the number of exporting peers and their revealed signals, defined by the average export growth to the same destination country observed from exporting peers in a firm's spatial networks, serve as the sources of knowledge diffusion among firms.

Empirical evidence suggests these learning effects are stronger when there are more geographically close neighbors to learn from, precision or strength of revealed signals increases, and when the firm starts exporting to a market dissimilar from its previously served markets. This knowledge diffusion also decays fast in space, where no significant learning effect is found beyond 300 meters of a focal firm. It confirms the logic of defining spatial neighborhoods at fine resolution. Overall, the relative strengths of geographically close neighbors and signals compared to their distant counterparts are consistent with the theoretical predictions, confirming the necessity of introducing internal geography setting and selective perception assumption into standard learning models.

The second chapter addresses two important issues in the literature: (a) most previous studies on shipments (e.g., Kropf and Sauré, 2014; Hornok and Koren, 2015a; Hornok and Koren, 2015b) do not take a firm's within-country location into consideration when estimating the cost of arranging a shipment; and the shipment cost in standard trade datasets only offers a pecuniary view, while a non-pecuniary dimension (e.g. time delays and administrative barriers) remains under-explored, and (b) the within-country spatial frictions measured by internal distance separating a firm and its nearest trade infrastructure play no role in affecting the firm's adjustments in intensive margin: shipment frequencies and volumes. With this consideration, this paper introduces an internal geography framework into a heterogenous firm trade model with endogenous shipment decisions. The model features location-specific heterogeneity in shipment costs, and a trade-off between these shipment costs and storage costs at destinations. Firms can save shipment costs by shipping less frequently but more at a time, but this strategy generates storage costs which accumulate over time before date of consumption.

Empirical evidence reveals that geographical proximity to the nearest port generates spatial dispersion in firms' shipment decisions. Consistent with the theoretical predictions, geographically distant firms optimally decrease shipment frequencies and increase shipment volumes given their locational disadvantages in arranging shipments. These empirical patterns are robust after accounting for potential endogeneity and controlling for an exhaustive set of fixed effects and firm-level controls. These findings reflect that a within-country spatial dimension is necessary to account for the observed spatial variations in shipment decisions.

The theoretical model allows for a simple structural estimation of shipment cost at the firm-product-destination level, which depends only on standard gravity variables, observed shipment frequency and volume. By adjusting the parameter governing the non-interest storage costs, the model delivers a set of estimations that are comparable to existing trade costs in standard trade dataset. The estimated average shipment cost is significantly larger than that without a non-pecuniary dimension. In addition, the estimation results indicate that shipment cost is positively correlated with the internal distance, bringing a new evidence to the fields of economic geography and estimation of trade costs. These results raise questions concerning the estimation strategies for trade costs in the absence of an internal geography dimension.

The third chapter first documents empirical patterns on the role of within-country spatial frictions on the price-setting behavior of exporters. Unlike previous studies which link export price and characteristics of importing countries (e.g., market size, distance from exporting countries, etc.), evidence suggests that the free-on-board export unit price decreases systematically with internal distance to the nearest port infrastructure, and this effect is stronger in shipments of differentiated or knowledge-intensive products, and in non-core products of exporters. Furthermore, within product categories, higher productivity firms ship products at higher unit prices, yet the negative effect of internal distance on unit price is significantly weakened compared to their lower productivity counterparts. These results indicate not only quality sorting across space, but also substantial within-firm variations of unit prices across products and destinations.

This chapter also presents a simple theoretical framework extending Melitz and Ottaviano (2008) (hereafter abbreviated as MO) that features quality differentiation across space to rationalize empirical patterns on how internal spatial frictions could drive the price-setting decisions of exporters. A major limitation of quality augmented MO is the lack of internal geography dimension to account for the spatial heterogeneity in transportation costs and fixed costs of innovation. The within-firm variations in unit prices across also reveal that product attributes (e.g., degree of differentiation, knowledge intensity, core vs. non-core products, etc.), jointly with internal distance, play a crucial role in shaping export prices. Two approaches are adopted to address these issues. First, this chapter introduces a product- and location-specific fixed cost of quality upgrading that is increasing in both product complexity and internal distance, to account for the greater specific upfront investment in acquiring technological knowledge, imported raw materials and industrial equipment. Second, this chapter considers a distinction between process and product productivity as in Hallak and Sivadasan (2013) to account for the differences in variable costs of producing core and non-core products. With this theoretical framework, the geographical proximity to the nearest trade infrastructure generates spatial variations in quality sorting and export prices that are consistent with the empirical findings.

Literature Review

My thesis studies the role of within-country locations and geographical characteristics of firms as sources of heterogeneity in firms' decisions along exporting activities, namely the extensive margin of export (i.e. entry to a new foreign market), intensive margin of export (i.e. shipment frequency and volume), and price-setting behavior.

The first chapter analyzes a learning environment within a spatial neighborhood at fine resolution and studies its effects on firms' knowledge diffusion and market entry decisions. Firms acquire specific trade-specific information to facilitate export transactions. Several previous studies build on firm networks, knowledge diffusion, and trade patterns. Fernandes and Tang (2014) find that the export growth of same-city neighbors increases the likelihood of a firm's entry to a new market, while the number of same-city neighbors has insignificant effects. Kamal and Sundaram (2016) find that the presence of neighbors improves the likelihood of importer-exporter matches. Bisztray et al. (2018) find significant knowledge spillovers in both spatial and managerial networks, highlighting the benefits of knowledge diffusion in facilitating importing activities. Mion and Opromolla (2014) and Mion et al. (2016) provide empirical evidence on how managers and managerial practices diffuse export knowledge and improve firms' performance. Fafchamps and Quinn (2018) document the diffusion of business practices through business and community organizations. Cai and Szeidl (2018) exploit a randomized experiment to find positive effects of business associations and meetings on firm profit, the number of partners, and other trade performance measures. This chapter generalizes these studies with a new Bayesian learning model that (i) indexes locations of exporting neighbors of varying geographical proximity to a firm, and (ii) allows a firm to value geographically close neighbors and their signals more than the distant ones. This work also improves identification strategy by using a definition of spatial neighborhood at fine resolution to avoid confounding variation from omitted spatially correlated variables.

The second chapter examines the relationship between internal trade barriers, shipment costs, and export performance. A vast literature highlights the importance of trade barriers (both external and internal) and relate them to exporting decisions. Kropf and Sauré (2014) develop a heterogeneous firm trade model to estimate fixed costs per shipment, and find that they are negatively correlated with language commonalities and trade agreements. Similarly, Hornok and Koren

(2012) build a model to analyze the welfare effects of per-shipment administrative trade costs, and find that fewer shipments (holding the total volume of trade fixed) entails a welfare cost. Atkin and Donaldson (2015) find that the effect of log distance on trade costs within Ethiopia or Nigeria is 4 to 5 times larger than in the United States. Coşar and Fajgelbaum (2016) develop an internal geography model in which internal transport costs lead to regional specialization in export-oriented industries in port regions. Volpe Marticus and Blyde (2013) exploit the 2010 Chilean earthquake as a natural experiment and find that diminished transportation infrastructure had a negative impact on firms' exports. Van Leemput (2021) quantifies the size of trade barriers using Indian sector-level data, and finds that internal trade barriers make up 40% of total trade barriers on average. This chapter considers a heterogeneous firm model with endogenous shipment frequency and an explicit spatial structure within the exporting country, in order formalize the role of within-country spatial frictions in shipment decisions. This work also structurally estimates the shipment costs at the firm-product-destination level, and extends the previous studies by uncovering the rich relationship between within-country trade frictions (measured by the distance separating a firm and its nearest port) and shipment costs.

The third chapter studies the relationship between within-country trade frictions, quality differentiation, and export prices. Previous studies focus on the role of gravity on systematic heterogeneity in the export prices. Bastos and Silva (2010) find that CN 8-digit export prices at the firm-product-country level are positively related to cross-country distance, market size, and income per capita. Baldwin and Harrigan (2011) use a distance step function and find the relative HS 10-digit export prices are positively related to cross-country distance, but negatively related to market size and income per capita. Manova and Zhang (2012) also find that exporters charge higher prices in bilaterally more distant importing countries. There are also a number of studies on the role of spatial quality differentiation and innovation in exporting. Harrigan et al. (2015) find that highly productive firms and skill-intensive firms charge higher prices and that U.S. firms exhibit strong positive price-distance effects. Lugovskyy and Skiba (2015) find that the product quality increases in transportation costs as well as preferences for quality of the destinations. Kneller and Yu (2016) find that the average unit values of the majority of Chinese exports increase with both cross-country distance and market size. Anderson et al. (2019) document that export prices are negatively associated with cross-country distance, and relate these patterns to high innovation costs. All these studies primarily focus on the relationship between geographic characteristics of importing countries, exporters' attributes, and export prices. This chapter takes an alternative perspective to study how exporters' locations within the country and ease of access to trade infrastructure could shape price-setting behavior. It establishes the link between within-country spatial frictions and the scope of quality differentiation, and its implications on export unit prices. This chapter also provides one of the earliest empirical evidence on how internal distance to the nearest port infrastructure affects export unit prices, and unit prices of varying distances relative to the core products within multi-product exporters.

Chapter 1

Spatial Networks, Knowledge Diffusion, and International Trade

Abstract

This paper studies knowledge diffusion among exporting firms. I extend the standard Bayesian learning model with a structure of internal geography and selective perception, which captures the idea that firms value highly the information from geographically close neighbors because of spatial frictions in learning. The model features heterogeneous knowledge diffusion effects, in which firms place heavier weights on signals from close neighbors than distant ones. These learning effects are stronger when there are more close neighbors to learn from, precision or strength of signal increases, and when the firm starts exporting to a market dissimilar from its previously served markets. Using transaction-level data on Chinese exporters and their spatial networks over the 2004-2006 period, I find strong evidence supporting the main predictions of the model. The model rationalizes patterns of firms' export entry decisions, initial export sales, and survival probability observed in the universe of Chinese manufacturing firms.

JEL Classifications: F1, D8, R1, R3

Keywords: spatial networks, knowledge diffusion, export behavior, internal geography, uncertainty

1.1 Introduction

High productivity firms self-select to export (Melitz, 2003), and exports have large effects on firm productivity (Clerides et al., 1998; Benkovskis et al., 2017), yet there is substantial heterogeneity in firms' exporting behavior. A possible explanation for this heterogeneity is the existence of informal trade barriers, which acts as frictions to market-specific knowledge diffusion among firms for a profitable export relationship to take place. With the presence of informal trade barriers, importing may diffuse from firm to firm through personal and business connections (Bisztray et al., 2018). Trade literature document this knowledge diffusion for exports, and relate it to diffusion of managers' experience (Mion and Opromolla, 2014; Mion et al., 2016), learning from neighbors' experience (Fernandes and Tang, 2014), and buyer-seller relationships (Kamal and Sundaram, 2016). However, at present there is limited evidence on how firms' entry decisions and export performance are associated with heterogeneous learning effects due to geographical proximity of neighbors, and how learning effects decay with distance.

This paper examines the effects of geographical proximity on knowledge diffusion in exporting. The answers can shed light on the cross-firm heterogeneity in exporting and its productivity benefits. In this paper, I incorporate a structure of internal geography à la Coşar and Fajgelbaum (2016) to the standard Bayesian learning model of export behavior to study how firms learn differentially from geographically close and distant neighbors about foreign market demand. The model delivers several micro-founded hypotheses about how heterogeneous learning diffusion affects exporters' entry decisions, initial export sales, and survival probability. I take these hypotheses to the detailed transaction-level data in the universe of Chinese exporters. With detailed geodetic data, I construct a large dataset of spatial distribution of Chinese firms and study how the firms' learning from spatial networks shapes their export behavior. The wide geographical dispersion of exporters, as well as high degree of industrial specialization and agglomeration, make China a particularly suitable country for this empirical exercise.

The model incorporates Bayesian learning into a standard heterogeneous firm model of international trade. It is assumed that the exporter's operating profit depends on three components: (1) firm's own productivity; (2) market-specific demand; and (3) firm-specific product appeal. The timeline of a representative firm's entry decision is as follows: First, each firm draws a productivity before entry, but does not know its export profit due to uncertainty in market-specific demand and firm-specific product appeal. Second, the firm observes neighbors' average export revenues to a specific market, then updates its prior on market-specific demand. Given that unobserved firm-specific product appeal also plays a role in export profit, the observed neighbors' average export revenues to a specific market can only serve as a noisy signal about foreign market demand. Third, based on the characteristics of the Bayesian learning model, the observed signals converge to the true state of demand when (i) there are more geographically close neighbors revealing information, and (ii) signal-to-noise ratio increases. Lastly, a firm will start exporting after receiving signal that lowers entry productivity threshold.

The model shows that a firm's export entry decision and post-entry performance depend not only on the neighbors' export revenues, but also on several observable factors, including the number and geographical proximity of exporters currently selling to that market, as well as the heterogeneity of firm-specific product appeal measured by standard deviation of neighbors' average export growth to that market, ex ante market-specific uncertainty measured by geographical distance of export destination from China, and also extended gravity variables including common language, and per-capita income level differences.

While this paper also documents information spillovers in international trade as in previous studies, it stresses on the relative importance on information received from geographically close versus distant neighbors, and how this knowledge diffusion decays in space. Both the strength and sign of signals matter: when there are more geographically close neighbors revealing information about a specific market, the exporters' entry into new market increases (decreases) when the signal is positive (negative). Following Fernandes and Tang (2014), the model uses an interaction term between the signal and number of neighbors to empirically identify information spillovers in trade.

The model has four key predictions. First, it predicts that higher average neighbors' export growth (i.e. a positive signal) induces more firms to start exporting and increases initial sales among the other exporters in the same market. Second, the learning effects are stronger when the precision of signal increases, due to more geographically close neighbors revealing it. Third, firms show a weaker response to export entry to a positive signal when the signal-to-noise ratio is lower (i.e. the observed neighbors' average export growth is more dispersed), the ex ante market-specific uncertainty is smaller, and when the new market is similar to the firm's previously served markets.

Finally, the model shows that a new exporter's survival rate in a market is independent of the number of geographically close and distant exporting neighbors serving that market, conditional on the observed neighbors' export growth and firm productivity. Instead, the strength of signal lowers the export entry thresholds for potential entrants, which in turn lowers the survival probability of export entrants. This effect is further magnified if the signal is revealed by more geographically close neighbors. It is because, a more positive signal delivered by geographically close neighbors could induce more lower-productivity firms to start exporting. Given per-period fixed export costs, the lower-productivity exporters are more likely to exit ex post.

The transaction-level trade and firm-level data for the universe of Chinese manufacturing firms over 2004-2006 are aggregated from China Customs Office and Annual Survey of Industrial Production (ASIP) of National Bureau of Statistics of China, respectively. In addition, I use Baidu's geocoding API to obtain precise geographic coordinates of firms' addresses and their 12-digit administrative region codes, where a 12-digit code refers to a village or community, the most disaggregated level of neighborhood in China assigned by the ASIP. With fine-grained geodetic data, I build a spatial network dataset which focuses on small spatial neighborhoods, each separated by a 50-meter interval, surrounding a focal firm. This explicitly addresses the problem of spatially correlated omitted variables. To limit confounding effects I also exclude ownership-connected firms by removing firms which share common legal person or same corporate names in different locations. This mitigates the concern that firms with managerial or ownership links could face correlated shocks which drive correlated firm decisions that are unrelated to learning from neighbors. To further rule out alternative mechanisms which drive correlated firm decisions, I (1) exclude village-year observations with number of same-industry firms is in the top decile across all village-years, and (2) exclude village-year observations with at least one firm from the geographically concentrated industries according to Lu and Tao (2009) to account for potentially correlated decisions with same-industry peers. Additionally, I sort village-year observations by their total exports, employment, domestic sales revenues, and profits, and exclude those village-year observations with these measures above the top decile, in order to account for potentially correlated decisions with leading exporters within their neighborhoods. For alternative learning mechanisms, I map each village to its closest ports and airports, and include port-country-year and airport-country-year fixed effects to account for firms' acquisitions of trade-specific information from trade infrastructure. Finally, I include a more stringent set of fixed effects, e.g. industry-village-year fixed effects, to further absorb any unobserved determinants of same-industry and same-village firms across years which could drive correlated entry decisions. All major empirical results remain intact.

I find strong supporting evidence for the main theoretical predictions. In the empirical analysis, I control for firm-year, village-country, country-year, and industry-country fixed effects, I find that the entry rate to a market is positively correlated with the strength of the geographically close signal, measured by the average growth rate of export revenue revealed by same-location neighbors to the same market. However, this correlation is less clear for geographically distant signal, indicating the presence of spatial frictions to knowledge diffusion. The learning effects on entry rate are quantitatively important.

Literature. This paper builds on literature on knowledge spillovers across spatial distribution of firms in international trade, most of which studies the knowledge diffusion of exporting. Previous studies focus on the knowledge diffusion related to export entry decisions, and obtain mixed results.[1] The paper is closely related to studies in the trade-specific knowledge spillovers, which firms utilize for deciding whether to export new markets (Koenig et al., 2010; Mayneris and Poncet, 2015). For instance, Kamal and Sundaram (2016) show that the presence of neighbors generates importer-exporter matches using trade transactions data between U.S. importers and Bangladeshi exporters. Fernandes and Tang (2014) formalize exporters' learning mechanism with a theoretical model and empirically examine the role of learning from same-city neighbors using Chinese trade transactions data. Using firm-level data from Hungary, Bisztray et al. (2018) focus on the import knowledge spillovers through spatial and managerial networks. While these papers provide empirical evidence of knowledge spillovers among neighboring firms, they do not examine how the geographical distribution of firms contribute to the heterogeneous learning effects of exporters. While Bisztray et al. (2018) define fine spatial neighborhoods to empirically study import knowledge spillovers using detailed addresses of firms headquartered in Budapest, I substantially generalize their work with a Bayesian learning model which formalizes a variety of factors driving the strength of learning effects of exporters. The spatial spillover results also improve identification by using the most precise and disaggregated level of neighborhoods: the firms' addresses and their

[1] Bernard and Jensen (2004) and Pupato (2010) found negative results, while Clerides et al. (1998) found positive effects. See Bisztray et al. (2018) for details.

12-digit administrative region codes. This ensures a much wider geographical dispersion of firms than previous studies to give meaning to heterogeneous learning effects across space. Defining these spatial networks at such fine resolution is useful to avoid confounding variation from omitted spatially correlated variables (Bisztray et al., 2018), and examine how networking benefits decay in space (Arzaghi and Henderson, 2008). The results show that knowledge diffusion decays fast, confirming the necessity of defining spatial networks at fine resolution. More broadly, this paper also contributes to spatial spillover literature with an analysis in heterogeneous learning effects associated with geographical distribution of firms.

Lastly, this paper documents and analyzes spatial networks of firms in the novel and important context of export knowledge spillovers. Several previous studies link firm networks and export patterns. Chaney (2014) develops a model of trade frictions where firms must use their existing networks to search remotely for new trading partners. Mion and Opromolla (2014) and Mion et al. (2016) provide empirical evidence on how managers and managerial practices help diffuse export knowledge and improve firms' performance. Fafchamps and Quinn (2018) document the diffusion of business practices using a field experiment in African manufacturing firms. Cai and Szeidl (2018) exploit a randomized experiment to study the effects of business associations and meetings on firm performance. However, a theoretical model which formalizes the effects of spatial networks on heterogeneous learning effects is missing, and this study aims to fill this gap in literature. This study is also the first to acknowledge firms' selective perception in learning the signals revealed by neighbors in the context of international trade.

The remainder of the paper is organized as follows. Section 2 describes the model, and discusses the role of spatial networks and detailed learning mechanisms of firms that affect a potential entrant's entry decisions and export performance. Section 3 describes the data and discusses the definitions of key variables. Section 4 provides empirical evidence on the predictions of the model. Section 5 concludes. Robustness checks are presented in Supplementary Appendix.

1.2 Theory

I begin with a simple model to analyze the heterogeneous learning effects on exporters' entry decisions and performance. This model has several key features. First, I focus on firms' learning about foreign market demand. Second, once each firm draws its own productivity upon entry, this productivity does not change over time. Thus, the only driving force of new export market entry is the export entry threshold inferred from firm's own prior beliefs and neighbors' signals. Third, upon updating, firms give heavier weights to signals revealed by geographically close neighbors. The key model hypotheses are built on a Bayesian learning model with an explicit structure of internal geography. These give additional insights on how geographical distribution of firms affect the strength of learning-from-neighbors effects.

1.2.1 Model

To decide whether to start export to a country, a firm holds a prior belief about the demand of that country. The prior distribution reflects the uncertainty about the mean value of foreign market demand. Observing its neighbor's export performance to that country, a firm updates its knowledge of prior expectation and variance for that country's demand. This static, partial equilibrium model à la Melitz (2003) features heterogeneous firm productivity, monopolistic competitive goods markets, and constant elasticity of substitution (CES) preferences. Before entering a new market, a firm draws productivity ρ from a cumulative distribution function $G(\rho)$.

Consider a representative firm i with productivity ρ selling to market m. Its gross (operating) profit will be $\pi^{oper}(D_{im}, \rho) = D_{im}\rho^{\sigma-1}$, where D_{im} is a demand shifter, and $\sigma > 1$ is the elasticity of substitution between varieties available in all markets. Assume that firm productivity does not change over time. While each firm knows its own productivity before entry, uncertainty still plays a role in determining the firm's ex-post export profit due to random market- and firm-specific demand components. In particular, as in Fernandes and Tang (2014), firm i's (log) demand shifter, $ln(D_{im})$, can be decomposed into three components as follows:

$$ln(D_{im}) = \alpha + \beta_m + \gamma_{im}, \tag{1}$$

where $\alpha = ln(A)$ is a constant. $\beta_m = ln(P_m^{\sigma} Y_m)$ is the market-specific demand component that is common for all firms exporting to market m, where P_m and Y_m are the ideal price index and total expenditure in market m, respectively. The total expenditure in market m is assumed to be exogenously given. $\gamma_{im} = ln(\mathit{\Gamma}_{im})$ is firm i's firm- and market-specific product appeal in market

m, which take the same interpretation as "firm appeal" or "product differentiation" described in Hottman et al. (2016). I assume that the product appeal cannot be inferred from neighbors' export performance and must be realized only after the firm's own first year of exporting. For simplicity, I assume that all three components are time-invariant. An immediate implication of this assumption is that, once firm i exports to market m, uncertainty in the last two components, β_m and γ_{im} , of Eq. (1) is resolved, and there is nothing more for firm i to learn about market m. In other words, firm i is certain about its export profits in market m in *any* future periods after the first year of exporting to market m.

Before exporting to market m, firm i does not know market-specific demand component β_m and holds a prior belief that β_m is normally distributed with mean $\bar{\beta}_m$ and variance σ^2_β:

$$\beta_m \sim N\left(\bar{\beta}_m, \sigma^2_\beta\right). \tag{2}$$

Both the realizations of β_m and γ_{im} affect the export profit in market m. Similarly, the product appeal component, γ_{im}, is assumed to be ex ante unknown to the firm itself and normally distributed with mean zero and variance σ^2_γ:

$$\gamma_{im} \sim N\left(0, \sigma^2_\gamma\right). \tag{3}$$

Both σ^2_β and σ^2_γ can vary across market m. I interpret a higher σ^2_β as firms having more dispersed prior knowledge about market m, and a higher σ^2_γ as a greater heterogeneity of firms' export performance to market m. As in Bernard et al. (2010), I assume that firm productivity ρ and product appeal σ^2_γ are independently distributed.

Before any learning takes place, the expected operating profit from exporting to market m is expressed as:

$$\begin{aligned} E\left[\pi^{oper}\left(D_{im}, \rho\right)\right] &= \rho^{\sigma-1} E\left[D_{im}\right] \\ &= \rho^{\sigma-1} A\left[exp\left(\bar{\beta}_m + \frac{\sigma^2_m}{2}\right)\right], \end{aligned} \tag{4}$$

where $\sigma_m^2 = \sigma_\beta^2 + \sigma_\gamma^2$.[2] Note that the firm's expected operating profit depends on both the mean $\bar{\beta}_m$ and variance σ_m^2.

Before entering market m, each firm needs to pay a sunk entry cost, f_m^e. The zero-profit condition (i.e. $E\left[\pi^{oper}\left(D_{im},\rho\right)\right] = f_m^e$) pins down the productivity threshold of exporters serving market m:

$$\tilde{\rho}\left(\bar{\beta}_m, \sigma_m^2\right) \equiv \underline{\rho}^{\sigma-1} = \frac{f_m^e}{Aexp\left(\bar{\beta}_m + \frac{\sigma_m^2}{2}\right)}, \tag{5}$$

such that firms with $\rho^{\sigma-1} > \underline{\rho}^{\sigma-1}$ would find exporting to market m profitable. The exporting firm chooses quantity of export, which equals the expected export sales divided by its price,

$$q\left(D_{im},\rho\right) = \frac{E\left[R\left(D_{im},\rho\right)\right]}{p\left(\rho\right)},$$

where $E\left[R\left(D_{im},\rho\right)\right] = \sigma E\left[\pi^{oper}\left(D_{im},\rho\right)\right]$ and $p\left(\rho\right) = \frac{\sigma}{\sigma-1}\frac{c}{\rho}$, a constant markup over marginal cost, $\frac{c}{\rho}$. After the first period of exporting, all uncertainty is resolved. The firm realizes demand shifter D_{im} and learning from neighbors is no longer relevant.

1.2.2 Learning from neighbors

Internal geography and neighbors. Assume the exporting country consists of a set of locations arbitrarily arranged on a map. Following Coşar and Fajgelbaum (2016), I index locations by geographical distance l, and assume without loss of generality that l represents the distance separating each location l from the focal firm (a potential entrant who learns from its neighbors), and denote all focal firms by $l = 0$. Let $\bar{l}$ be the maximum distance between a location inside the country and its focal firm. Suppose firm i is surrounded by $n_{l,m,t-1}$ neighbors, who entered at period $t-1$ or before and exported to market m at period $t-1$, and situated at locations l from firm i. I impose three additional assumptions to solve the model in closed form.

Assumption 1 (Geographic groups). To simplify analysis, I assume all neighbors exporting to market m can be classified into L groups, where their locations fall onto location intervals $(0, l_1]$,

[2] If a random variable X has a normal distribution with mean μ and variance σ^2, then $exp\left(X\right)$ has a log-normal distribution. In particular, the expected value is $E\left[exp\left(X\right)\right] = exp\left(\mu + \frac{\sigma^2}{2}\right)$ and its variance is $var\left[exp\left(X\right)\right] = \left[exp\left(\sigma^2\right) - 1\right] \times exp\left(2\mu + \sigma^2\right)$.

$(l_1, l_2]$, ..., $(l_{L-2}, l_{L-1}]$, and $\left(l_{L-1}, \bar{l}\right]$. Hence, the number of neighbors in each location interval is $n_{g,m,t-1}$, where $g = 1, ..., L$. I further assume that neighbors' export revenue to market m in each of these geographic groups is normally distributed with mean $\bar{r}$ and variance σ_r^2: $r_g \sim N\left(\bar{r}, \sigma_r^2\right)$, $\forall g = 1, ..., L$, and that $r_{l\in(0,l_1]} = \left(r_{1,1}, ..., r_{1,n_1,m,t-1}\right) \sim N\left(\bar{r}, \sigma_r^2/n_{1,m,t-1}\right)$, ..., $r_{l\in\left(l_{L-1},\bar{l}\right]} = \left(r_{L,1}, ..., r_{L,n_L,m,t-1}\right) \sim N\left(\bar{r}, \sigma_r^2/n_{L,m,t-1}\right)$. Note that $\sum_{g=1}^{L} n_{g,m,t-1} = n_{m,t-1}$ represents the total number of neighbors exporting to market m at time $t-1$ observed by a potential entrant. Hereafter, for any neighbor pairs with locations indexed as l' and l'', where $0 < l' < l'' \leq \bar{l}$, I refer to the firm at l' as a geographically close neighbor, and the firm at l'' as a geographically distant neighbor, respectively. The close and distant location intervals are defined in a similar way.

Assumption 2 (Selective perception). Assume that firm i observes and values more highly the average export revenue to market m at $t-1$ from geographically close neighbors. That is, firm i places larger selection weights on the average export revenue observed from geographically close locations, and these selection weights are assumed to be inversely proportional to the neighbor's distance l. This "selective perception" assumption captures the idea that firms tend to give favourable interpretation to some subsets of information (Bullock, 2007; Gerber and Green, 1999). It also reflects spatial barriers to transferring knowledge, similar to that in Keller and Yeaple (2013), and relates to the role of social connections, where firms tend to obtain more trade-specific information from geographically close neighbors via more frequent interactions.

Assumption 3 (Conditional productivity). As in Fernandes and Tang (2014), I assume that firm knows the time-varying conditional mean of average neighbors' productivity, $\hat{\rho}_{m,t-1} = E\left[\rho|\rho^{\sigma-1} > \tilde{\rho}_{m,t-1}\right]$, where $\tilde{\rho}_{m,t-1}$ is the productivity threshold for export entry to market m at $t-1$, taking the form of Eq. (5). In other words, the exporters have limited memory and cannot recall any productivity thresholds for export entry before year $t-1$.

I denote with $I_{m,t-1}$ an indicator variable of whether there exists neighbors exporting to market m at $t-1$ (i.e. $I_{m,t-1} = 1$ if there exists neighbors serving market m at $t-1$; $I_{m,t-1} = 0$ otherwise). A firm which exports to market m holds a belief that:

$$\tilde{\rho}_{m,t-1} = \begin{cases} \tilde{\rho}\left(\bar{\beta}_m, \sigma_m^2\right) & if\, I_{m,t-1} = 0; \\ \tilde{\rho}\left(\bar{\beta}_{m,t-1}^{post}, \sigma_{m,t-1}^2\right) & if\, I_{m,t-1} = 1, \end{cases} \tag{6}$$

where $\bar{\beta}^{post}_{m,t-1}$ and $\sigma^2_{m,t-1}$ refer to the posterior mean and variance after observing neighbors' export performance to market m at $t-1$. That is, a firm would learn from neighbors' signals and infer export entry productivity thresholds based on posterior mean and variance when there exists neighbors exporting to market m at $t-1$; but would use prior mean and variance to infer productivity thresholds when no exporting neighbors exist. The details of learning mechanisms which give rise to $\bar{\beta}^{post}_{m,t-1}$ and $\sigma^2_{m,t-1}$, will be discussed below.

Based on the knowledge on productivity threshold $\tilde{\rho}_{m,t-1}$, the number of neighbors, $n_{g,m,t-1}$ for all geographic groups $g = 1, ..., L$, and the observed export revenue, $\bar{R}_{g,m,t-1}$, the firm infers the demand level of market m as:

$$\bar{\beta}^{learn}_{g,m,t-1} = \frac{\left(\bar{R}_{g,m,t-1}/n_{g,m,t-1}\right)}{\tilde{\rho}^{\sigma-1}_{m,t-1}}, \tag{7}$$

where $g = 1, ..., L$ represents the sets of neighbors in all location intervals. With these assumptions, the mean of the posterior is given by Bullock (2007, p.101) and Gerber and Green (1999):

$$\begin{aligned}\bar{\beta}^{post}_{m,t-1}\left(n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right) = E\left[\beta_{mt} | n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right] &= \left[\frac{\frac{1}{\sigma^2_\beta}\bar{\beta}_m}{\frac{1}{\sigma^2_\beta} + \sum_{g=1}^{L}\frac{n_{g,m,t-1}}{\sigma^2_\gamma}}\right] \\ &+ \left[\frac{\sum_{g=1}^{L}\frac{\psi_g n_{g,m,t-1}}{\sigma^2_\gamma}\bar{\beta}^{learn}_{g,m,t-1}}{\frac{1}{\sigma^2_\beta} + \sum_{g=1}^{L}\frac{\psi_g n_{g,m,t-1}}{\sigma^2_\gamma}}\right],\end{aligned} \tag{8}$$

where ψ_g for $g = 1, ..., L$, are the selection weights assigned to all location intervals. To emphasize the spatial frictions to knowledge diffusion, I further assume ψ_g is inversely proportional to the geographical distances separating exporting neighbors in geographic groups g and a potential entrant.

In the absence of selective perception, $\psi_g = 1$, $\forall g$; then the analysis is reduced to the standard Bayesian learning model without considering spatial distribution of firms, i.e. firms value knowledge from all neighbors equally. In other words, Eq. (8) indicates that firms selectively perceive information from close neighbors to be more important. Putting selection weights aside, Eq. (8) is a standard Bayesian updating result: the posterior mean is a weighted average of the prior mean $\bar{\beta}_m$ and the observed means $\bar{\beta}^{learn}_{g,m,t-1}$. The weight on the prior mean is proportional to the precision of prior mean $\left(1/\sigma_\beta^2\right)$, and the weight on the observed mean is proportional to the precision of the observed mean $\left(n_{g,m,t-1}/\sigma_\gamma^2\right)$.

The conditional variance of β_{mt}, given $n_{g,m,t-1}$ and $\bar{\beta}^{learn}_{g,m,t-1}$, can be expressed as:

$$\begin{aligned}\sigma_{mt}^2\left(n_{g,m,t-1},\sigma_\beta^2,\sigma_\gamma^2\right) &= \frac{\sigma_\gamma^2\sigma_\beta^2}{\sigma_\gamma^2+\left(\sum_{g=1}^{L}\psi_g n_{g,m,t-1}\right)\sigma_\beta^2}\\ &= \left(\frac{1}{\sigma_\beta^2}+\sum_{g=1}^{L}\frac{\psi_g n_{g,m,t-1}}{\sigma_\gamma^2}\right)^{-1}. \end{aligned} \tag{9}$$

It means that the variance of observed (weighted) mean is smaller than the variance of prior mean $\left(\sigma_\beta^2\right)$ and smaller than the variance of the observed mean $\left(\sigma_\gamma^2/n_{g,m,t-1}\right)$. That is, combining the information from the prior and the observations from neighbors gives a more precise estimate than using either information sources by itself.

Comparative Statics. Let the weights on $\bar{\beta}_m$ and $\bar{\beta}^{learn}_{g,m,t-1}$ in geographic group g in Eq. (8) be δ_{0t} and δ_{gt}, respectively. Thus,

$$\begin{aligned}\delta_{0t} &\equiv \left[\frac{\frac{1}{\sigma_\beta^2}}{\frac{1}{\sigma_\beta^2}+\sum_{g=1}^{L}\frac{\psi_g n_{g,m,t-1}}{\sigma_\gamma^2}}\right] = \left[1+\frac{\sum_{g=1}^{L}\psi_g n_{g,m,t-1}}{\left(\sigma_\gamma^2/\sigma_\beta^2\right)}\right]^{-1};\\ \delta_{gt} &\equiv \left[\frac{\frac{\psi_g n_{g,m,t-1}}{\sigma_\gamma^2}}{\frac{1}{\sigma_\beta^2}+\sum_{g=1}^{L}\frac{\psi_g n_{g,m,t-1}}{\sigma_\gamma^2}}\right] = \left[\frac{\left(\sigma_\gamma^2/\sigma_\beta^2\right)+\psi_g n_{m,t-1}}{\psi_g n_{g,m,t-1}}\right]^{-1}. \end{aligned} \tag{10}$$

Partial differentiation of Eq. (10) yields the following comparative statics regarding the relationship between the number of neighbors, the precision of the prior, and the precision of the signal:

$$\begin{aligned}&\frac{\partial\delta_{0t}}{\partial n_{g,m,t-1}}<0 \ ; \ \frac{\partial\delta_{0t}}{\partial\left(\sigma_\gamma^2/\sigma_\beta^2\right)}>0;\\ &\frac{\partial\delta_{gt}}{\partial n_{g,m,t-1}}>0 \ ; \ \frac{\partial\delta_{gt}}{\partial\left(\sigma_\gamma^2/\sigma_\beta^2\right)}<0 \ ; \ \frac{\partial\delta_{gt}}{\partial\psi_g}>0. \end{aligned} \tag{11}$$

When updating the prior, a potential entrant will put a larger weight on its neighbors' signals about demand in market m and a smaller weight on its own prior belief, if there are more neighbors, either close or distant, revealing the signals. Clearly, a potential entrant also places a heavier weight on information revealed by geographically close neighbors, as seen in the selection perception parameter ψ_g. Notice that when $\psi_g \to 1$ for all $g = 1, ..., L$, a potential entrant becomes unresponsive to the spatial distribution of neighbors, i.e. it values information from neighbors equally highly. On the other hand, when the signal from neighbors is less precise, captured by a higher σ_γ^2, due to more dispersed product appeal, all else being equal, the firm will put a smaller weight on the neighbors' signals. Similarly, the firm will put a larger weight on the signals if it is less informed about market m ex ante, captured by a higher σ_β^2.

The posterior variance of the signal, $\sigma_{mt}^2\left(n_{g,m,t-1}, \sigma_\beta^2, \sigma_\gamma^2\right)$, depends on $n_{g,m,t-1}$, σ_β^2, and σ_γ^2 as follows:

$$\frac{\partial \sigma_{mt}^2}{\partial n_{g,m,t-1}} < 0 \;\; ; \;\; \frac{\partial \sigma_{mt}^2}{\partial \sigma_\beta^2} > 0 \;\; ; \;\; \frac{\partial \sigma_{mt}^2}{\partial \sigma_\gamma^2} > 0 \;\; ; \tag{12}$$

$$\frac{\partial \sigma_{mt}^2}{\partial \psi_g} = \frac{-\sigma_\gamma^2 n_{g,m,t-1}\left(\sigma_\beta^2\right)^2}{\left[\left(\sigma_\gamma^2 + \sum_{g=1}^{L} \psi_g n_{g,m,t-1}\right)\sigma_\beta^2\right]^2} < 0. \tag{13}$$

The precision of the posterior, $\left(\sigma_{mt}^2\right)^{-1}$, increases with the number of neighbors, either close or distant, revealing the signal. In the extreme case when $n_{g,m,t-1} \to \infty$, the firm observes the true demand in market m, β_m^*, according to (12) as $\sigma_{mt}^2 \to 0$. The firm will then ignore its own prior and rely solely on its neighbors' revealed signal. The last two inequalities in (12) are intuitive: either a higher variance in prior or product appeal leads to lower precision of the posterior. When the number of neighbors exist in a geographic group approaches to zero, i.e. $n_{g,m,t-1} \to 0$, or when the product appeal becomes highly heterogeneous, i.e. $\sigma_\gamma^2 \to +\infty$, then the effect of a greater selective weight on posterior variance is minimal. Intuitively, the signals from neighbors, albeit geographically close, are uninformative, when there are too few neighbors or when signal-to-noise ratio is sufficiently small.

1.2.3 Entry into new markets

First, I analyze the firms' decisions in export entry after observing neighbors' export performance. A potential entrant will enter market m only when the inferred demand from the average neighbors' export revenue exceeds its own prior. In this decision making process, the potential entrant places heavier selection weights on information from geographically close neighbors. Intuitively, knowledge flows are stronger when firms are concentrated, and firms tend to value information from spatial networks around them more highly. If more close neighbors reveal a better-than-average signal (i.e. higher average close neighbors' export revenue than that of all neighbors), then the productivity threshold will be lowered more significantly.

A potential entrant will start exporting to market m after receiving a signal that lowers the entry productivity threshold. Similar to (5), the zero-profit condition pins down the posterior productivity threshold:

$$\tilde{\rho}^{post}_{m,t}\left(\bar{\beta}^{post}_{mt}, \sigma^2_{mt}\right) \equiv \underline{\rho}^{\sigma-1}_{m,t} = \frac{f^e_m}{Aexp\left(\bar{\beta}^{post}_{mt} + \frac{\sigma^2_{mt}}{2}\right)}, \tag{14}$$

where $\bar{\beta}^{post}_{mt}$ and σ^2_{mt} are defined in (8) and (9) above, respectively.

Consider a firm observes $n_{g,m,t-1}$ neighbors from all geographic groups $g = 1, ..., L$ exporting to market m. A positive signal revealed by exporting neighbors to market m's demand level at $t-1$ causes $\bar{\beta}^{learn}_{m,t-1} > \bar{\beta}^{learn}_{m,t-2}$. The entry threshold at t will be lower than that at $t-1$, i.e. $\tilde{\rho}^{post}_{m,t} < \tilde{\rho}^{post}_{m,t-1}$. Specifically, firms with $\rho^{\sigma-1}$ that is lower than $\tilde{\rho}^{post}_{m,t-1}$ but higher than $\tilde{\rho}^{post}_{m,t}$ will start exporting to market m at t. To examine the learning effects on entry, I define the semi-elasticity of $\tilde{\rho}^{post}_{m,t}$ with respect to $\bar{\beta}^{learn}_{m,t-1}$ as $\varepsilon_{gm\rho t} \equiv \frac{\partial ln \tilde{\rho}^{post}_{m,t}}{\partial \bar{\beta}^{learn}_{g,m,t-1}}$, where $g = 1, ..., L$, which can be expressed as:

$$\varepsilon_{gm\rho t} = -\delta_g\left(n_{g,m,t-1}\right) \equiv -\left[\frac{\left(\sigma^2_\gamma/\sigma^2_\beta\right) + \sum_{g=1}^{L} \psi_g n_{g,m,t-1}}{\psi_g n_{g,m,t-1}}\right]^{-1} < 0. \tag{15}$$

In words, a stronger positive signal revealed by neighbors in geographic groups $g = 1, ..., L$ lowers the entry threshold $\tilde{\rho}^{post}_{m,t}$, inducing a potential entrant to enter market m. The learning-from-neighbors effects on entry thresholds depend on the number of exporting neighbors in different geographic groups, the dispersion of the prior, σ^2_β, and the dispersion of the neighbors' export performance, σ_γ^2. The semi-elasticity tends to increase in magnitude (i.e. the entry threshold response tends to be larger) when a potential entrant places a heavier weight, ψ_g, on that geographic group, or when there are more neighbors, $n_{g,m,t-1}$, observed in that geographic group.

To further examine the relationship between semi-elasticity $\varepsilon_{gm\rho t}$ and prevalence of neighbors $n_{g,m,t-1}$, I have:

$$\frac{\partial \varepsilon_{gm\rho t}}{\partial n_{g,m,t-1}} = \frac{\psi_g \left[\psi_g n_{g,m,t-1} - \sum_{g=1}^{L} \psi_g n_{g,m,t-1}\right] - \left(\sigma_\gamma^2/\sigma_\beta^2\right)}{\left[\left(\sigma_\gamma^2/\sigma_\beta^2\right) + \sum_{g=1}^{L} \psi_g n_{g,m,t-1}\right]^2} < 0. \tag{16}$$

In words, either a heavier weight on information from close neighbors or an increase in the number of close neighbors will result in a larger decrease in the threshold, $\tilde{\rho}_{m,t}^{post}$, given a positive signal. I summarize the theoretical result of this sub-section by the following proposition:

Proposition 1 (Neighbors, signals, and export entry). In response to a positive signal, the likelihood of a firm's entry into a new export market is increasing in the number of exporting neighbors, strength of the signal about the market's demand inferred from neighbors' export performance, and more so if the signal is revealed by geographically close neighbors.

Proof of Proposition 1: It follows immediately from (14), (15) and (16). $\square$

It is noted that firms will respond differently in a response to a negative signal. An increase in the number of neighbors will raise export entry threshold and deter firm entry, if the signal is negative. Moreover, the number of close neighbors plays a role in magnifying the strength of signal in the model: with more geographically close neighbors revealing worse-than-average signals, the productivity threshold would rise above that without considering the spatial distribution of neighbors.

I then examine the effects of signal dispersions and entry threshold responses in response to a positive signal. Differentiate the semi-elasticity $\varepsilon_{gm\rho t}$ in expression (16) with respect to the variances of product appeal component and prior market-specific knowledge, respectively:

$$\frac{\partial \varepsilon_{gm\rho t}}{\partial \sigma_\gamma^2} = \left[\frac{\left(\sigma_\gamma^2/\sigma_\beta^2\right) + \sum_{g=1}^{L} \psi_g n_{g,m,t-1}}{\psi_g n_{g,m,t-1}}\right]^{-2} \left(\sigma_\beta^2 \psi_g n_{g,m,t-1}\right)^{-1} > 0, \tag{17}$$

$$\frac{\partial \varepsilon_{gm\rho t}}{\partial \sigma_\beta^2} = \left[\frac{\left(\sigma_\gamma^2/\sigma_\beta^2\right) + \sum_{g=1}^{L} \psi_g n_{g,m,t-1}}{\psi_g n_{g,m,t-1}}\right]^{-2} \left[\frac{-\sigma_\gamma^2 \left(\sigma_\beta^2\right)^2}{\psi_g n_{g,m,t-1}}\right] < 0. \tag{18}$$

In words, in response to a positive signal, a potential entrant will show smaller entry response when the product appeal component is noisier, i.e. higher σ_γ^2, and will show larger entry response when the market-specific demand component is more dispersed. With spatial networks, a heavier selection weight on information from close neighbors leads to a smaller entry response to a given positive signal when the product appeal is more heterogeneous; and a more dispersed prior on foreign market demand leads to a larger entry response. Intuitively, when signal-to-noise ratio increases, a potential entrant will not value neighbors' signals as much because it cannot infer the firm-specific product appeal from neighbors' export performance. In response to a positive signal, a larger selection parameter ψ_g in combination with a higher signal-to-noise ratio leads to a larger (smaller) reduction in entry response to the information obtained from close (distant) neighbors. This is because information revealed by close neighbors exerts a larger influence on reduction in export entry threshold, given the signal is positive.

I summarize the relationship between signal-to-noise ratio and entry response by the following proposition:

Proposition 2 (Signal-to-noise ratio and entry response). In response to a positive signal, a firm's entry response about a market from neighbors is smaller in magnitude if the signals are noisier with firm-specific product appeal (higher σ_γ^2), all else being equal. On the other hand, the entry response is greater in magnitude if the firm itself has a more dispersed prior on foreign market demand (higher σ_β^2), all else being equal. The entry response is magnified if there are more geographically close neighbors revealing the signal.

Proof of Proposition 2: It follows immediately from (17) and (18). $\square$

1.2.4 Initial export sales

In this section, I generate predictions on exporters' initial sales in a new market after learning neighbors' signals. Previous studies document that exporters tend to scale down exports when they first enter a market (Eaton et al., 2007; Albornoz et al., 2012). A possible explanation is that uncertainty about a new market exists, so firms prefer to start with smaller quantities in order to resolve some uncertainty (Rauch and Watson, 2003), given that some ex ante investment may be irreversible (Levchenko, 2007). To see if heterogeneous learning effects play a role in mitigating uncertainty, I explore if the size of initial export sales is related to the strength and the precision of the signals from neighboring exporters. The initial export sales of a new exporter with productivity ρ is given by:

$$\begin{aligned} x_t\left(n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right) &= \varepsilon\sigma\rho^{\sigma-1}E\left[D_{im}|n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right] \\ &= \varepsilon\sigma\rho^{\sigma-1}exp\left(\bar{\beta}^{post}_{mt}\left(n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right) + \frac{\sigma^2_{mt}\left(n_{g,m,t-1}\right)}{2}\right). \end{aligned}$$

The initial export sales $x_t\left(n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right)$ depends on the firm productivity, ρ, posterior expected demand level in market m and the variance of the signal driven by neighbors in different geographic groups, as defined in (8) and (9). I can show that initial export sales increases with posterior expected demand level, $\bar{\beta}^{learn}_{g,m,t-1}$:

$$\frac{\partial ln\left(x_t\left(n_{g,m,t-1}, \bar{\beta}^{learn}_{g,m,t-1}\right)\right)}{\partial\bar{\beta}^{learn}_{g,m,t-1}} = \delta_g\left(n_{g,m,t-1}\right) \equiv \left[\frac{\left(\sigma^2_\gamma/\sigma^2_\beta\right) + \sum_{g=1}^{L}\psi_g n_{g,m,t-1}}{\psi_g n_{g,m,t-1}}\right]^{-1} > 0. \tag{19}$$

With spatial networks, my focus is on the selection parameters, ψ_g, and firms' heterogeneous learning effects from neighbors. Learning from close information sources allows firms to resolve a greater degree of market demand uncertainty, thus increasing initial export sales more than the situation when firms do not take spatial networks into consideration.

Notice that the effect of an increase in the number of neighbors on initial export sales is ambiguous. For a specific geographic group, while more neighbors will magnify the effect of a positive signal on initial export sales, as seen from Eq. (8) and condition (19), $\frac{\partial \bar{\beta}^{post}_{m,t-1}}{\partial n_{g,m,t-1}} > 0$; meanwhile, from condition (12), $\frac{\partial \sigma^2_{mt}(n_{m,t-1})}{\partial n_{m,t-1}} < 0$, it indicates that more neighbors will also increase the precision of the signal, lowering the spread of the expected operating profits in Eq. (4). Whether initial export sales increases will depend on the strength of these two opposing forces, and the net effect on initial export sales is thus ambiguous.

However, I can examine the interactive effect of number of neighbors, $n_{g,m,t-1}$, and the signal ,$\bar{\beta}^{learn}_{g,m,t-1}$, on the initial export sales:

$$\frac{\partial}{\partial n_{g,m,t-1}}\left(\frac{\partial ln\left(x_t\right)}{\partial \bar{\beta}^{learn}_{g,m,t-1}}\right) = \frac{\left(\sigma^2_\gamma/\sigma^2_\beta\right) + \psi_g\left(\sum_{g=1}^{L}\psi_g n_{g,m,t-1} - \psi_g n_{g,m,t-1}\right)}{\left[\left(\sigma^2_\gamma/\sigma^2_\beta\right) + \sum_{g=1}^{L}\psi_g n_{g,m,t-1}\right]^2} > 0. \tag{20}$$

In response to a positive signal, there is a positive interactive effect on initial export sales in a new market. The theoretical prediction on new exporters' initial export sales is summarized below:

Proposition 3 (Strength of signals and initial export sales). In response to a positive signal, an exporter's initial export sales in a new market is increasing in the strength of the signal about the market's demand level revealed by neighbors, and more so if the signal is revealed by geographically close neighbors.

Proof of Proposition 3: It immediately follows from (19) and (20). □

1.2.5 Survival after export entry

In this section I analyze the probability of survival of exporters in a new market m. After the first year of exporting to market m at t, a firm with productivity ρ resolves all uncertainty in foreign market demand β_m, and thus the survival probability will depend on the realization of firm-specific product appeal γ_{im}. Assume an exporter needs to pay a per-period country-specific fixed cost of exporting, F_m. Then the realized net export profits of a firm with productivity ρ to market m is given by: $\pi_{mt}\left(\rho, \beta^*_m\right) = \rho^{\sigma-1} exp\left(\beta^*_m + \gamma_{im}\right) - F_m$, where β^*_m is the actual demand level of market m. The firm will continue to export in $t+1$ as long as this realized net export profits remain positive.

Hence, the probability of survival is given by:

$$\begin{aligned}\Lambda_{t+1}^{survival}(\rho, \beta_m^*) &= Pr\left[\rho^{\sigma-1} exp\left(\beta_m^* + \gamma_{im}\right) \geq F_m\right] \\ &= 1 - \Phi\left(\frac{1}{\sqrt{\sigma_\gamma^2}}\left(ln\left(\frac{F_m}{\rho^{\sigma-1}}\right) - \beta_m^*\right)\right),\end{aligned}$$

where Φ is the standard normal cumulative distribution function. A lower per-period country-specific fixed cost of exporting, F_m, a higher firm productivity, ρ, a higher actual demand level of market m, β_m^*, and a more heterogeneous product appeal, ρ_γ^2, all have independently positive effects on export survival. Specifically,

$$\frac{\partial \Lambda_{t+1}^{survival}(\rho, \beta_m^*)}{\partial \beta_m^*} = \frac{1}{\sqrt{\sigma_\gamma^2}}\phi\left(\frac{1}{\sqrt{\sigma_\gamma^2}}\left(ln\left(\frac{F_m}{\rho^{\sigma-1}}\right) - \beta_m^*\right)\right) > 0, \quad (21)$$

where ϕ is the probability distribution function of γ_{im}. Notice that $\Lambda_{t+1}^{survival}(\rho, \beta_m^*)$ depends on the actual demand level rather than the observed average demand inferred from neighbors, $\bar{\beta}_{mt}^{learn}$. Notice that the actual demand level β_m^* is unobservable, thus I will follow Fernandes and Tang (2014) to use $\bar{\beta}_{mt}^{learn}$ to proxy for it in the empirical analysis below. It is also noted that survival probability $\frac{\partial \Lambda_{t+1}^{survival}(\rho, \beta_m^*)}{\partial \beta_m^*}$ is independent of the number of neighbors $n_{g,m,t-1}$ for $g = 1, ..., L$, even though prevalence of neighbors, either close or distant, could affect the export entry productivity threshold $\underline{\rho}_{m,t}^{\sigma-1}$. In other words, while the number of neighbors could affect entry decisions, it has no effects on survival probability.

However, selection bias arises because the number of neighbors $n_{g,m,t-1}$ and signal about foreign market demand $\bar{\beta}_{m,t-1}^{learn}$ revealed by neighbors could affect entry decisions, the sample of entrants, and thus the survival probability of exporters conditional on exporting. Specifically, through Bayesian updating, a potential entrant's entry productivity threshold, $\underline{\rho}_{m,t}^{\sigma-1}$, is lower in response to a positive signal and more geographically close neighbors revealing it. As a result, the average productivity level of entrants decreases. Conditional on entry and the presence of per-period country-specific fixed cost of exporting, the firms with lower productivity levels are more likely to exit ex post, which lowers the overall exporters' survival probability. In this empirical analysis below, I account for this selection bias. The analysis employs Heckman (1976) two-step approach to analyze the survival probability of these exporters. In the first step selection equation, a probit model is run to estimate the probability of entry to a foreign market. From this I obtain the inverse Mills ratio, which addresses the selection bias. After accounting for the selection bias, I expect the exporters' survival probability in a new market is positively correlated with the strength of the signal, but independent of the number of neighbors.

The theoretical prediction on new exporters' survival probability is summarized as follows:

Proposition 4 (Strength of signals and survival probability). In response to a positive signal, exporters' survival probability in a new market is positively correlated with the strength of the signal about the market's demand revealed by neighbors, but is independent of the number of geographically close and distant neighbors.

Proof of Proposition 4: It follows immediately from (21). □

In the subsequent sections, I will first describe the data and identification strategy, followed by empirical analysis which tests the main theoretical predictions in the model.

1.3 Data and Identification

1.3.1 Data construction and description

The firm-transaction level dataset is constructed using two data sources: the transaction-level data on the universe of China's international trade transactions from China Customs Office, and the firm-level data from Annual Survey of Industrial Production (ASIP) from China's National Bureau of Statistics. My identification strategy requires very fine resolution of neighborhoods to study the learning effects of exporting peers and their signals. Thus, I use Baidu's geocoding API to obtain the geographic coordinates of all firm locations.[3] The data used in this study cover export transactions of Chinese manufacturing exporters from 2004 to 2006, where detailed firms' addresses and 12-digit administrative region codes are available. In the baseline sample, there are 1,908 Chinese manufacturing exporters from 477 12-digit administrative regions (villages) serving 83 export destinations. Each of these datasets is described in details below.

[3]Baidu Maps is one of the largest web mapping service sites in China, offering satellite imagery, street maps, and geocoded information of Chinese locations.

Transaction-level Customs data. The China Customs data report the free-on-board value of firm export transactions (in U.S. dollars), trade regimes (e.g. processing trade or non-processing trade), destination countries, and products in the 8-digit Harmonized System (HS) classification. For the customs data, I follow Fernandes and Tang (2014) and He and Dai (2017) to include only trade transactions that are labelled as non-processing trade transactions (also known as "ordinary trade transactions"). I then exclude export transactions to Hong Kong because it serves as an entrepôt to many Chinese firms, which they re-export final products to foreign markets. In addition, I aggregate firms' monthly export transactions to the year level to average out noises associated with infrequent export activities. Finally, I collapse the product dimension because the primary interest is firms' learning about foreign market demand.

Firm-level data. The ASIP is a census of Chinese private establishments with more than 5 million yuan (about 610,000 U.S. dollars in 2004-2006) in annual revenue, and all state-owned enterprises (SOEs). It reports firm names, firm ownership statuses or registration types, administrative region codes ("geographic codes"), and manufacturing industries in 4-digit Chinese Industrial Classification (CIC) system. Each firm-year cell has information on employment, assets, sales revenue, value added, and profits by private firms and SOEs.[4] For the baseline sample of firms, I follow standard practice to drop all SOEs, because they are under control of Chinese government, and not necessarily profit-maximizing (Manova et al., 2015). I also follow Ahn et al. (2011) to drop trade intermediaries which do not engage in manufacturing but serve as an import-export facilitation between domestic exporters and foreign importers. I then merge these two datasets using firms' names and postal codes.

Spatial networks. To construct the spatial networks of firms, I use a highly localized definition of spatial networks, following Bisztray et al. (2018). In the ASIP dataset 2004-2006, all firms' addresses and detailed 12-digit administrative region codes assigned by China's Ministry of Civil Affairs are reported, and they are used to geographically locate a firm and its exporting neighbors. I use Baidu's geocoding API to obtain a firm's latitude and longitude with its full address and 12-digit administrative region.[5] I identify geographically close neighbors as those exporting neighbors

[4]Brandt et al. (2014) describe the data and present stylized facts about Chinese exporters in the context of international trade. The unit of observation is a legal unit, which roughly corresponds to the "establishments" in the United States (Brandt et al., 2014; Imbert et al., 2019). I follow both Brandt et al. (2014) and Imbert et al. (2019) to refer these legal units as firms.

[5]Each 12-digit administrative region code contains detailed geographic information of a firm. The first two digits

who have prior exporting experience to the same market who share the same geographic coordinates with the focal firms. With these detailed geocoded information, I further map a representative firm to its nearby exporting neighbors within 1,000 meters, in 50-meter intervals.[6] These firms are regarded as geographically distant neighbors. To study peer interactions and knowledge diffusion within a highly localized neighborhood, I need to ensure an active learning environment for learning-from-neighbors and knowledge diffusion to take place. Hence, I focus on a sample of firm-country observations with at least one same-village neighbor exporting to the same market, and at least one neighbor within the radius of 1,000 meters of a focal firm exporting to the same market.[7,8]

Destination countries and gravity variables. Lastly, a market is an export destination country in the empirical analysis. In addition, I use bilateral distance, common language, and per-capita income level differences (measured by the differences in GDP per capita), between China and the destination countries to serve as proxies for uncertainty in exports. The data are obtained from the *Centre d'Etudes Prospectives et d'Informations Internationales* (CEPII) Database.

1.3.2 Identification

The main hypothesis, as stated in Proposition 1, is that the prevalence of exporting neighbors and their revealed signals about a foreign market's demand increase the likelihood of export entry of potential entrants. However, in a spatial network, the mechanism might not be learning from neighbors or knowledge diffusion. Instead, it is possible that common owners' or managers' knowledge causes firms to make correlated entry decisions. For example, same-industry firms are more

correspond to the highest level of administrative division, province. The next two (3rd and 4th) digits summarize the location for the associated prefecture or city. The next two (5th and 6th) digits represent a county. The next three (7th to 9th) digits give information of the town. The last three (10th to 12th) digits refer to a village or community, the most disaggregated level of administrative divisions. For notational convenience, I use "province", "city", "county", "town", and "village" to indicate these classifications accordingly.

[6] The most recent spillover literature, Baum-Snow et al. (2020) find that neighbors' impacts fully decay within 250 meters. Bisztray et al. (2018) discuss how the the learning-from-neighbors effects decay in space. They estimate that the neighbor spillovers decline by 5.6% every meter, compared to Arzaghi and Henderson (2008) estimates on networking benefits of about 0.3% per meter, Rossi-Hansberg et al. (2010) estimates on housing externalities of about 0.2% per meter, Ahlfeldt et al. (2015) estimates on production and residential externalities of 0.4% and 1% per meter, respectively. In the empirical results, I mostly focus on the neighborhoods within 300 or 500 meters depending on specifications, because I observe the learning-from-neighbors effects weaken considerably beyond these distances.

[7] This sample restriction is consistent with Lu et al. (2019) that do not consider any cross-county spillovers. The empirical results focus on the neighborhoods within villages and always control for village-country fixed effects because the local governments conduct land appraisals and outline development plans based on 12-digit administrative region (village or community) units. See Lu et al. (2019) for details.

[8] I also construct spatial networks beyond 300 meters of a representative firm. However, beyond this range of distance the neighbors and corresponding signal terms do not have a statistically significant effect on entry decisions, indicating that my results are consistent with previous spillover literature.

likely to co-locate and exhibit correlated export behavior, and that firms could also learn from alternative information sources like ports and airports instead of peers. As in Manski (1993) and Bisztray et al. (2018), the challenges to identification are endogenous peer groups and spatially correlated omitted variables. Following Bisztray et al. (2018), I address the endogeneity problem by focusing on neighborhoods at fine spatial scales, in combination with placebo tests and sample definition choices that rule out several omitted variables. In robustness checks, I take additional steps to rule out alternative mechanisms which drive correlated export behavior that are unrelated to learning. The details of research design are described as follows.

Destination country variation. I address the concern that exporters tend to stay connected with other exporters. Following Mion et al. (2016) and Bisztray et al. (2018), I study the effects of neighboring exporters' same-country export knowledge on a firm's decision whether to start exporting to the same country. By including country-year and firm-year fixed effects, I effectively exploit variation across destination countries. As a result, the remaining threat to identification must be based on destination country variation, that is, firms tend to co-locate with each other when they export to a specific country. With this research design I address the basic concern that exporters tend to co-locate and make correlated export decisions.

Ownership-connected firms. Firms with common owners or top managers could induce firms to make correlated decisions that are unrelated to learning from neighbors. To limit confounding effects, I exclude ownership-connected firms, defined by firms with the same legal person in the ASIP dataset, from the baseline sample. It is also common that large corporations or multinationals set up multiple firms with different firm names in different locations. Hence, I also exclude these firms under the same corporations with the reasons described above.[9] By excluding these firms with ownership links, I remove omitted variables based on joint ownership and management decisions.

Highly spatially localized spillovers and placebo spatial groups. For spatial networks I follow Bisztray et al. (2018) to focus on highly spatially localized knowledge spillovers, as described in Section 3.1. Previous spillover literature, for example, Bisztray et al. (2018) and Baum-Snow et al. (2020), find that the peer effects decay fast in distance. Therefore, I expect, beyond some points in distance, the placebo effects of some geographically distant neighbors become small and

[9]Among those firms under large corporations or multinationals, a few notable examples are: General Electric, Mitsubishi Electric, Panasonic Corp., Samsung Electronics, and TCL Technology.

insignificant. These placebo effects will confirm the logic of my identification strategy. By exploiting neighborhoods at fine spatial scales, I compare three geographic groups: (1) same-location neighbors, (2) distant neighbors, and (3) placebo neighbors. This identification is consistent with Arzaghi and Henderson (2008) that as long as spillovers are more spatially concentrated than the omitted variables, greater-magnitude coefficients on neighbors and signals for geographically close spatial networks are evidence for knowledge diffusion.

Same-industry clustering. The extent of industrial agglomeration in China is considerably lower than many developed countries such as France, United Kingdom and United States (Lu and Tao, 2009).[10] This alleviates the concern over same-industry clustering. In robustness checks, I compute the number of same-industry firms for all village-year observations, and then drop those village-year observations when the number of same-industry firms is above its 90th percentiles across all village-years. Based on Lu and Tao (2009) study on the extent of industrial agglomeration in China, I also drop village-year observations with at least one firm from the most geographically concentrated industries to further eliminate the possibility of correlated decisions driven by industrial agglomeration. In addition, I include industry-village-year fixed effects in my specifications, in order to rule out the explanation that correlated shocks among same-industry firms could lead to correlated decisions.

Alternative learning mechanisms. Geographical proximity to trade infrastructure, e.g. ports and airports, can serve as an alternative channel of learning and knowledge diffusion. Firms could obtain necessary trade-specific information which infer foreign market demand, deal with foreign importers and customs procedures, could also shape entry decisions. Export-oriented firms may co-locate around ports and airports, and tend to make correlated decisions. I obtain port and airport data from the *National Ports Layout Plan*, Ministry of Transport, and the *Statistics Report*, Civil Aviation Administration of China, respectively.[11] As an attempt to rule out this alternative

[10] Using the ASIP dataset from 1998 to 2005 on 2,862 Chinese counties, Lu and Tao (2009) compute the Ellison and Glaeser (1997) γ indices and find that the most geographically concentrated industries are stationery, educational and sports goods (24), electronic and telecommunications (40), and leather, furs, down and related products (19).

[11] The *National Ports Layout Plan*, an official document published by China's Ministry of Transport in 2006 to identify ports which connect China and international destinations. The document contains information on Chinese ports, including whether they are "core" ports (i.e. leading ports in their corresponding geographical or economic clusters that tend to serve surrounding provinces and serve primarily as an international gateway connecting China and foreign destinations), their port facilities (e.g. container transport system, crude oil, coal loading and transport system, and etc.) and their corresponding geographical clusters. The *Statistics Report* of Civil Aviation Administration of China in 2006 provides information of all public airports in each province. Defunct and non-commercial airports are excluded.

learning mechanism, I obtain the latitude and longitude information of each of these ports and airports, and map each 12-digit administrative region (village) to its closest ports and airports.[12] I then include port-country-year and airport-country-year fixed effects to account for the possibility that firms may learn from these alternative information sources instead of neighbors.

Non-learning mechanisms. Firms may adhere to nearby leading firms and make correlated decisions for non-knowledge related reasons. I rank village-year observations by (i) total exports, (ii) total employment, (iii) domestic sales revenues, and (iv) profits of their firms, and drop all village-year observations when these measures are above 90th percentiles across all village-years. This rules out an alternative mechanism that smaller firms tend to adhere to leading firms and make correlated decisions with them.

For the above research design it is able to account for the most plausible confounding effects which may drive the empirical results. In the next section I begin the analysis to demonstrate knowledge diffusion among firms. The empirical results regarding same-industry clustering, alternative learning mechanisms, and non-learning mechanisms are presented in Supplementary Appendix.

1.3.3 Summary statistics

Summary statistics of key variables are reported in Table 1. Panel A reports firm-level export sales for both first-time and continuing exporters, and initial export sales for first-time exporters. The initial export sales have smaller mean and dispersion than the export sales for all types of exporters, which is consistent with the explanation that firms tend to scale down initial export sales to resolve some trade-specific uncertainty (Rauch and Watson, 2003). Panel B reports number of neighbors in different geographic groups and their revealed signals, measured by the average neighbors' export growth to the same market in that geographic group. In all spatial networks a large proportion of firms are isolated with no neighbors, which is consistent with Bisztray et al. (2018). Firms also observe stronger and more dispersed positive signals from same-location neighbors than in other geographic groups. Panel C shows that aggregate level summary of baseline sample, which consists of 1,977 firms from 477 villages serving 83 destination countries.

[12] I exclude ports and airports that do not have a valid location identifier: UN/LOCODE (United Nations Code for Trade and Transport Locations) and International Air Transport Association (IATA) airport code. I also exclude ports and airports that were not in operation before 2004.

Table 1: Summary statistics of key variables.

	Mean	SD	10pct	90pct
Panel A: Firm level				
Exports, thousand U.S. dollars	371.17	1343.63	34.50	813.02
Initial sales, thousand U.S. dollars	146.00	718.19	13.00	275.10
Panel B: Spatial networks and signals				
Number of same-location neighbors	0.65	1.37	0.00	2.00
Number of (0,250]-meter geographic group neighbors	0.34	0.87	0.00	1.00
Number of (250,500]-meter geographic group neighbors	0.41	0.78	0.00	1.00
Same-location signals	0.15	1.12	−0.34	0.94
(0,250]-meter geographic group signals	0.07	0.85	0.00	0.36
(250,500]-meter geographic group signals	0.07	0.93	−0.26	0.64
Panel C: Aggregate level				
Entry rate	0.25			
Number of destinations	83			
Number of firms	1908			
Number of villages	477			
Exports, million U.S. dollars	5520			

Table 1 reports summary statistics for key variables. Panel A reports the firm-level export values and initial export sales in baseline sample. Panel B reports spatial networks and neighbors' revealed signals. Spatial networks and signals are categorized into three groups as described in Section 3.1.: (i) same-location as the focal firm, (ii) within $(0, 250]$-meters, and (iii) within $(250, 500]$-meters of the focal firm. Signals are defined as the average neighbors' export growth rates between years $t-1$ and t exporting to the same market m. See Eq. (23) in Section 4.1. for details. Panel C reports the aggregate level of export trade activities in baseline sample. A village refers to a 12-digit administrative region, the most disaggregated level of neighborhood in China. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. Ownership-connected firms are excluded. The sample includes firm-country-year observations with at least one same-village neighbor exporting to the same market m, and at least one neighbor within the radius of 1,000 meters of a focal firm exporting to the same market m. Source: Author's calculations based on ASIP and China Customs Data, 2004-2006.

Figure 1: Spatial networks.

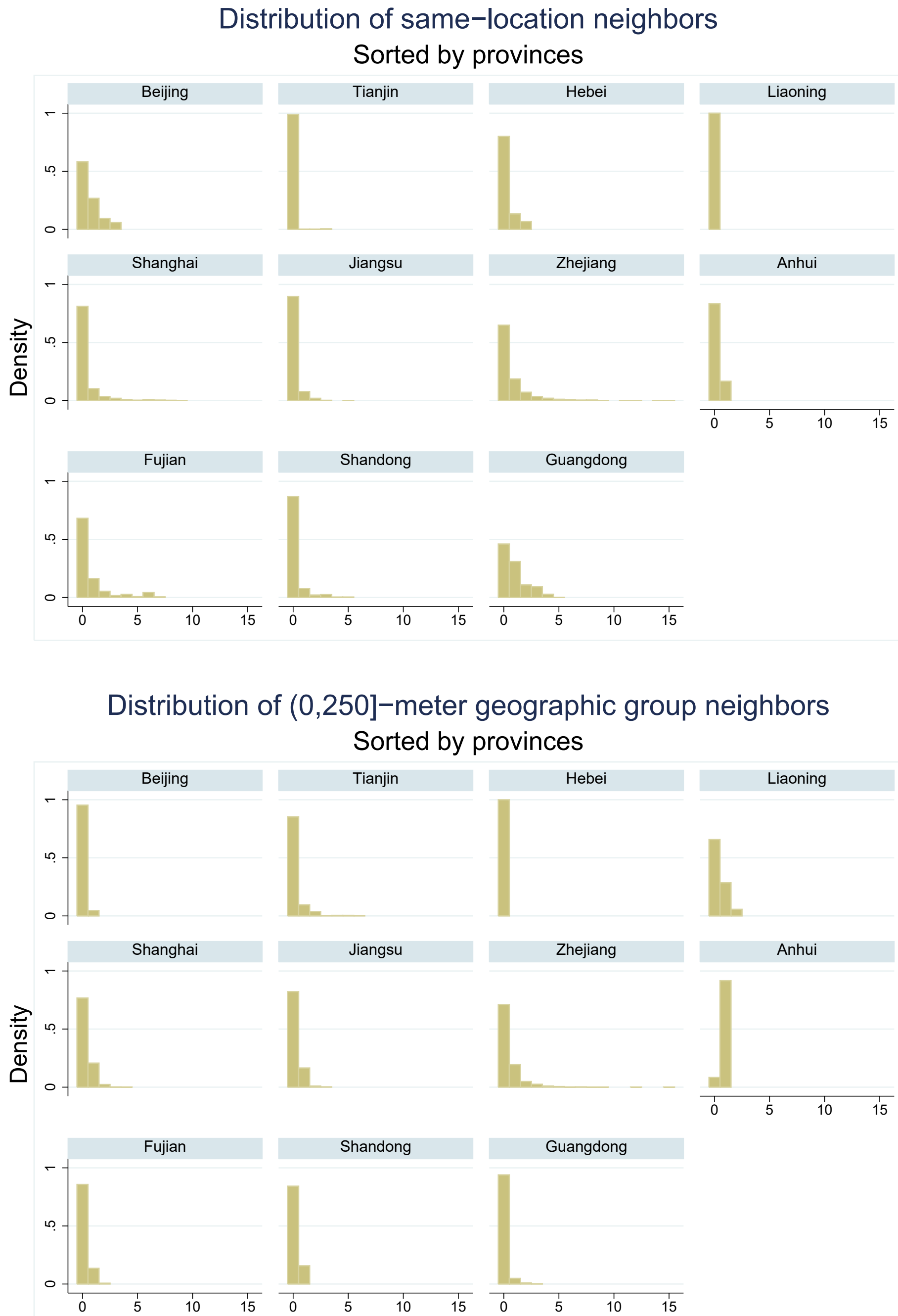

Figure 1 shows the distribution of spatial networks within the first 250 meters of the focal firms. Spatial networks are categorized into three groups as described in Section 3.1.: (i) same-location as the focal firm, (ii) within $(0, 250]$-meters, and (iii) within $(250, 500]$-meters of the focal firm. Signals are defined as the average neighbors' export growth rates between years $t-1$ and t exporting to the same market m. See Eq. (23) in Section 4.1. for details. Panel C reports the aggregate level of export trade activities in baseline sample. A village refers to a 12-digit administrative region, the most disaggregated level of neighborhood in China. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. Ownership-connected firms are excluded. The sample includes firm-country-year observations with at least one same-village neighbor exporting to the same market m, and at least one neighbor within the radius of 1,000 meters of a focal firm exporting to the same market m. Source: Author's calculations based on ASIP and China Customs Data, 2004-2006.

Figure 2: Neighbors' signals.

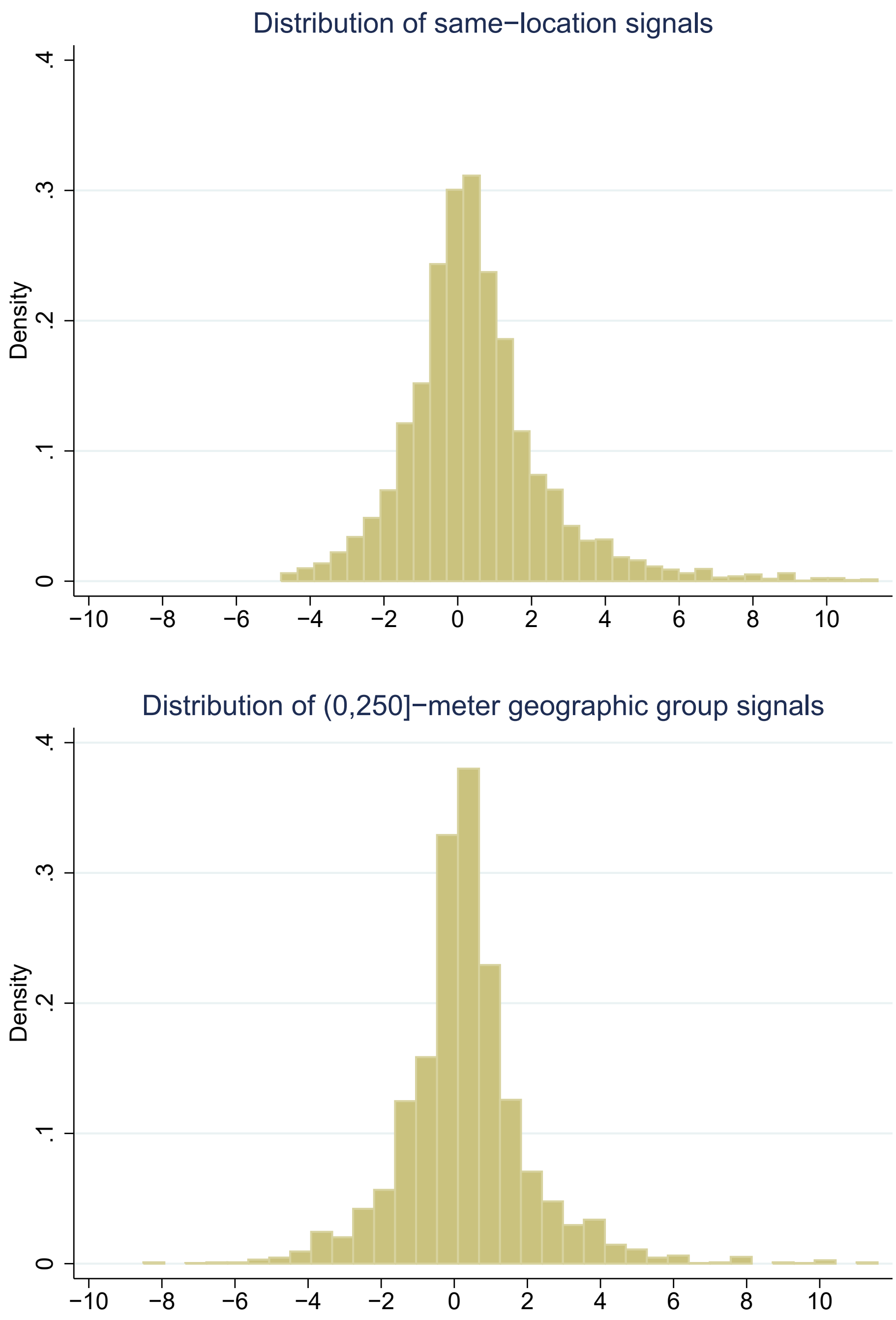

Figure 2 shows the distribution of neighbors' signals within the first 250 meters of the focal firms. Spatial networks and signals are categorized into three groups as described in Section 3.1.: (i) same-location as the focal firm, (ii) within $(0, 250]$-meters, and (iii) within $(250, 500]$-meters of the focal firm. Signals are defined as the average neighbors' export growth rates between years $t-1$ and t exporting to the same market m. See Eq. (23) in Section 4.1. for details. Panel C reports the aggregate level of export trade activities in baseline sample. A village refers to a 12-digit administrative region, the most disaggregated level of neighborhood in China. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. Ownership-connected firms are excluded. The sample includes firm-country-year observations with at least one same-village neighbor exporting to the same market m, and at least one neighbor within the radius of 1,000 meters of a focal firm exporting to the same market m. Source: Author's calculations based on ASIP and China Customs Data, 2004-2006.

Figure 1 demonstrates substantial heterogeneity of firm's spatial networks of same-location and $(0, 250]$-meter geographic group neighbors across 11 2-digit administrative regions (provinces) in baseline sample. Firms located in Guangdong are among the most geographically concentrated, and tend to have more neighbors to learn from than other provinces. These patterns reflect the differential industrial and trade development policies implemented by Chinese Central Government from 1970s to late 1980s. In 1970s, the Chinese government started experimenting with Special Economic Zones (SEZs), where stronger private property protection and tax incentives were introduced to encourage foreign investment and joint ventures with Chinese entities (Wang, 2013). Three out of the four initial SEZs were assigned to Guangdong, and later expanded to other provinces.[13] Figure 2 demonstrates the distributions of both same-location and $(0, 250]$-meter geographic group revealed signals, where signal is defined as the average neighbors' export growth exporting to market m from years $t-1$ and t, as described in Eq. (23). The majority of signals fall into the range between -4 and $+6$ (i.e. negative 400% to positive 600%). The means of average neighbors' export growth in these two geographic groups are 0.15 and 0.07, respectively. This is consistent with the overall upward trend of export volumes of the universe of Chinese manufacturing exporters.

1.4 Empirical Evidence

This section presents the empirical analysis of the four main theoretical predictions in the model.

1.4.1 Empirical results

1.4.1.1 Export entry

To empirically examine Propositions 1 and 2 about firm's entry decisions, I first define the dependent variable as follows:

$$Entry_{icmt} = \begin{cases} 1 \;\; if \;\; x_{icm,t-1} = 0, \quad x_{icmt} > 0 \\ 0 \;\; if \;\; x_{icm,t-1} = 0, \quad x_{icmt} = 0. \end{cases} \tag{22}$$

[13] The first SEZs are Shenzhen, Zhuhai and Shantou in Guangdong Province, and Xiamen in Fujian Province (Wang, 2013).

That is, $Entry_{icmt} = 1$ if firm i in village c did not export to country m in year $t-1$, but started exporting to m in year t. Note that firms which bear the status $Entry_{icmt} = 1$ include those new exporters who just start exporting and existing exporters that further expand their export destination countries in year t. To study the entry decisions, I set firm i's $Entry_{icmt} = 0$ for all potential destinations that were not served by firm i, but served by at least one neighbor in year $t-1$. In other words, destination countries that have not been served by any neighbors are excluded from the sample. Existing exporters that were already serving country m in year $t-1$ (but did not further expand their export destination countries to $m^{'} \neq m$ in year t) are also excluded from the sample. It guarantees that there exists exporting neighbors for learning to take place. All observations from the first year (2004) of the sample are dropped because I need information of the previous-year export status to define export entry as in definition (22).

Following Fernandes and Tang (2014), I use the average growth rate of export revenue of existing firms in geographic group g to country m between year $t-1$ and t as the baseline proxy for foreign demand $\bar{\beta}^{learn}_{g,m,t-1}$ inferred by a potential entrant. It serves as a good proxy for the signal from neighbors because it isolates time-invariant neighbors' heterogeneous productivity. For a potential entrant in village c, the average neighbors' export growth from geographic group g to country m in year t is defined as:

$$\triangle ln\left(x_{icgmt}\right) = \frac{1}{n_{icgm,t-1}} \sum_{i \in N_{icgm,t-1}} \left[ln\left(x_{icgmt}\right) - ln\left(x_{icgm,t-1}\right)\right], \tag{23}$$

where $N_{icgm,t-1}$ is the set of existing firms in geographic group g that export to market m in both years $t-1$ and t, $n_{icgm,t-1}$ is the number of exporters in the set, and x_{icgmt} ($x_{icgm,t-1}$) refers to the export value of a exporting neighbor in the set in year t ($t-1$). The geographic groups are categorized into: (i) same-location geographically close neighbors; (ii) geographically distant neighbors that fall into the intervals of $(0, 250]$ meters, and (iii) placebo neighbors that are $(250, 300]$ meters away from the focal firm.

Proposition 1 states that the likelihood of a firm entering a new market is increasing in the number of exporting neighbors, strength of the signal about the market's demand, and more so if there are more geographically close neighbors revealing the signal. Following Bernard and Jensen (2004) and Albornoz et al. (2012), I estimate a linear probability model of entry decisions as follows:

$$Entry_{icmt} = \alpha + \sum_g \delta_g n_{icgm,t-1} + \sum_g \gamma_g \triangle ln\left(x_{icgmt}\right) + \sum_g \beta_g \left[n_{icgm,t-1} \times \triangle ln\left(x_{icgmt}\right)\right] + \{FE\} + \xi_{icmt}. \tag{24}$$

The variables of interest include the number of neighbors in geographic group g exporting to market m in both years $t-1$ and t, $n_{icgm,t-1}$, the proxy for the signal inferred from neighbors, $\triangle ln\left(x_{icgmt}\right)$, defined in Eq. (23), and the interaction between these two variables. The raw number of neighbors and their revealed signals capture learning opportunities among firm managers and inferred foreign market demand.

I include a large set of fixed effects $\{FE\}$ to control for unobserved determinants of export patterns. I always include village-country fixed effects which account for all time-invariant unobserved factors between a village and a foreign market, e.g. distance, infrastructure, and historical factors, that may determine export patterns, as well as firm-year fixed effects which account for firm heterogeneity. In addition, I control for country-year (to account for aggregate shocks that affect the foreign market demand), and industry-country (to account for industry-specific shocks that affect exporting to a foreign market) fixed effects in the empirical specifications. Importantly, including firm-year fixed effects allows for the possibility to examine within-firm cross-country correlation between new exporters' performance and the prevalence of neighbors' export activities. Thus, I address the potential sample selection bias that arises from the endogenous entry decisions that vary across heterogeneous firms.

Table 2 reports the estimates of specification (24). All columns include village-country and firm-year fixed effects. In addition, columns (3) and (4) include country-year fixed effects, columns (5) and (6) include industry-country fixed effects. In all even-numbered columns, I additionally include other market variables, which are defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries ($-m$) within the same village. Across columns (1) to (6), the coefficients of number of neighboring exporters, average neighbors' export growth, and their interaction term are reported. To control for potential heteroscedasticity and serial correlation, I cluster standard errors at the village level. I first examine the coefficients on the regressors of interests, the number of neighbors and their revealed signals, in different geographic groups g.

Regarding the same-location neighbors and signals, the coefficients are all positive and statistically significant at the 1% level. Specifically, from column (6), the coefficient of 0.0762 on same-location neighbors suggests that an additional same-location neighbor is associated with a 7.62 percentage-point increase in the probability of entry into a new market. Similarly, the coefficient of 0.0162 on same-location signals suggests that an one-standard-deviation increase in same-location signal is associated with a 1.81 percentage-point increase in the entry probability. For geographic groups that fall into the intervals of $(0, 250]$ meters away from a potential entrant, I still observe positive effects of the prevalence of exporting neighbors on likelihood of export entry in new market. From column (6), an additional neighbors within $(0, 250]$ meters of a potential entrant is associated with a 6.84 percentage-point increase in entry probability. However, the coefficients on signal terms drops to roughly half of the magnitude of same-location signals and lose statistical significance. This indicates that knowledge diffusion declines rapidly with distance.[14]

In the empirical specifications, I also include a more distant geographic group that falls into the intervals of $(250, 300]$ meters away from a potential entrant, and that the corresponding coefficients of neighbor terms decline rapidly with distance. In particular, from column (6), the $(250, 300]$-meter geographic group gives an even smaller (i.e. 0.0376) and insignificant effect on entry probability. This confirms the logic of my identification strategy: if the results are driven by some spatially correlated omitted variables, I would expect these omitted variables to affect the firms in further geographic groups as well. Taken together, these estimates strongly support the learning-from-neighbors effects in export entry, and indicate that identifying spatial networks based on geographical distances is necessary to study the knowledge diffusion among firms.

The same-location and $(0, 250]$-meter geographic group interaction terms are negative and significant at 1% level, while those of $(250, 300]$-meter placebo group become insignificant. The negative

[14]Bisztray et al. (2018) study the effect of peer experience on same-country *import* entry. They find positive learning effects from same-building and neighbor-building peers, while cross-street building peers do not have any positive effects on import entry, indicating fast decay in knowledge diffusion. It is noted that their peer (neighbor) variable is an indicator variable which equals one if there is at least one firm in a potential entrant's peer group exporting to market m in year $t-1$, and zero otherwise. In addition, their empirical work do not consider firms' learning from neighbors' signals.

same-location interaction terms could indicate competition effect among firms within the small neighborhoods, when more geographically close neighbors revealing strong positive signals could mean more intense export competition for a potential entrant. The competition effect is consistent with the findings of Shimamoto et al. (2019) that peers' export share has a negative and significant effect on own exporting activities. While my theory does not model competition among firms explicitly, the selection weight on each geographic group could reconcile with peer competition as firms may put less trust on information revealed by exporting neighbors who share similar technological expertise, product scope, and set of destination countries served with themselves.[15] In this paper, I do not incorporate strategic interactions among firms to avoid complicating the model substantially. The selection weight is assumed to be negatively related to distance to focus on how learning decays in space.

Overall, Table 2 shows that the probability of entering market m is increasing in number of exporting neighbors and the average neighbors' export growth serving the same market, and the learning-from-neighbors effects decay fast in space.

1.4.1.2 Market uncertainty, signal-to-noise ratio, and entry response

I then examine the relationship between market certainty, signal-to-noise ratio and a firm's entry response. Proposition 2 states that a firm's entry response to positive signals about a market from neighbors is smaller in magnitude if the signals are noisier with firm-specific product appeal (i.e. higher σ_γ^2), but greater in magnitude if the firm itself has a more dispersed prior on foreign market demand (i.e. higher σ_β^2).

I begin with the empirical tests of theoretical predictions related to the firm-specific product appeal σ_γ^2 first. If there is substantial heterogeneity of firm-specific product appeal (i.e. higher σ_γ^2), a potential entrant would foresee a less predictable export performance, and thus put a smaller weight on neighbors' signals in Bayesian updating. Similar to Fernandes and Tang (2014), I use

[15] Shimamoto et al. (2019) use data of micro, small, and medium-sized enterprises in rural Vietnam to study the effects of social interactions on firms' exporting activities. They find that peers' export share has a negative and significant effect on own export share, indicating a competition effect. In terms of information revelation, Cao et al. (2018) find a negative relation between technological peer pressure and product disclosure because the latter reveals firms' strategies, allocations, and progress of technological investments in product development to competitors. In workplace settings, Bandiera et al. (2005) find that high ability workers intentionally withhold their efforts when working with their friends under a relative performance scheme.

Table 2: Export entry and learning from spatial networks.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Signal × Neighbor	−0.0064***	−0.0061***	−0.0064***	−0.0062***	−0.0059***	−0.0055***
	(−4.25)	(−4.18)	(−4.00)	(−3.97)	(−4.63)	(−4.55)
Signal	0.0231***	0.0178***	0.0224***	0.0167**	0.0215***	0.0162***
	(3.61)	(2.95)	(3.29)	(2.58)	(3.88)	(3.12)
Neighbor	0.0748***	0.0738***	0.0769***	0.0761***	0.0777***	0.0762***
	(3.63)	(3.59)	(3.67)	(3.67)	(4.50)	(4.42)
Other geographic groups						
(0,250] meters						
Signal × Neighbor	−0.0051***	−0.0048***	−0.0051***	−0.0048***	−0.0047***	−0.0044***
	(−2.92)	(−2.76)	(−2.78)	(−2.65)	(−2.90)	(−2.74)
Signal	0.0107	0.0060	0.0106	0.0053	0.0119*	0.0075
	(1.57)	(0.90)	(1.49)	(0.76)	(1.67)	(1.10)
Neighbor	0.0649***	0.0633***	0.0656***	0.0643***	0.0705***	0.0684***
	(2.85)	(2.74)	(2.89)	(2.81)	(3.38)	(3.24)
(250,300] meters						
Signal × Neighbor	−0.0068	−0.0043	−0.0077	−0.0055	−0.0051	−0.0023
	(−0.82)	(−0.50)	(−0.96)	(−0.66)	(−0.63)	(−0.28)
Signal	0.0123	0.0085	0.0118	0.0081	0.0037	−0.0001
	(0.88)	(0.57)	(0.88)	(0.56)	(0.27)	(−0.01)
Neighbor	0.0434	0.0426	0.0428	0.0425	0.0371	0.0376
	(1.50)	(1.51)	(1.46)	(1.49)	(1.36)	(1.43)
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Country-year FE	*N*	*N*	*Y*	*Y*	*N*	*N*
Industry-country FE	*N*	*N*	*N*	*N*	*Y*	*Y*
Observations	14864	14864	14857	14857	14638	14638
Adjusted R^2	0.465	0.470	0.460	0.466	0.468	0.474

Table 2 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries ($-m$) within the same village. Columns (3) and (4) additionally include country-year fixed effects. Columns (5) and (6) additionally include industry-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

a conventional measure of uncertainty: the standard deviation of neighbors' export growth in the same town-country-year cell, to proxy for the heterogeneity of firm-specific product appeal. For the dispersion of prior on foreign market demand (i.e. higher σ_β^2), I use (log) geographical distance between China and export destinations from CEPII as a proxy. Longer cross-country distances are interpreted as greater market demand uncertainty to resolve before exporting. In this case, the theory expects a potential entrant will put a larger weight on signals revealed by neighbors, inducing a larger entry response, and more so if there are more geographically close neighbors revealing the signals.

To further empirically examine the relationship between heterogeneous learning effects and export entry decisions, I also use the extended gravity measures proposed by Morales et al. (2019), to proxy for the firm's uncertainty about the new foreign market. Extended gravity refers to the path dependence in entry costs as these costs in a new foreign market tend to be smaller for firms that have previously exported to similar markets (Morales et al., 2019). Specifically, I use common language and similar per-capita income level (measured by differences in GDP per capita between China and destination countries), as the extended gravity variables.[16,17] Extended gravity data are obtained from CEPII. If a potential market exhibits a higher degree of similarity (dissimilarity) with a firm's previously served markets, the theory expects the new exporter to place a smaller (greater) weight on signals inferred from neighbors.

I estimate the following specification to empirically examine Proposition 2:

$$\begin{aligned} Entry_{icmt} = {} & \alpha + \iota_g V + \sum_g \theta_g \left[V \times \triangle ln\left(x_{icgmt}\right)\right] + \sum_g \delta_g n_{icgm,t-1} + \sum_g \gamma_g \triangle ln\left(x_{icgmt}\right) \\ & + \sum_g \beta_g \left[n_{icgm,t-1} \times \triangle ln\left(x_{icgmt}\right)\right] + \{FE\} + \xi_{icmt}, \end{aligned} \tag{25}$$

where V refers to the measures of dispersion of signals, and $V \times \triangle ln\left(x_{icgmt}\right)$ refers to its interac-

[16] Two countries share a common language when it is spoken by at least 9% of the population. Source: CEPII.

[17] The construction of extended gravity variables is as follows: First, I map a firm's market(s) m in year t to all its previously served markets in year $t-1$. Second, I examine if this firm's market(s) in year t share a common language with any of its previously served markets in year $t-1$. I assign 1 to the market m in year t if the firm has at least 1 previously served market which shares a common language with market m, and 0 otherwise. For GDP per capita which is a continuous measure, I obtain the minimum of the differences in GDP per capita of market m in year t and all previously served markets in year $t-1$. This captures the acquisition of experience of serving a market in year $t-1$ which has similar income level as the potential market m in year t. The larger the minimum of differences in GDP per capita between market m and previously served markets, the more dissimilarity they share.

tion with observed neighbors' signals as defined in Eq. (23). The three main variables of interest, number of neighbors in different geographic groups, $n_{icgm,t-1}$, average neighbors' export growth, $\triangle ln\left(x_{icgmt}\right)$, and their interaction terms, $n_{icgm,t-1} \times \triangle ln\left(x_{icgmt}\right)$, remain the same as specification (24). The dispersion of signals, V, can be: (i) heterogeneity of firm-specific product appeal, measured by the standard deviation of neighbors' export growth in the same town-country-year cell (gmt); (ii) ex ante market-specific uncertainty, measured by the geographical distance between China and destination countries (m); and (iii) firm-specific extended gravity variables which vary across firm-country-year cells ($icmt$). According to the theoretical predictions, the sign of the estimated θ_g is expected to be negative for the first measure V_{gmt}, positive for the second measure V_m, and negative for the extended gravity measures V_{icmt}. Intuitively, greater heterogeneity in firm-specific product appeal makes inferred foreign market demand less relevant in predicting export profits, thus a potential entrant will put a smaller weight on observed signals and show weaker entry responses. Firms tend to put a larger weight on observed neighbors signals, which are more informative about foreign market demand (i.e. higher signal-to-noise ratios), in response to greater ex ante market-specific uncertainty. Lastly, the entry response tends to be weaker when the new markets are similar to the existing markets currently served by the same firm.[18] Tables 3 to 5 will present results of the signal-to-noise ratio, market-specific uncertainty, prior knowledge to a potential market, and heterogeneous learning effects on firms' entry response.

Table 3 reports results using specification (25). For all columns, I include signal dispersion variable, V_{gmt}, measured by the standard deviation of neighbors' export growth in the same town-country-year cell, and its interaction with the neighbors' signals, $V_{gmt} \times \triangle ln\left(x_{icgmt}\right)$.[19] Across all columns, the coefficients on same-location signal dispersion interaction term are negative and remain fairly stable in magnitudes. In the preferred specification, column (6), which I additionally control for industry-country fixed effects, the coefficient on signal dispersion interaction term is negative at -0.0150 and statistically significant at the 5% level. For $(0, 250]$-meter geographic group, the coefficients on signal dispersion interaction terms becomes insignificant. This is consistent with Proposition 2, which predicts weaker entry response when the signal-to-noise ratio is lower.

[18]The prediction of negative signs applies to common language because it captures similarity between a potential market m in year t and the previously served markets in year $t-1$ of a firm. However, the predicted signs on income level difference should be positive because this variable captures dissimilarity instead.

[19]I do not include this interaction term for geographic groups beyond 250 meters, because Table 2 shows that a potential entrant does not respond to average neighbors' export growth beyond 250 meters of its own location.

Table 3: Export entry, signal-to-noise ratio, and learning from spatial networks.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Dispersion × Signal	−0.0141*	−0.0156**	−0.0149*	−0.0161**	−0.0134*	−0.0150**
	(−1.73)	(−2.00)	(−1.80)	(−2.02)	(−1.68)	(−1.97)
Signal × Neighbor	−0.0062***	−0.0059***	−0.0062***	−0.0060***	−0.0056***	−0.0053***
	(−3.60)	(−3.38)	(−3.39)	(−3.25)	(−3.36)	(−3.11)
Signal	0.0266***	0.0221***	0.0267***	0.0218***	0.0249***	0.0204***
	(4.00)	(3.35)	(3.97)	(3.26)	(3.75)	(3.08)
Neighbor	0.0773***	0.0762***	0.0789***	0.0780***	0.0792***	0.0776***
	(7.17)	(7.24)	(7.20)	(7.29)	(7.12)	(7.23)
Other geographic groups						
(0,250] meters						
Dispersion × Signal	0.0140	0.0141	0.0135	0.0141	0.0149	0.0152*
	(1.54)	(1.56)	(1.52)	(1.60)	(1.61)	(1.66)
Signal × Neighbor	−0.0048**	−0.0044**	−0.0048**	−0.0045**	−0.0042**	−0.0039*
	(−2.31)	(−2.09)	(−2.26)	(−2.08)	(−2.09)	(−1.89)
Signal	0.0017	−0.0031	0.0020	−0.0036	0.0024	−0.0023
	(0.23)	(−0.41)	(0.26)	(−0.47)	(0.31)	(−0.30)
Neighbor	0.0691***	0.0675***	0.0694***	0.0680***	0.0727***	0.0704***
	(5.34)	(5.30)	(5.29)	(5.29)	(5.40)	(5.36)
(250,300] meters						
Signal × Neighbor	−0.0078	−0.0054	−0.0088	−0.0067	−0.0067	−0.0040
	(−1.11)	(−0.71)	(−1.30)	(−0.93)	(−0.88)	(−0.48)
Signal	0.0136	0.0098	0.0132	0.0096	0.0047	0.0011
	(0.93)	(0.65)	(0.91)	(0.64)	(0.32)	(0.07)
Neighbor	0.0378	0.0370	0.0392	0.0390	0.0333	0.0341
	(1.53)	(1.50)	(1.58)	(1.58)	(1.30)	(1.33)
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Signal dispersion	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Country-year FE	*N*	*N*	*Y*	*Y*	*N*	*N*
Industry-country FE	*N*	*N*	*N*	*N*	*Y*	*Y*
Observations	14321	14321	14319	14319	14102	14102
Adjusted R^2	0.464	0.469	0.458	0.463	0.470	0.475

Table 3 reports estimation results using Eq. (25) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). The proxy for the heterogeneity of firm-specific product appeal is the standard deviation of neighbors' export growth in the same town-country-year cell. All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries ($-m$) within the same village. Columns (3) and (4) additionally include country-year fixed effects. Columns (5) and (6) additionally include industry-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Other variables of interest, number of neighbors, $n_{icgm,t-1}$, and average neighbors' export growth, $\triangle ln\left(x_{icgmt}\right)$, in different geographic groups g, exhibit similar behavior as in Table 2. Same-location neighbors and observed signals have individually positive effects on firms' entry in new market. The neighbors and signals from $(0,250]$-meter geographic groups have weaker effects on entry probability, and this learning effect continues to decay beyond 250 meters. Overall, these results showcase the importance of spatial networks in studying the learning among firms, because firms tend to respond to knowledge from different spatial networks differently.

Table 4 reports results using (25) as the empirical specification. I explore the heterogeneous learning effects across export destinations. Similar to Table 3, I include interaction terms of signal dispersion variable, V_m, measured by (log) population-weighted geographical distance from China and neighbors' signals, $V_m \times \triangle ln\left(x_{icgmt}\right)$, for same-location and $(0,250]$-meter geographic groups. I want to examine if a firm exhibits stronger learning-from-neighbors effects to a subset of more uncertain destination countries. For the same-location geographic group, while I find positive and significant coefficients on the interaction terms from the three quintiles Q2 to Q4, I do not find the same patterns in the bottom and top quintiles. Intuitively, the uncertainty exporting to a geographically close market is minimal that neighbors' signals are less relevant to infer foreign market demand. While the ex ante market-specific uncertainty to destination countries in the top quintile is the greatest, the proxy for uncertainty, the (log) population-weighted geographical distance from China, also captures transportation costs exporting to these countries. A foreign importer could take the transportation costs into consideration and refrain from importing from Chinese exporters in order to save these costs. In that case, neighbors' signals are less likely to increase entry probability because transportation costs add complexity to the learning mechanism - inferring a foreign market's demand and determining the entry productivity threshold. For the $(0,250]$-meter geographic group, firms do not show stronger entry response to market uncertainty, except the quintile Q3. This is consistent with the theoretical prediction that a potential entrant relies more on geographically close neighbors in making entry decisions. Regarding our main variables of interest, same-location neighbors continue to show the strongest positive effects on export entry, whereas $(0,250]$-meter geographic group neighbors have weaker yet significant effects. Consistent with the previous tables, the learning-from-neighbors effect decays rapidly beyond 250 meters. Overall, a potential entrant exhibits stronger learning related to ex ante market-specific uncertainty when it comes to entry decisions.

In Table 5 I apply the idea of path dependence of export entry costs and empirically examine whether a firm's previously served markets can affect a potential entrant's prior and affect its export entry patterns. I follow Morales et al. (2019) and use extended gravity measures to capture market (dis)similarity. I use common language and per-capita income level differences (measured by the differences in GDP per capita between China and the destination countries) as the extended gravity variables. In columns (1) and (2) I use common language to group export destinations. The coefficients on the interactions between the common language with the bundle of previously served export destinations and the signal, $V_{icmt} \times ln\,(x_{icgmt})$, in both the same location and $(0, 250]$-meter geographic group are negative yet insignificant. In columns (3) and (4) I obtain the minimum of differences in GDP per capita between a firm's potential market m in year t and all its previously served markets in year $t-1$. The larger the minimum of income level differences, the more dissimilarity is present between the market m and the set of previously served markets. I find a potential entrant tends to learn more when the new export destination is more dissimilar with its previously served markets, but this effect is only significant at the 5% level for the same-location neighbors' signals in column (4). The neighbors' signals from $(0, 250]$-meter geographic group have positive yet insignificant effects on export entry. In columns (5) and (6), I include interactions between neighbors' signals and two extended gravity variables, common language, and per-capita income level differences. The interaction terms of per-capita income level differences remain positive and significant at the 10% and 5%, respectively. Lastly, the main variable of interest, number of neighbors, $n_{icgm,t-1}$, remain stable in magnitudes and significant at the 1% level for same-location and $(0, 250]$-meter geographic groups.

To summarize, extended gravity variables could affect the prior of firms, and induce them to learn more when they are less familiar with the new market m, and vice versa. Moreover, firms are responsive to the knowledge set obtained from previously served markets, but only adjust their learning intensity from same-location signals. These results are consistent with Proposition 2 that when firms export to a new foreign market which are similar to the set of their previously served markets. The entry response is larger in magnitude when firms react to the signal revealed by geographically close neighbors compared to that of distant neighbors for all extended gravity variables.

Table 4: Export entry, uncertainty, and learning from spatial networks.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Signal × Quintiles of Distance						
Q1	0.0179*	0.0125	0.0165*	0.0109	0.0122	0.0067
	(1.81)	(1.35)	(1.65)	(1.16)	(1.21)	(0.70)
Q2	0.0288***	0.0222**	0.0265**	0.0190*	0.0230**	0.0162*
	(2.96)	(2.34)	(2.42)	(1.77)	(2.42)	(1.75)
Q3	0.0287***	0.0235***	0.0274***	0.0220**	0.0294***	0.0242***
	(3.30)	(2.73)	(2.76)	(2.21)	(4.02)	(3.44)
Q4	0.0308***	0.0256***	0.0343***	0.0285***	0.0342***	0.0294***
	(2.98)	(2.87)	(3.26)	(3.14)	(3.18)	(3.17)
Q5	0.0008	−0.0026	0.0002	−0.0032	0.0022	−0.0015
	(0.07)	(−0.23)	(0.02)	(−0.27)	(0.20)	(−0.14)
Signal × Neighbor	−0.0057***	−0.0055***	−0.0058***	−0.0056***	−0.0054***	−0.0051***
	(−3.37)	(−3.40)	(−3.15)	(−3.22)	(−3.79)	(−3.81)
Neighbor	0.0771***	0.0759***	0.0794***	0.0783***	0.0801***	0.0785***
	(3.80)	(3.75)	(3.85)	(3.84)	(4.70)	(4.63)
Other geographic groups						
(0,250] meters						
Signal × Quintiles of Distance						
Q1	0.0048	−0.0007	0.0048	−0.0010	0.0029	−0.0021
	(0.49)	(−0.07)	(0.49)	(−0.10)	(0.30)	(−0.21)
Q2	0.0039	0.0001	0.0045	−0.0003	−0.0005	−0.0032
	(0.41)	(0.01)	(0.46)	(−0.03)	(−0.04)	(−0.25)
Q3	0.0285***	0.0222**	0.0260***	0.0194*	0.0357***	0.0297***
	(3.08)	(2.27)	(2.71)	(1.92)	(3.91)	(3.18)
Q4	0.0251*	0.0204	0.0273*	0.0219	0.0238*	0.0191
	(1.76)	(1.48)	(1.86)	(1.54)	(1.78)	(1.47)
Q5	−0.0030	−0.0054	−0.0033	−0.0061	0.0017	−0.0007
	(−0.26)	(−0.50)	(−0.28)	(−0.54)	(0.14)	(−0.06)
Signal × Neighbor	−0.0050**	−0.0048**	−0.0050**	−0.0048**	−0.0048***	−0.0046***
	(−2.56)	(−2.48)	(−2.43)	(−2.37)	(−2.68)	(−2.61)
Neighbor	0.0683***	0.0664***	0.0690***	0.0674***	0.0743***	0.0719***
	(3.23)	(3.09)	(3.26)	(3.15)	(3.90)	(3.72)
(250,300] meters						
Signal × Neighbor	−0.0070	−0.0046	−0.0079	−0.0057	−0.0054	−0.0027
	(−0.84)	(−0.52)	(−0.98)	(−0.68)	(−0.68)	(−0.32)
Signal	0.0131	0.0093	0.0127	0.0090	0.0048	0.0009
	(0.92)	(0.61)	(0.93)	(0.61)	(0.34)	(0.06)
Neighbor	0.0424	0.0416	0.0416	0.0415	0.0356	0.0364
	(1.45)	(1.47)	(1.41)	(1.45)	(1.31)	(1.38)
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Country-year FE	*N*	*N*	*Y*	*Y*	*N*	*N*
Industry-country FE	*N*	*N*	*N*	*N*	*Y*	*Y*
Observations	14858	14858	14851	14851	14634	14634
Adjusted R^2	0.466	0.471	0.461	0.467	0.469	0.475

Table 4 reports estimation results using Eq. (25) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). The proxy for the ex ante market-specific uncertainty is the (log) population-weighted geographical distance of an export destination from China. All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries $(-m)$ within the same village. Columns (3) and (4) additionally include country-year fixed effects. Columns (5) and (6) additionally include industry-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 5: Export entry, extended gravity, and learning from spatial networks.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Common Language × Signal	-0.0032	-0.0021			-0.0007	0.0006
	(-0.48)	(-0.33)			(-0.10)	(0.09)
GDPpc × Signal			0.0045^{*}	0.0047^{**}	0.0044^{*}	0.0047^{**}
			(1.89)	(1.99)	(1.86)	(1.99)
Signal × Neighbor	-0.0077^{***}	-0.0072^{***}	-0.0079^{***}	-0.0074^{***}	-0.0080^{***}	-0.0074^{***}
	(-4.40)	(-4.44)	(-4.81)	(-4.87)	(-4.71)	(-4.82)
Signal	0.0283^{***}	0.0213^{***}	-0.0051	-0.0126	-0.0039	-0.0129
	(3.83)	(3.05)	(-0.29)	(-0.75)	(-0.22)	(-0.71)
Neighbor	0.1050^{***}	0.1028^{***}	0.1048^{***}	0.1027^{***}	0.1049^{***}	0.1027^{***}
	(4.42)	(4.33)	(4.41)	(4.32)	(4.42)	(4.32)
Other geographic groups						
(0,250] meters						
Common Language × Signal	-0.0087	-0.0056			-0.0083	-0.0051
	(-0.63)	(-0.40)			(-0.60)	(-0.37)
GDPpc × Signal			0.0015	0.0025	0.0015	0.0026
			(0.43)	(0.78)	(0.44)	(0.80)
Signal × Neighbor	-0.0036^{*}	-0.0033^{*}	-0.0037^{*}	-0.0035^{*}	-0.0036^{*}	-0.0034^{*}
	(-1.77)	(-1.71)	(-1.83)	(-1.75)	(-1.78)	(-1.72)
Signal	0.0117	0.0050	-0.0046	-0.0165	0.0006	-0.0133
	(0.92)	(0.40)	(-0.19)	(-0.79)	(0.02)	(-0.53)
Neighbor	0.0714^{**}	0.0700^{**}	0.0712^{**}	0.0699^{**}	0.0715^{**}	0.0702^{**}
	(2.55)	(2.47)	(2.54)	(2.47)	(2.54)	(2.47)
(250,300] meters						
Signal × Neighbor	0.0067	0.0079	0.0066	0.0078	0.0069	0.0080
	(0.61)	(0.71)	(0.62)	(0.73)	(0.65)	(0.75)
Signal	-0.0018	-0.0045	-0.0018	-0.0045	-0.0018	-0.0046
	(-0.51)	(-1.29)	(-0.50)	(-1.30)	(-0.52)	(-1.31)
Neighbor	0.0285	0.0283	0.0285	0.0282	0.0286	0.0283
	(0.83)	(0.82)	(0.85)	(0.84)	(0.86)	(0.84)
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Extended gravity variables	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Country-year FE	*N*	*N*	*Y*	*Y*	*N*	*N*
Industry-country FE	*N*	*N*	*N*	*N*	*Y*	*Y*
Observations	14315	14315	14315	14315	14315	14315
Adjusted R^2	0.226	0.235	0.227	0.236	0.227	0.236

Table 5 reports estimation results using Eq. (25) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). The extended gravity variables refer to the common language and per-capita income level differences between the set of previously served markets and China. Columns (1) and (2) use common language to group countries. Columns (3) and (4) use per-capita income level differences (measured by differences in GDP per capita between China and destination countries) to group countries. Columns (5) and (6) include both common language and per-capita income level differences, and their corresponding interactions. All columns include the extended gravity variables, and their interactions with the average neighbors' export growth to the same markets m. All columns include firm-year and village-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

1.4.1.3 Initial export sales

In this subsection I turn to the heterogeneous learning effects from neighbors on an exporter's initial sales in a new market m. Proposition 3 states that in response to a positive signal, the strength of the signal about the market demand, $\triangle ln\left(x_{icgmt}\right)$, and the interactive effect of $n_{icgm,t-1} \times \triangle ln\left(x_{icgmt}\right)$ increase an exporter's initial export sales in a new market, more so if the signal is revealed by geographically close neighbors. To empirically examine Proposition 3, I estimate specification (24) but using the (log) firm i's initial export sales to market m from village c in year t, $ln\left(x_{icmt}\right)$, instead of export entry, as the dependent variable. The sample includes firm-country-year observations with at least one same-village neighbor exporting to the same market m. The sets of fixed effects are the same as in the previous subsection.

Across all columns, the coefficients on same-location interaction terms are positive and statistically significant at least at the 5% level. In column (3), when I additionally control for industry-country fixed effects, the coefficient on same-location interaction term is positive at 0.0082 and significant at the 1% level, suggesting that in the baseline sample average export growth of same-location neighbors, one standard-deviation increase in the number of same-village neighbors exporting to a market (i.e. 1.37 same-location firms) is associated with an additional 0.17% ($0.0082 \times 0.15 \times 1.37 \times 100$) increase in initial export sales in the same market. Evaluated at the mean initial export sales (146 thousand U.S. dollars), this is equivalent to a 250 U.S. dollar increase in initial export sales for each standard-deviation increase in same-location neighbors. Across all columns, I do not find evidence that the initial export sales is increasing in the strength of same-location neighbors' signals. Consistent with previous tables, the corresponding coefficients on interaction terms for distant geographic groups are insignificant. These results confirm the positive interactive effect in Proposition 3, and most importantly, the learning effects decay rapidly in space.

Another main variable of interest, number of same-location neighbors, has a negative and significant effect on initial export sales. This is also consistent with the theory: while the prevalence of neighbors will magnify the effect of a positive signal, it also increase the precision of signal, as seen from $\frac{\partial \sigma^2_{mt}(n_{icgm,t-1})}{\partial n_{icgm,t-1}} < 0$ in condition (12), which lowers the spread of the expected operating profits. Intuitively, a potential entrant would scale down the initial export sales because neighbors' signals reveal that taking advantage of the upside of an uncertain market is unlikely. As a result,

Table 6: Initial sales and learning from spatial networks.

	(1)	(2)	(3)
	Dependent variable: (log) Initial sales		
Same location			
Signal × Neighbor	0.0054**	0.0050**	0.0082***
	(2.50)	(2.25)	(3.32)
Signal	−0.0225	−0.0244	−0.0538
	(−0.73)	(−0.78)	(−1.60)
Neighbor	−0.1186***	−0.1338***	−0.1880***
	(−3.32)	(−3.53)	(−4.15)
Other geographic groups			
(0,500] meters			
Signal × Neighbor	−0.0403	−0.0345	−0.0455
	(−1.62)	(−1.33)	(−1.42)
Signal	0.0701	0.0672	0.0075
	(0.75)	(0.70)	(0.07)
Neighbor	−0.0422	−0.0593	−0.0601
	(−0.58)	(−0.83)	(−0.86)
Village-country FE	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*
Country-year FE	*N*	*Y*	*N*
Industry-country FE	*N*	*N*	*Y*
Observations	10520	10502	9929
Adjusted R^2	0.205	0.182	0.130

Table 6 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable is $ln\,(x_{icmt})$, the natural logarithms of firm i's initial export sales from village c to market m in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters in geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include village-country and firm-year fixed effects. Column (2) additionally includes country-year fixed effects. Column (3) additionally includes industry-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}\,p < 0.05$, $^{*}p < 0.10$.

whether initial export sales increases will depend on the strength of these two opposing forces, and the net effect on initial export sales is thus ambiguous.

To summarize, the findings in Table 6 are consistent with Proposition 3. A first-time exporter shows stronger learning effects from same-location neighbors to resolve uncertainty about foreign market demand, and increases initial export sales accordingly. Insignificant interactive effects on initial export sales from other-location geographic groups indicate strong spatial frictions to knowledge diffusion.

1.4.1.4 Survival

Proposition 4 predicts that an exporter's survival probability in a new market m is positively correlated with the strength of the neighbors' revealed signal, but is independent of the number of neighbors in each geographic group. Intuitively, while the number of neighbors increases (decreases) the number of entrants by lowering (raising) the export entry threshold given the signal is positive (negative), conditional on entry, any ex ante information was already taken into account by the entrant at the time of entry and will no longer affect its exit decision.

To empirically examine Proposition 4, I construct the export survival status as follows:

$$Survival_{icmt} = \begin{cases} 1 & if\ x_{icm,t-1} = 0,\ x_{icm,t} > 0,\ x_{icm,t+1} > 0; \\ 0 & if\ x_{icm,t-1} = 0,\ x_{icm,t} > 0,\ x_{icm,t+1} = 0. \end{cases} \tag{26}$$

That is, $Survival_{icmt}$ equals 1 if the exporter was not exporting to market m in year $t-1$, but starts exporting in year t and continues in $t+1$ (i.e. continuing exporters), and $Survival_{icmt}$ equals 0 if the firm exports in year t but ceases exporting in year $t+1$ (i.e. occasional exporters). I examine Proposition 4 by estimating specification (24), but with the dependent variable replaced by $Survival_{icmt}$. I use the same baseline proxy for the signal, measure of neighbors, and the interaction terms as in previous subsections. As described in Section 2, through Bayesian updating, a firm's entry productivity threshold, $\underline{\varrho}_{m,t}^{\sigma-1}$, is lower in response to a positive signal and more geographically close neighbors revealing it. As a result, the average productivity level of new exporters decreases. These lower-productivity firms are more likely to exit ex post, which lowers the overall exporters' survival probability. This analysis employs Heckman (1976) two-step procedure to account for selection bias and examine the survival probability of new exporters. In the selection equation, a probit model is run to estimate the probability of entry to a foreign market. From this I obtain the inverse Mills ratio, which addresses the selection bias. Similar to Keller and Yeaple (2013), I use the cost of starting a business in a destination country (measured by the number of start-up procedures to register a business) as the exclusion restriction variable in the sample selection equation. As a dependent variable, survival probability, is related to a foreign market demand, it is not directly determined by the costs of starting a business in a new market. This motivates the use of this exclusion restriction variable. After accounting for the selection bias, I expect the exporters' survival probability in a new market is positively correlated with the strength of the signal, but independent of the number of neighbors. The results are reported in Table 7.

In all columns (1) to (3), the coefficients on same-location signals are negative and significant, while that on same-location neighbors are sufficiently close to zero in magnitudes and insignificant. For $(0, 500]$-meter geographic group, I do not observe a significant effect of neighbors' signals or prevalence of neighbors on survival probability. For the first-stage selection equation, the cost of starting a business enters all specifications with predicted negative signs, which is consistent with the hypothesis that firms are less likely to enter a foreign market with higher fixed costs of starting a business. The variables of interest, number of neighbors, average neighbors' signals, and their interactions enter the selection equation with predicted signs. In addition, the significant Mills ratio indicates that selection is an issue. Overall, I find some evidence on the theoretical prediction: the new exporters' survival probability is independent of the number of neighbors. However, evidence does not suggest that the survival probability is positively correlated with the neighbors' signals.

1.4.2 Robustness checks

I perform several robustness checks to rule out alternative mechanisms which could drive correlated decisions of firms. First, I compute the number of same-indsutry (defined by 2-digit industry according to Chinese Standard of Industrial Classification) firms for all village-year observations, and then drop those village-year observations when the number of same-industry firms is above its 90th percentiles across all village-years. Second, I exclude village-year observations with at least one firm from the geographically concentrated industries according to Lu and Tao (2009). Results

Table 7: Export survival and learning from spatial networks.

	(1)	(2)	(3)
	Dependent variable: Export survival		
Second stage			
Same location			
Signal × Neighbor	0.0011	0.0013*	0.0013*
	(1.60)	(1.83)	(1.80)
Signal	−0.0156	−0.0153	−0.0140
	(−1.42)	(−1.37)	(−1.27)
Neighbor	0.0003	−0.0018	−0.0013
	(0.08)	(−0.54)	(−0.40)
Other geographic groups			
(0,500] meters			
Signal × Neighbor	−0.0113	−0.0097	−0.0079
	(−0.50)	(−0.43)	(−0.36)
Signal	0.0205	0.0168	0.0152
	(0.44)	(0.36)	(0.33)
Neighbor	−0.0300	−0.0322	−0.0291
	(−0.90)	(−0.94)	(−0.87)
Selection Equation			
Cost of starting business		−0.0162***	
		(−2.69)	
Same location			
Signal × Neighbor		−0.0019***	
		(−3.00)	
Signal		0.0213*	
		(1.85)	
Neighbor		0.0137***	
		(4.57)	
Mills ratio: λ	−0.5044***	−0.5314***	−0.5016***
	(−3.04)	(−3.16)	(−3.03)
Wald chi2 (d.o.f.=70)	54.61	99.85	142.88
Prob > chi2	0.00	0.00	0.00
Industry FE	*Y*	*N*	*Y*
City FE	*N*	*Y*	*Y*
Observations	6646	6646	6646

Table 7 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Survival_{icmt} = 1$ for the firm-village-country-year observation if a new exporter i that survived the year t and continued to export in the next year $t+1$. $Survival_{icmt} = 0$ if a new exporter i exported only in the first year t and ceased exporting in the next year $t+1$. The sources of knowledge diffusion are measured by the number of neighboring exporters in geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include the following variables in both stages: neighbors, average neighbors' export growth, and their interactions in the same location, and within $(0, 500]$-meter of a focal firm (not all coefficients reported). The first stage additionally includes the neighbors, average neighbors' export growth, and their interactions in the same village (not all coefficients reported). The second stages in Column (1) include industry fixed effects, Column (2) include city fixed effects, and Column (3) include both industry and city fixed effects. t statistics are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

are reported in Table 8 and Table 9. These robustness checks attempt to account for potentially correlated decisions among same-industry firms which have tendency to co-locate. Third, I rank village-year observations by (i) total exports, (ii) total employment, (iii) domestic sales revenues, and (iv) profits of firms, and drop all village-year observations whenever these measures are above 90th percentiles across all village-years. Results are reported in Table 10. This attempts to rule out an alternative mechanism that firms tend to adhere to large firms and make correlated decisions with them. Fourth, I include the more stringent industry-village-year fixed effects in my specifications to account for any industry-specific shocks affecting firms across village-years, as well as industry-country-year fixed effects to account for industry-specific shocks affecting exports to foreign markets. Results are presented in Table 11 and Table 12. This attempts to rule out an alternative explanation that correlated shocks among same-industry firms could lead to correlated export decisions. Finally, I obtain port and airport data from the *National Ports Layout Plan* from Ministry of Transport, and the *Statistics Report* from Civil Aviation Administration of China, respectively. I obtain the latitude and longitude information of each of these ports and airports, and map each 12-digit administrative region (village) to its closest ports and airports. I then include port-country-year and airport-country-year fixed effects to account for port- or airport-specific shocks affecting firms exporting to different destinations across years. Results are presented in Table 13. This attempts to rule out the possibility that firms may learn from these alternative information sources instead of their own neighbors. All key empirical results remain intact.

1.5 Conclusion

In this paper, I develop a simple Bayesian learning model of export behavior to study how firms learn from spatial networks about foreign market demand. Specifically, I incorporate an explicit structure of internal geography and selective perception assumption to rationalize heterogeneous learning-from-neighbors based on varying geographical distances. A potential entrant updates its expectation about the foreign market demand, using the weighted average between its prior and the observed neighbors' export growth to the same market. Meanwhile, the potential entrant places a larger selection weight on signal revealed by geographically close neighbors, meaning that it gives more favourable interpretation to information inferred from firms near them. This is a key assumption to capture the spatial barriers to transferring knowledge.

Four main testable predictions emerge from the theoretical model. First, it predicts that higher average neighbors' export growth (i.e. more positive signal) induces more firms to start exporting, and increases initial export sales among the other exporters in the same market, more so if the signals are revealed by geographically close neighbors. Second, the learning effects are stronger when the precision of signal increases, and when there are more geographically close neighbors revealing it. Third, firms show a weaker entry response to a positive signal when the signal-to-noise ratio is lower, i.e. the average neighbors' export growth to a market is more dispersed, when ex ante market-specific uncertainty is lower, and when the firm exports to a country which is similar to its previously served markets. Finally, the model predicts that a new exporter's survival probability is positively correlated with the strength of revealed signal, but independent of number of neighbors in different geographic groups.

I use transaction-level data for the universe of Chinese manufacturing firms over 2004-2006, the detailed latitude and longitude information for each firm's address and 12-digit administrative region codes, the most disaggregated level of administrative divisions in China, to compile the dataset of spatial distribution of Chinese manufacturing exporters. The findings provide strong evidence that the probability of entering market m is increasing in the average neighbors' export growth and the number of neighbors. Moreover, the learning from geographically close same-location neighbors is considerably stronger than from distant other-location neighbors. I also find that new exporters' responses to a positive signal about foreign market are stronger when the heterogeneity of firm-specific product appeal (measured by standard deviation of neighbors' export growth to the same market) is smaller, the ex-ante market-specific uncertainty is greater, and the firms export to a new market which is more dissimilar to its previously served markets (measured by common language and per-capita income level differences). In addition, I find positive interactive effects of neighbors and observed signals on initial export sales, and that the survival probability is independent of number of neighbors in different geographic groups. These findings are consistent with the model predictions, and highlight the importance of differential learning-from-neighbors effects in spatial networks, and the decay of knowledge diffusion across space. In addition, the spatial barriers play an important role in shaping new exporters' entry decisions and initial export sales, as suggested by the results that firms show stronger response to the signal revealed by geographically close neighbors. Learning benefits decay rapidly with distance. The model sheds light on the role of geographic proximity in resolving trade uncertainty, and how firms may benefit from more effective knowledge transmission with agglomeration and regional specialization.

Appendix to Chapter 1

Spatial Networks, Knowledge Diffusion, and International Trade

Table 8: Robustness checks. Excluding the most geographically concentrated industries.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Signal × Neighbor	−0.0066***	−0.0062***	−0.0067***	−0.0064***	−0.0064***	−0.0060***
	(−3.75)	(−3.63)	(−3.73)	(−3.62)	(−3.85)	(−3.74)
Signal	0.0246***	0.0188***	0.0245***	0.0183***	0.0231***	0.0170***
	(3.96)	(3.16)	(3.93)	(3.12)	(3.78)	(2.91)
Neighbor	0.0879***	0.0869***	0.0904***	0.0894***	0.0868***	0.0860***
	(4.33)	(4.28)	(4.38)	(4.35)	(5.38)	(5.37)
Other geographic groups						
(0,250] meters						
Signal × Neighbor	−0.0060***	−0.0058***	−0.0060***	−0.0057***	−0.0055***	−0.0053***
	(−3.80)	(−3.62)	(−3.68)	(−3.51)	(−3.65)	(−3.50)
Signal	0.0130*	0.0081	0.0131*	0.0079	0.0128*	0.0077
	(1.77)	(1.11)	(1.77)	(1.08)	(1.74)	(1.06)
Neighbor	0.0782***	0.0769***	0.0776***	0.0764***	0.0785***	0.0770***
	(3.83)	(3.64)	(3.79)	(3.62)	(4.06)	(3.93)
(250,300] meters						
Signal × Neighbor	−0.0048	−0.0018	−0.0067	−0.0040	0.0005	0.0036
	(−0.69)	(−0.25)	(−1.02)	(−0.57)	(0.10)	(0.61)
Signal	0.0157	0.0106	0.0173	0.0123	−0.0017	−0.0069
	(1.10)	(0.69)	(1.22)	(0.80)	(−0.12)	(−0.46)
Neighbor	0.0591*	0.0602*	0.0605*	0.0618*	0.0449	0.0476
	(1.73)	(1.79)	(1.76)	(1.84)	(1.38)	(1.50)
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Country-year FE	*N*	*N*	*Y*	*Y*	*N*	*N*
Industry-country FE	*N*	*N*	*N*	*N*	*Y*	*Y*
Observations	12726	12726	12717	12717	12505	12505
Adjusted R^2	0.471	0.476	0.465	0.471	0.472	0.478

Table 8 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns drop village-year observations with number of same-industry firms is in the top decile across all village-years, where industry refers to a 2-digit industry in Chinese Standard of Industrial Classification. All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries $(-m)$ within the same village. Columns (3) and (4) additionally include country-year fixed effects. Columns (5) and (6) additionally include industry-country fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 9: Robustness checks. Excluding village-year observations with industrial clustering.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Export entry					
Same location						
Signal × Neighbor	−0.0055	−0.0052	−0.0113***	−0.0110***	−0.0059	−0.0058
	(−1.46)	(−1.45)	(−4.81)	(−4.77)	(−1.07)	(−1.10)
Signal	0.0240***	0.0177**	0.0332***	0.0268***	0.0197*	0.0146
	(2.80)	(2.16)	(4.81)	(3.86)	(1.79)	(1.39)
Neighbor	0.1262***	0.1245***	0.1305***	0.1297***	0.1134***	0.1119***
	(6.43)	(6.30)	(5.06)	(5.13)	(5.56)	(5.50)
Other geographic groups						
(0,250] meters						
Signal × Neighbor	−0.0084	−0.0084	−0.0101***	−0.0097***	−0.0002	−0.0001
	(−1.25)	(−1.33)	(−3.98)	(−3.90)	(−0.03)	(−0.02)
Signal	0.0270**	0.0219*	0.0237**	0.0187**	0.0078	0.0038
	(2.07)	(1.68)	(2.51)	(2.02)	(0.67)	(0.32)
Neighbor	0.1248***	0.1239***	0.1145***	0.1138***	0.1183***	0.1164***
	(6.02)	(6.04)	(3.63)	(3.57)	(4.89)	(4.85)
(250,300] meters						
Signal × Neighbor	−0.0023	0.0004	0.0032	0.0054	−0.0048	−0.0022
	(−0.26)	(0.05)	(0.64)	(0.91)	(−0.63)	(−0.27)
Signal	−0.0054	−0.0087	0.0091	0.0083	0.0026	−0.0018
	(−0.27)	(−0.41)	(0.55)	(0.45)	(0.16)	(−0.11)
Neighbor	0.0447	0.0457	0.0830***	0.0842***	0.0548**	0.0561**
	(1.34)	(1.42)	(2.78)	(2.73)	(1.97)	(2.08)
Excluding 2-digit industry:						
Leather, Furs, Down & Related Products	*Y*	*Y*	*N*	*N*	*N*	*N*
Stationery, Educational & Sports Goods	*N*	*N*	*Y*	*Y*	*N*	*N*
Electronics & Telecommunications	*N*	*N*	*N*	*N*	*Y*	*Y*
Other market variables	*N*	*Y*	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Industry-country FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	11112	11112	8914	8914	11609	11609
Adjusted R^2	0.498	0.505	0.503	0.509	0.481	0.486

Table 9 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year, village-country and industry-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries ($-m$) within the same village. Columns (1) and (2) exclude the industry of leather, furs, down and related products. Columns (3) and (4) exclude the industry of stationery, educational and sports goods. Columns (5) and (6) exclude the industry of electronics and telecommunications. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}\, p < 0.05$, $^{*}p < 0.10$.

Table 10: Robustness checks. Excluding village-year observations with large firms.

	(1)	(2)	(3)	(4)
	Dependent variable: Export entry			
Same location				
Signal × Neighbor	−0.0084	−0.0128*	−0.0075**	−0.0084**
	(−1.60)	(−1.91)	(−2.10)	(−2.09)
Signal	0.0221**	0.0265**	0.0197**	0.0215***
	(2.03)	(2.15)	(2.45)	(2.61)
Neighbor	0.1587***	0.1755***	0.1311***	0.1250***
	(7.77)	(7.13)	(4.60)	(4.90)
Other geographic groups				
(0,250] meters				
Signal × Neighbor	−0.0123***	0.0020	−0.0059	−0.0136***
	(−2.63)	(0.19)	(−0.59)	(−3.97)
Signal	0.0177*	−0.0013	0.0007	0.0156*
	(1.66)	(−0.08)	(0.05)	(1.90)
Neighbor	0.1484***	0.1423***	0.1242***	0.1249***
	(6.24)	(4.63)	(5.52)	(5.80)
(250,300] meters				
Signal × Neighbor	−0.0061	−0.0075	−0.0049	−0.0054
	(−0.69)	(−0.95)	(−0.50)	(−0.55)
Signal	0.0241	0.0293*	0.0110	0.0128
	(1.27)	(1.80)	(0.52)	(0.59)
Neighbor	0.0697**	0.0578*	0.0345	0.0319
	(2.00)	(1.82)	(0.88)	(0.80)
Excluding the top decile:				
Export	*Y*	*N*	*N*	*N*
Employment	*N*	*Y*	*N*	*N*
Revenue	*N*	*N*	*Y*	*N*
Profit	*N*	*N*	*N*	*Y*
Other market variables	*Y*	*Y*	*Y*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*
Industry-village-year FE	*Y*	*Y*	*Y*	*Y*
Observations	10660	11064	11017	11025
Adjusted R^2	0.337	0.323	0.330	0.338

Table 10 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year, village-country and industry-village-year fixed effects. All columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries ($-m$) within the same village. Column (1) excludes the top decile of village-year observations in terms of total exports. Column (2) excludes the top decile of village-year observations in terms of total employment. Column (3) excludes the top decile of village-year observations in terms of total domestic sales revenue. Column (4) excludes the top decile of village-year observations in terms of total profits. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 11: Robustness checks. Including industry-village-year fixed effects.

	(1)	(2)	(3)	(4)
	Dependent variable: Export entry			
Same location				
Signal × Neighbor	-0.0059^{***}	-0.0055^{***}	-0.0064^{***}	-0.0061^{***}
	(-4.63)	(-4.55)	(-4.25)	(-4.18)
Signal	0.0215^{***}	0.0162^{***}	0.0231^{***}	0.0178^{***}
	(3.88)	(3.12)	(3.61)	(2.95)
Neighbor	0.0777^{***}	0.0762^{***}	0.0748^{***}	0.0738^{***}
	(4.50)	(4.42)	(3.63)	(3.59)
Other geographic groups				
(0,250] meters				
Signal × Neighbor	-0.0047^{***}	-0.0044^{***}	-0.0051^{***}	-0.0048^{***}
	(-2.90)	(-2.74)	(-2.92)	(-2.76)
Signal	0.0119^{*}	0.0075	0.0107	0.0060
	(1.67)	(1.10)	(1.57)	(0.90)
Neighbor	0.0705^{***}	0.0684^{***}	0.0649^{***}	0.0633^{***}
	(3.38)	(3.24)	(2.85)	(2.74)
(250,300] meters				
Signal × Neighbor	-0.0051	-0.0023	-0.0068	-0.0043
	(-0.63)	(-0.28)	(-0.82)	(-0.50)
Signal	0.0037	-0.0001	0.0123	0.0085
	(0.27)	(-0.01)	(0.88)	(0.57)
Neighbor	0.0371	0.0376	0.0434	0.0426
	(1.36)	(1.43)	(1.50)	(1.51)
Other market variables	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*
Industry-country FE	*Y*	*Y*	*N*	*N*
Industry-village-year FE	*N*	*N*	*Y*	*Y*
Observations	14638	14638	14864	14864
Adjusted R^2	0.468	0.474	0.316	0.323

Table 11 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries $(-m)$ within the same village. Columns (1) and (2) additionally include industry-country fixed effects. Columns (3) and (4) additionally include industry-village-year fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 12: Robustness checks. Including additional fixed effects.

	(1)	(2)	(3)	(4)
	Dependent variable: Export entry			
Same location				
Signal × Neighbor	-0.0060^{***}	-0.0057^{***}	-0.0070^{***}	-0.0066^{***}
	(-4.33)	(-4.30)	(-4.89)	(-4.88)
Signal	0.0211^{***}	0.0154^{***}	0.0218^{***}	0.0149^{**}
	(3.59)	(2.80)	(3.43)	(2.51)
Neighbor	0.0801^{***}	0.0789^{***}	0.0875^{***}	0.0862^{***}
	(4.55)	(4.52)	(4.82)	(4.82)
Other geographic groups				
(0,250] meters				
Signal × Neighbor	-0.0047^{***}	-0.0044^{***}	-0.0052^{***}	-0.0049^{***}
	(-2.78)	(-2.65)	(-3.83)	(-3.72)
Signal	0.0115	0.0067	0.0114^{*}	0.0056
	(1.55)	(0.93)	(1.75)	(0.88)
Neighbor	0.0717^{***}	0.0699^{***}	0.0735^{***}	0.0717^{***}
	(3.55)	(3.44)	(4.10)	(4.07)
(250,300] meters				
Signal × Neighbor	-0.0060	-0.0035	-0.0069	-0.0043
	(-0.77)	(-0.44)	(-0.99)	(-0.59)
Signal	0.0036	-0.0001	0.0042	0.0005
	(0.27)	(-0.01)	(0.36)	(0.04)
Neighbor	0.0374	0.0387	0.0283	0.0302
	(1.39)	(1.48)	(1.01)	(1.10)
Other market variables	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*
Country-year FE	*Y*	*Y*	*N*	*N*
Industry-country FE	*Y*	*Y*	*N*	*N*
Industry-country-year FE	*N*	*N*	*Y*	*Y*
Observations	14631	14631	14238	14238
Adjusted R^2	0.469	0.475	0.468	0.475

Table 12 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries $(-m)$ within the same village. Columns (1) and (2) additionally include country-year and industry-country fixed effects. Columns (3) and (4) additionally include industry-country-year fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 13: Robustness checks. Alternative learning mechanisms.

	(1)	(2)	(3)	(4)
	Dependent variable: Export entry			
Same location				
Signal × Neighbor	-0.0073^{***}	-0.0070^{***}	-0.0075^{***}	-0.0072^{***}
	(−4.70)	(−4.73)	(−4.52)	(−4.53)
Signal	0.0241^{***}	0.0172^{***}	0.0253^{***}	0.0183^{***}
	(3.63)	(2.66)	(3.61)	(2.64)
Neighbor	0.0833^{***}	0.0824^{***}	0.0844^{***}	0.0835^{***}
	(3.96)	(3.99)	(3.90)	(3.94)
Other geographic groups				
(0,250] meters				
Signal × Neighbor	-0.0057^{***}	-0.0054^{***}	-0.0056^{***}	-0.0053^{***}
	(−3.58)	(−3.54)	(−3.49)	(−3.43)
Signal	0.0132^{**}	0.0069	0.0120^{*}	0.0054
	(2.04)	(1.08)	(1.81)	(0.84)
Neighbor	0.0692^{***}	0.0683^{***}	0.0705^{***}	0.0697^{***}
	(3.06)	(3.05)	(2.98)	(2.97)
(250,300] meters				
Signal × Neighbor	−0.0076	−0.0055	−0.0068	−0.0046
	(−1.02)	(−0.70)	(−0.82)	(−0.53)
Signal	0.0146	0.0110	0.0115	0.0073
	(1.08)	(0.75)	(0.85)	(0.51)
Neighbor	0.0427	0.0432	0.0542^{*}	0.0544^{*}
	(1.43)	(1.49)	(1.80)	(1.86)
Other market variables	*N*	*Y*	*N*	*Y*
Village-country FE	*Y*	*Y*	*Y*	*Y*
Firm-year FE	*Y*	*Y*	*Y*	*Y*
Port-country-year FE	*Y*	*Y*	*N*	*N*
Airport-country-year FE	*N*	*N*	*Y*	*Y*
Observations	14745	14745	14499	14499
Adjusted R^2	0.430	0.436	0.417	0.424

Table 13 reports estimation results using Eq. (24) as the empirical specification. Exports with state-owned enterprises (SOEs), trade intermediaries defined in Ahn, Khandelwal, and Wei (2011), and transactions to Hong Kong are excluded. Only ordinary trade transactions are included in the sample. The dependent variable, $Entry_{icmt} = 1$ for the firm-village-country-year observation if firm i did not export in year $t-1$ but started exporting to market m in year t. $Entry_{icmt} = 0$ for all destination countries that a new exporter did not export to market m in year $t-1$ and in year t. The sources of knowledge diffusion are measured by the number of neighboring exporters from geographic group g exporting to market m, $n_{icgm,t-1}$, and the average neighbors' export growth from geographic group g exporting to market m as defined by Eq. (23). All columns include firm-year and village-country fixed effects. All even-numbered columns include other market variables, defined as the raw number of neighbors, revealed signals, and their interaction term to other destination countries $(-m)$ within the same village. Columns (1) and (2) additionally include port-country-year fixed effects. Columns (3) and (4) additionally include airport-country-year fixed effects. t statistics, based on standard errors clustered at the village level, are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Chapter 2

Internal Geography, Trade Frictions, and Per-Shipment Costs

Abstract

This paper examines the role of within-country trade frictions on the volume and frequency of export shipments. I present a heterogeneous firm trade model with endogenous shipment frequency decisions, and an explicit spatial structure which generates location-specific heterogeneity in trade costs. The presence of within-country trade frictions, measured by a firm's distance to its nearest port facility, increases per-shipment costs, favouring large and infrequent shipments. I use a dataset of Chinese export transactions to infer the underlying per-shipment costs for each firm-product-destination combination. My estimates of per-shipment costs of the average Chinese manufacturing firms are economically large, ranging between 0.88% to 6.11% of the average shipment value. I also document that the per-shipment costs correlate positively with distances to the nearest port facilities, which raises questions concerning the estimation strategies for trade costs in the absence of an internal geography dimension.

JEL Classifications: F10, R12, O18

Keywords: shipment frequency, fixed costs, internal geography, trade frictions

2.1 Introduction

Fixed costs of exporting in combination with heterogeneous firm productivity have been extensively used to study the firms' export behavior since the seminal article by Melitz (2003). These fixed costs determine the productivity thresholds for exporting, which sort firms into the sets of lower-productivity firms which serve domestic markets, and higher-productivity firms which export to foreign destinations. This sorting mechanism generates rich empirical patterns on firm-level heterogeneity in exporting behavior. The existence of fixed costs of exporting implies many countries face substantial unexploited trade potential in the sense that firms are willing yet unable to export overseas. While much effort on has been made, the role of firm-specific heterogeneity on firms' fixed costs of exporting is still under-explored.[1]

This paper is to study, both analytically and empirically, firms' decision regarding their optimal shipment frequency and volume in the presence of per-shipment costs and show how their choices are influenced by these costs and by the distance between their manufacturing plant and the nearest port. Firms incur per-shipment costs every time when they export to a foreign destination. These costs include, but are not limited to the monetary and time costs of obtaining trade credit, processing export documents, inspection and clearance, monitoring and coordinating transit and transportation to border.[2] All these procedures have to be done within source country before having goods shipped to their foreign destinations. To save on per-shipment trade costs, exporting firms can ship goods less frequently but more at a time. This strategy, however, generates higher storage costs at export destinations, which pass onto the consumers and suppress export demand. Hence, facing a trade-off between paying higher per-shipment costs and storage costs, firms choose their optimal shipment frequency and the shipment volume. Geographical proximity to trade facilities also generates variations in location-specific heterogeneity in fixed and variable costs of exporting, which adds complications to firms' optimal shipping decisions.

[1] Recent literature studies the effects of time delays (to move an export container from the factory to the nearest port) on export volumes (Djankov et al., 2010); administrative barriers that accrue per shipment (e.g. filling in customs declaration, and having the cargo inspected by health and sanitary officials) on export volumes, shipping decisions, and welfare; as well as quality of trade facilitation (transit times, documentation, ports and customs) on export volumes.

[2] Djankov et al. (2010) provide an example of costly export procedures in Burundi, a landlocked African country. In Burundi (see Djankov et al. (2010), Figure 1), it takes 11 documents, 17 visits to various offices, 29 signatures, and 67 days on average for an exporter to move their goods from factory to the ship in 2005. The original data is from a World Bank questionnaire completed by trade facilitators at freight-forwarding companies in 146 countries.

The main contribution of this paper is to use a simple structural model to recover unobserved location-specific firm-product-destination per-shipment costs from observables and standard parameters in trade models. Following Kropf and Sauré (2014), I endogenize exporters' shipment frequency decisions and introduce an explicit spatial structure of the exporting country. I show that the optimal shipment frequency and shipment volume are functions of demand elasticities, discount rates, geographical proximity to trade facilities, and other standard gravity variables. Next, I use transaction-level customs data from Chinese manufacturing exporters to quantify per-shipment costs. The inferred per-shipment costs exhibit substantial heterogeneity across firms and within-country locations. These estimates are economically important. Depending on specifications, their net present value averages at about 211 to 1,375 U.S. dollars, which is equivalent to 0.88% to 6.11% of the shipment value. I also exploit the spatial distribution of Chinese exporters to study the impact of within-country trade frictions on firm's optimal shipment decisions. I show that doubling the internal distance separating a firm and its nearest international port facility is associated with a 40% increase in per-shipment costs at the firm-product-destination level. All these results are robust after controlling for a large set of fixed effects and firm-level characteristics.

The micro-founded theoretical model generates novel implications on empirical patterns observed from data. First, with per-shipment costs, I examine a new margin of adjustment for exporting firms: shipment frequency and volume. While there are many studies on traditional extensive margin (whether a firm exports or not) and intensive margins (adjusting export volumes, optimal product varieties and/or product churning), shipment frequency and volume are rarely studied. With detailed transaction-level and geospatial data, I generate rich theoretical predictions on how per-shipment costs and firms' shipment behavior vary across within-country locations. Second, with a structure of internal geography and its associated trade frictions, I study how within-country geographical proximity to trade facilities shapes the optimal shipment decisions of firms, compared to standard gravity variables and firm-level characteristics. Quantifying the effect of internal trade costs on international trade is important for assessing the benefits of trade-related infrastructure. Lastly, while there is a vast literature which assumes per-period fixed costs that are destination country specific and in turn determines the set of exporters to a specific destination country, there are compelling reasons that per-period fixed costs depend on the distance separating a manufacturing establishment and its nearest port facility. Specifically, geographical proximity to port infrastructure could lower the direct costs of monitoring and coordinating transit and transportation to the border, as well as minimize the hassles involving delays of processing ports-and-customs documentation and communication. In this case, the location-specific heterogeneity in trade costs adds complexity to shipment frequency and volume decisions. Taking distance-associated costs into consideration, manufacturing establishments which are distant from ports may ship less frequently but more at a time, compared to their counterparts which are close to port regions. Building on a similar argument by Kropf and Sauré (2014), there is an ambiguity in defining exporter-status with the observed trade data of a given reporting frequency for firms of varying geographical proximity to their nearest trade facilities. Consider a firm which exports once in a year. It is classified as an exporter based on yearly data, but a non-exporter in 3 quarters based on quarterly data. Previous studies, e.g. Blum et al. (2013) and Békés and Muraközy, (2012), document a large number of firms that export discontinuously (i.e. occasional exporters) as opposed to those that export frequently (i.e. perennial exporters). However, this ambiguity in exporter-status (and classification of occasional versus perennial exporters) can be resolved by endogenizing the time between two consecutive shipments for firms with varying geographical proximity to port infrastructure. Studying per-shipment costs and optimal shipping frequency and volume decisions with an internal geography dimension provides us with a better understanding of firms' exits and re-entries in exporting.

Literature. Previous studies highlight the importance of fixed costs of exporting. Das et al. (2007) find a large sunk cost of entry using a dynamic structural model with Colombian plant-level data. Roberts and Tybout (1997) also find sunk costs to be significant, and firms' prior export experience could increase the probability of exporting by up to 60 percentage points. Moxnes (2010) finds that both global and country-specific components exist in sunk entry costs in exporting, and estimates that country-specific costs are about three times the magnitude of global costs. This work is most related to Kropf and Sauré (2014) who build a heterogeneous firm trade model to estimate fixed costs per shipment using Swiss export data, and show that they are negatively correlated with language commonalities and trade agreements. I extend these studies by uncovering the rich relationship between within-country trade frictions and per-shipment costs. In addition, I provide evidence on how the per-shipment costs vary with internal distances to international port facilities and a large set of firm-level characteristics, which is absent in previous literature.

I build on literature in infrastructure and trading technology across spatial distribution of firms and their relations with intra-national trade costs in international trade. Atkin and Donaldson (2015) find that the effect of log distance on trade costs within Ethiopia or Nigeria is 4 to 5 times larger than in the US. Coşar and Fajgelbaum (2016) develop an internal geography model in which internal transport costs lead to regional specialization in export-oriented industries in regions close to ports. Coşar and Demir (2016) find that internal transportation infrastructure plays an important role in accessing international markets using Turkish data. Volpe Martincus and Blyde (2013) use the 2010 Chilean earthquake as a natural experiment and find that diminished transportation infrastructure had a significant negative impact on firms' exports. Van Leemput (2021) quantifies the size of internal and external trade barriers using Indian sector-level data, and finds that internal trade barriers make up 40% of total trade barriers on average, and the distance to the closest port is a source of heterogeneity of these internal trade barriers. This paper adds to the line of literature by incorporating an internal geography dimension into the estimation of shipment costs, and analyzing the importance of within-country trade frictions in optimal shipping decisions, using a unique set of transaction-level and geospatial data.

This paper is closely related to the literature dealing with transaction costs of international trade. Specifically, I make use of the concept of optimal inventory management of importers with fixed costs of importing and transportation delays in Alessandaria et al. (2010, 2011), and introduce storage costs into my model. Following Alessandria et al. (2010) and setting annualized storage costs to 35% of a firm's inventories and demand elasticities at 1.5, I obtain similar values of per-shipment costs. Together with the reported cost to export from *World Development Indicators*, these sources confirm that my estimates are plausible. Finally, I show that the estimates are robust after taking biases arising from random exits, low-productivity firms, and maximum shipping weights into consideration.

I also contribute new empirical evidence on transaction-level behavior of exporters, and that the shipment frequency constitutes an important margin of adjustment in international trade. Békés and Muraközy (2012) use Hungarian firm-transaction level data to show that a half of firm-product-destination export spells are short-lived or temporary each year, casting doubts to the validity of comparative advantage and sunk nature of entry costs. They explain that the temporary trade depends on productivity and capital cost of the firm, as well as some gravity variables of destinations. Békés et al. (2017) examine how exporting firms adapt to the uncertainty stemming from demand volatility with adjustment of shipment frequency. Using detailed geospatial firm-transaction level data from Chinese manufacturing exporters, I show that the shipment frequency is negatively related to internal distance to the nearest port at the firm-product-destination level. It indicates geographically distant firms tend to adjust shipment frequencies in response to high per-shipment costs, confirming the necessity of introducing an internal geography dimension into the analysis of firms' shipment decisions.

The remainder of the paper is organized as follows. Section 2 describes the model, and discusses the role of per-shipment costs and storage costs, as well as the location-specific heterogeneity which affect an exporter's optimal shipment decision. Section 3 describes the data and definitions of key variables. Section 4 provides estimation results and establishes the relationship between per-shipment costs and internal distance to the nearest port. Section 5 concludes. Robustness checks and additional results are presented in the Supplementary Appendix.

2.2 Theory

I consider a theoretical framework similar to that of Kropf and Sauré (2014) which incorporates the firm's decision on frequency of export shipments into a standard Melitz (2003) model of heterogeneous firms. In addition, I introduce an explicit Coşar and Fajgelbaum (2016) spatial structure which allows for location-specific heterogeneity of trade costs of shipments. The model is static in nature. I index exporting country by i, destination countries by j, and firms (and their varieties) by k. For simplicity, population sizes, technologies and trade barriers are assumed to be constant. The model focuses on the partial equilibrium analysis that deals with the decision making problem of a single firm. Whenever there is no risk of confusion, the subscript i is omitted for notational simplicity.

2.2.1 Economic environment

2.2.1.1 Consumption

Consider a world with J countries, indexed by $j = 1, 2, ..., J$. Every country produces and consumes a continuum of products. The utility of a representative consumer in country j is:

$$u_j = \left(\int_{\Omega_j} q_{jk}^{\frac{\sigma-1}{\sigma}} dk \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $1 < \sigma < +\infty$ is the constant elasticity of substitution across products, q_{jk} is consumption of variety k and Ω_j is the set of varieties sold in country j. Consumers derive utility according to Eq. (1) at each point in time. There are no seasonal effects in demand. The overall infinite-horizon utility is:

$$U_j = \int_0^\infty e^{-\rho t} u_j dt, \tag{2}$$

where $e^{-\rho t}$ is the discount factor under continuous discounting. Let Y_j be the expenditure of country j. Then country j's demand for variety k is:

$$q_{jk} = p_{jk}^{-\sigma} \frac{Y_j}{P_j^{1-\sigma}}, \tag{3}$$

where p_{jk} is the price of variety k in country j and P_j is the country's ideal price index. An individual firm is small so it does not affect the price index P_j nor expenditure Y_j.

2.2.1.2 Production

Firms are heterogeneous and characterized by their draw of unit labor requirement φ. The unit labor requirement φ is distributed according to a cumulative distribution function $G(\varphi)$, with support $[\underline{\varphi}, \bar{\varphi}]$, where $0 < \underline{\varphi} < \bar{\varphi}$. Each firm k has the following production technology:

$$q_k = \frac{h_k}{\varphi_k}, \tag{4}$$

where q_k is the quantity of production, and h_k is the amount of labor employed. Workers are paid $w_k = \varphi_k \omega_i$, where ω_i is the prevailing wage of labor in exporting country i. w_k is also interpreted as the constant firm-specific marginal production cost of firm k.

2.2.1.3 Spatial structure of exporting country

Following Coşar and Fajgelbaum (2016), I introduce an explicit spatial structure to the exporting country. The country consists of a set of locations arbitrarily distributed on a map. I index these locations by l, and assume that only some locations can trade directly with destination markets j. All goods must pass through a domestic port to be shipped to international markets. Specifically, I assume without loss of generality that l represents the distance between each location l from its nearest port, and denote all ports by $l = 0$. Given this spatial structure, a location indexed $l = 0$ can be interpreted as a seaport, airport, or location equipped with technology trading with the rest of the world. The key point is to introduce location-specific heterogeneity in technology for international trade for firms in each location l. Let the maximum distance between a location inside the exporting country and its nearest port be $\bar{l}$. As will be discussed next subsection, the distance l matters for the construction of both marginal trade costs and per-shipment costs.

2.2.1.4 Variable trade costs

Firms pay destination- and location-specific iceberg-type trade costs to ship their goods first from location $l \geq 0$ to location $l = 0$, and subsequently from location $l = 0$ to the rest of the world. The variable trade costs are formally given by:

$$\pi_{ijl} = \pi_{ij}\pi_i\left(l\right), \tag{5}$$

such that $\pi_{ijl} \geq 1$ units of goods must be shipped from location $l \geq 0$ for each unit of goods to arrive in destination market j.[3,4] Assume the standard iceberg-type external (cross-country)

[3] This structure of variable trade costs is similar to that of Eq. (10) in Duranton et al. (2014), where they decompose the cost of shipping of a unit of output from city i and sector k to city j into three components: (i) the cost of leaving city i in sector k, (ii) the cost of going from city i to city j, and (iii) the cost of entering city j. The cost of transportation between cities increases with the network distance between cities. Here, I focus on the component (ii) in Duranton et al. (2014) because I am interested in shipments which pass through cities and finally leave source country for a foreign market.

[4] Hamano and Vermeulen (2020) assume that the within-country transportation costs are port-specific. Van

variable transport costs $\pi_{ij} \geq 1$, the internal (within-country) variable transport costs $\pi_i(l) \geq 1$, and that $\pi_i^{'}(l) > 0$, $\pi_i^{''}(l) \geq 0$, with $\pi_i(0) = 1$. Both variable transport costs must be paid at the date of the shipment.

2.2.1.5 Per-shipment costs

Firms in country i pay a destination-specific export entry fixed cost, F_{ij}, in local labor units, to export to country j. In addition, firms incur a per-shipment cost for each time they ship goods from location $l \geq 0$ in country i to destination market j. The per-shipment cost, in monetary units, is given by:

$$f_{ijl} = f_{ij} f_i(l), \tag{6}$$

where f_{ijl} refers to the per-shipment costs from location $l \geq 0$ in country i to destination market j. It consists of two components: (i) the conventional (cross-country) fixed cost term f_{ij} which depends on characteristics of exporting country i and destination market j, and (ii) the internal geography (within-country) fixed cost term $f_i(l)$ which increases with the distance separating an exporting firm and its closest international port facilities. Assume $ln(f_{ij}) > 0$ and $ln(f_i(l)) > 0$, thus $ln(f_{ijl}) > 0$. I further assume $f_i^{'}(l) > 0$ and $f_i^{''}(l) \geq 0$, with $f_i(0) = 1$. These assumptions indicate that firms further away from $l = 0$ must pay higher per-shipment costs to ship goods to locations where technology trading with the rest of the world is available ($l = 0$). As described by Kropf and Sauré (2014) and Hornok and Koren (2015), these per-shipment costs include fixed costs of monitoring and coordinating the actual transportation to the receiver, documentation, customs clearance and etc. Thus, it is plausible that these per-shipment costs are increasing with distance l separating an exporting firm and its closest port facilities. Several studies also document that geographic proximity is a good proxy for information (Portes et al., 2001; Portes and Rey, 2005), and that fixed costs increase with distance (Albornoz et al., 2016). As expected, firms located at $l^{'} > l > 0$ face larger within-country trade frictions to organize and ship their goods to its closest port facilities than those located at l. The higher per-shipment costs also capture information

Leemput (2021) assumes both intra-state and inter-state transport costs using state-level data in India.

frictions arising from geographical remoteness.[5]

2.2.1.6 Storage costs

Another key feature of this model is that there is a time gap between the date of shipment and the date of consumption. While firms can save on per-shipment costs by shipping less frequently but more at a time, this feature generates storage costs $R > 0$ at destination markets j. Similar to Kropf and Sauré (2014), storage costs act like a tax on varieties that are shipped at time $t = 0$ but which are consumed at $t^{'} > 0$. Let R be the rate of ad valorem storage cost. The gross ad valorem costs are $e^{Rt^{'}}$, and the net ad valorem costs are then $\left(e^{Rt^{'}} - 1\right)$.

2.2.2 Firm pricing

2.2.2.1 Optimal prices

Consider firm k, which is located in country i and faces the constant marginal costs w_k. This firm maximizes profits by setting the optimal price of its unique variety to:

$$\tilde{p}_k = \frac{\sigma}{\sigma - 1} w_k, \tag{7}$$

which is a constant mark-up over its marginal costs. When the dates of shipping and consumption do not coincide, consumers are charged for storage costs, which accrue at rate $R > 0$. Consumer prices equal optimal prices stated in Eq. (7) plus sum of transport costs and storage costs. The unit price of variety k produced at location l faced by consumers in country j which consumes at time $t^{'} > 0$ is given by:

$$p_{jk}\left(t^{'}\right) = \left(\pi_{ij}\pi_i\left(l\right)\right) e^{Rt^{'}} \frac{\sigma}{\sigma - 1} w_k. \tag{8}$$

[5]Several recent studies introduce location-specific fixed costs. Allen (2014) introduces a region-specific fixed cost of search, which farmers pay to search and learn the actual prices elsewhere. Huang and Xiong (2018) introduce an industry- and location (origin)-specific fixed cost of production. Hamano and Vermeulen (2020) assume that exporting from country i to j requires port-specific fixed costs.

2.2.2.2 Operating profits

Using demand for variety in Eq. (3) and prices in Eq. (8), the flow of operating profits from sales of variety k to country j consumed at time $t^{'} > 0$ after shipment is expressed as:

$$\pi_{jk}\left(t^{'}\right) = \sigma^{-1}\left[\left(\pi_{ij}\pi_{i}\left(l\right)\right)e^{Rt^{'}}\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{1-\sigma} Y_j. \tag{9}$$

2.2.2.3 Present value of operating profits

With constant expenditures Y_j, prices P_j, trade costs π_{ij} and π_i, I next compute the present value of profits generated by a single shipment. Consider a firm k indexed by location l in country i ships to country j. Let the time difference between two consecutive shipments by $\triangle$. Using Eq. (9), the present value of operating profits is obtained by integrating over discounted operating profits:

$$\Pi_{jk}\left(\triangle\right) = \int_{0}^{\triangle} e^{-rt^{'}}\pi_{jk}\left(t^{'}\right)dt^{'} = A_{jk}\frac{1-e^{-(r+R(\sigma-1))\triangle}}{r+R\left(\sigma-1\right)}, \tag{10}$$

where $A_{jk} = \sigma^{-1}\left[\left(\pi_{ij}\pi_{i}\left(l\right)\right)\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{1-\sigma} Y_j$, and $r > 0$ refers to the firm's effective discount rate, which is exogenously given. Following Alessandria et al. (2010), I assume storage costs are no smaller than firm's discount rate (i.e. $R \geq r$) in the subsequent analysis.[6] Following Kropf and Sauré (2014), I normalize the time span, a year, to unity. Thus, the shipment interval $\triangle$ is expressed as a fraction of years. Consequently, the inverse of $\triangle$ (i.e. $\triangle^{-1}$) is the number of shipments per year (i.e. shipment frequency) between country pairs (i, j) for firm k.

2.2.2.4 Exporter status and shipment decisions

There are two criteria for a firm to be an exporter. The first determines whether a firm exports, while the second determines how frequent a firm ships their varieties. Consider a firm faces an export entry fixed cost, F_{ij}, and a per-shipment cost, $f_{ij}f_i\left(l\right)$. First, a firm will export only if the

[6] Alessandria et al. (2010) find that the typical importer holds about 36% of its annual purchase, which is equivalent to a monthly *total* carrying cost of 3%. They draw on a large literature and find that annual *non-interest* inventory carrying costs range from 19 to 43% of a firm's inventories, which imply monthly carrying costs ranging from 1.5 to 3.5%. Therefore, in their benchmark calibration, they choose a monthly *non-interest* carrying cost at 2.5% and a monthly *interest* carrying cost of 0.5%. Following Alessandria et al. (2010), I assume that the *non-interest* storage cost R is larger than *interest* cost r, which is consistent with the empirical findings of previous literature.

present value of profits from all shipments is higher than the export entry fixed costs F_{ij}, as in Melitz (2003). Second, a firm will arrange a new shipment if the sum of its operating profits between two consecutive shipments exceeds the per-shipment cost. Formalizing the latter requirement, firm k in location l in country i exports to country j if and only if:

$$A_{jk}\frac{1-e^{-(r+R(\sigma-1))\triangle}}{r+R\left(\sigma-1\right)}\geq f_{ij}f_i\left(l\right) \tag{11}$$

is satisfied. Conditional on having paid an export entry fixed cost, firm k from location l in country i whose productivity satisfies condition (11) generate positive operating profits from exporting to country j. Clearly, firms further away from their nearest port facilities face higher productivity thresholds in order to recover higher per-shipment costs.

2.2.3 Optimal shipment frequency and shipment volume

With shipment frequency as a new margin, firms do not only choose their optimal prices, but also, the timing of their shipments. By Eq. (1) and Eq. (2), consumers in country j derive utility from consumption of varieties at each point in time. Consequently, firms face a trade-off between shipment costs and storage costs: (i) firms can export less frequently and more at a time in order to save on per-shipment costs, but this would incur higher storage costs because there is a larger time difference between the date of shipment and the date of consumption; and (ii) firms can export more frequently and fewer at a time to lower storage costs, but this would incur multiple times of per-shipment costs. By introducing storage costs to the trade model, the timing of shipments becomes endogenous as firms only arrange a new shipment if the sum of its operating profits between two consecutive shipments exceeds the per-shipment costs.

2.2.3.1 Shipment frequency

Consider firm k located in country i exporting to market j. The expression for present value of operating profits per shipment from Eq. (10) becomes:

$$\Pi_{jk}\left(\triangle_{jk}\right)=A_{jk}\frac{1-\gamma_{jk}^{r+R(\sigma-1)}}{r+R\left(\sigma-1\right)},$$

where $\gamma_{jk} = e^{-\triangle_{jk}}$. Having assumed that Y_j, P_j, r, R are time-invariant, the firm's optimal choice $\triangle_{jk}$ is also time-invariant.[7] The firm chooses $\triangle_{jk}$ to maximize the present value of profits from all present and future shipments from location l in country i to market j. This present value may be written as:

$$
\begin{aligned}
NPV_{jk} &= \left[\Pi_{jk}\left(\triangle_{jk}\right) - f_{ij}f_i\left(l\right)\right]\left(1 + e^{-r\triangle_{jk}} + e^{-r\left(2\triangle_{jk}\right)} + e^{-r\left(3\triangle_{jk}\right)} + ...\right) \\
&= \left[\Pi_{jk}\left(\triangle_{jk}\right) - f_{ij}f_i\left(l\right)\right]\left[1 + \left(\gamma_{jk}^{r}\right) + \left(\gamma_{jk}^{r}\right)^2 + \left(\gamma_{jk}^{r}\right)^3 + ...\right] \\
&= \frac{\Pi_{jk}\left(\triangle_{jk}\right) - f_{ij}f_i\left(l\right)}{1-\gamma_{jk}^{r}}.
\end{aligned}
\tag{12}
$$

Compared to standard trade models, there are two additional terms in Eq. (12). First, the term $\frac{1-\gamma_{jk}^{r+R(\sigma-1)}}{r+R(\sigma-1)}$ arises from the storage costs. Second, the terms $f_{ij}f_i\left(l\right)$ and $\pi_{ij}\pi_i\left(l\right)$ from A_{jk} arise from within-country trade frictions and trading technology in remote locations $l > 0$ which are not equipped with port facilities. Differentiating Eq. (12) with respect to γ_{jk} gives the profit-maximizing shipment frequency:

$$
\frac{r + R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)} - \left(r + R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}}{r + R\left(\sigma-1\right)} = \frac{rf_{ij}f_i\left(l\right)}{A_{jk}}.
\tag{13}
$$

It is straightforward to verify that LHS is decreasing in γ_{jk} for all $\gamma_{jk} \in (0,1)$. Moreover, when $\gamma_{jk} \to 0$, LHS approaches to $\frac{r}{r+R(\sigma-1)}$; when $\gamma_{jk} \to 1$, LHS approaches to 0. Hence, there exists a unique $\gamma_{jk} \in (0,1)$ solving condition (13). I refer to the optimal shipment frequency from (13) as $\bar{\gamma}_{jk}$, and give the first proposition as follows.

Proposition 1 (Optimal shipment frequency and trade costs). The shipment frequency of firm k in location l in country i exporting to country j (i.e. $\triangle_{jk}^{-1}$) increases with: (i) export market size (Y_j), (ii) price level (P_j), and (iii) demand elasticity (σ); but it decreases with: (iv) firm-specific production costs (w_k), (v) iceberg trade costs (π_{ij}), (vi) distance from ports, via variable trade costs ($\pi_i\left(l\right)$), and (vii) distance from ports, via per-shipment costs ($f_i\left(l\right)$).

Proof of Proposition 1. See Supplementary Appendix. □

[7] It is also assumed that σ, l, π_{ij}, φ_k, and w_i are time-invariant.

Proposition 1 (i) to (v) are standard trade model predictions. Firms tend to ship more frequently when the destination markets are larger, competition is less intense, lower marginal costs of production, and lower trade barriers. Regarding (iii), firms ship out varieties of greater demand elasticity more frequently. Intuitively, lower shipment frequency means leaving these varieties at the destination markets for a longer time and incurring larger storage costs. The larger storage costs are incorporated into the final prices of these varieties. Consequently, consumers are more likely to purchase substitutes for these varieties, due to its nature of substitutability. Thus, firms will lose their market shares if their varieties are high σ inherently.

Incorporating spatial structure of exporting country into standard trade models generates additional effects of location-specific heterogeneity in trade costs on firms' shipment frequency decisions. Within-country trade frictions and poorer trading technology (i.e. large l) increase per-shipment costs (through the term $f_{ij} f_i(l)$), inducing firms to ship less frequently, such that the sum of operating profits between two consecutive shipments could recover the per-shipment costs. The internal trade costs $\pi_i(l)$ exhibits similar behavior as that of iceberg-type transport costs π_{ij}.

2.2.3.2 Shipment volume

By integrating demand Eq. (3) over the period $[0, \triangle_{jk}]$, using prices Eqs. (6) and (10), the volume of a shipment from country i to country j is:

$$x_{jk} = \frac{A_{jk}}{R} \left(1 - \bar{\gamma}_{jk}^{R\sigma}\right), \tag{14}$$

where $\bar{\gamma}_{jk}$ is the unique solution satisfying condition (13). By Proposition 1 and Eq. (14), an increase in $f_i(l)$ decreases $\bar{\gamma}_{jk}$, but leaves A_{jk} in condition (13) unchanged. Thus, the shipment volume is increasing in fixed costs of trade.

Lastly, I examine how shipment volume x_{jk} responds to the changes in A_{jk} and internal distance l. Taking implicit derivatives of condition (13) gives:

$$\frac{\partial \bar{\gamma}_{jk}}{\partial A_{jk}} = -\frac{r f_{ij} f_i(l)}{A_{jk}^2} \frac{1}{R(\sigma-1)} \frac{1}{\bar{\gamma}_{jk}^{r+R(\sigma-1)} \left(1 - \bar{\gamma}_{kj}^{-r}\right)}. \tag{15}$$

Combining expressions (14) and (15) gives:

$$\frac{\partial ln\left(x_{jk}\right)}{\partial A_{jk}} > 0. \tag{16}$$

Thus, the shipment volume x_{jk} is increasing in A_{jk}. Again, using expressions (14) and (15) gives:

$$\frac{dx_{jk}}{dl} = (1-\sigma)\frac{\pi_i^{'}(l)}{\pi_i(l)}x_{jk} - \frac{rf_{ij}f_i^{'}(l)\left[(\sigma-1)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R^2(\sigma-1)\bar{\gamma}_{jk}^{r}\left(1-\bar{\gamma}_{jk}^{-r}\right)}. \tag{17}$$

Proposition 2 summarizes the theoretical predictions for shipment volume and trade costs.

Proposition 2 (Shipment volume and trade costs). The volume per shipment of firm k in location l in country i exporting to country j (x_{jk}) increases with: (i) export market size (Y_j), (ii) price level (P_j), and (iii) fixed costs of exporting (f_{ij}); decreases with: (iv) firm-specific production cost (w_k), (v) iceberg trade costs (π_{ij}), (vi) storage costs (R); but is ambiguously affected by (vii) distance from ports, via variable trade costs ($\pi_i(l)$) and per-shipment costs ($f_i(l)$).

Proof of Proposition 2. See Supplementary Appendix. □

Proposition 2 summarizes the relationship between shipment volume and trade costs. A longer distance separating a firm and its nearest port gives ambiguous effects on shipment volume. Notice that the first term $(1-\sigma)\frac{\pi_i^{'}(l)}{\pi_i(l)}x_{jk} < 0$ because of assumption $1 < \sigma < +\infty$, while the second term $-\frac{rf_{ij}f_i^{'}(l)\left[(\sigma-1)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R^2(\sigma-1)\bar{\gamma}_{jk}^{r}\left(1-\bar{\gamma}_{jk}^{-r}\right)} > 0$ because $\left(1-\bar{\gamma}_{jk}^{-r}\right) < 0$ and all the remaining terms are positive. Intuitively, the first term refers to the negative effects of distance-induced variable trade costs on foreign demand, while the second term points to the fact that firms need to ship larger quantities at a time in order to recover the higher distance-induced per-shipment costs.

Propositions 1 and 2 summarize how the firms adjust shipping frequency and volume in response to standard trade parameters in a standard Melitz (2003) heterogeneous firm model, as well as the firm's own geographic proximity to trade facilities.

2.2.4 Aggregate bilateral exports

This section characterizes the marginal exporters and aggregate bilateral trade flows. Let $w_k \equiv \varphi_k\omega_i$ be the marginal cost of firm k, located in country i with unit labor requirement φ_k.

2.2.4.1 Productivity thresholds for export entry

Firms in country i must pay fixed costs of entry F_{ij} before entering a foreign market j. Combining Eqs. (12) and (13) to obtain NPV_{jk}, the present value of exporting must cover the fixed costs of entry:

$$NPV_{jk} = \frac{A_{jk}}{r}\bar{\gamma}_{jk}^{R(\sigma-1)} \geq F_{ij}. \tag{18}$$

Eqs. (11) and (13), and condition (18) jointly determine the productivity thresholds $\tilde{\varphi}_{ij}^{-1}$ of exporters from location l in country i to country j. With productivity threshold $\tilde{\varphi}_{ij}$ defined, set shipment frequency $\tilde{\gamma}_{ij} = \bar{\gamma}_{ij}(\tilde{\varphi})$. Thus, substituting A_{ij} with Eqs. (13) and (18) yields:

$$\frac{r\tilde{\gamma}_{ij}^{-R(\sigma-1)} + R(\sigma-1)\tilde{\gamma}_{ij}^{r}}{r + R(\sigma-1)} - 1 = \frac{f_{ij} f_i(l)}{F_{ij}}. \tag{19}$$

With time-invariant parameters σ, R, r, F_{ij}, l, and f_{ij}, the value of $\tilde{\gamma}_{ij}$ is also time-invariant. Hence, using Eq. (18), $\tilde{A}_{ij}$ is time-invariant and with $A_{jk} = \sigma^{-1}\left[(\pi_{ij}\pi_i(l))\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{1-\sigma} Y_j$:

$$\tilde{\varphi} = C \cdot \frac{P_j}{(\pi_{ij}\pi_i(l))\,\omega_i} Y_j^{\frac{1}{\sigma-1}}, \tag{20}$$

where $C \equiv \sigma^{-\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma}A_{jk}^{-\frac{1}{\sigma-1}}$. Eq. (20) shows that the productivity thresholds for exporters, $\tilde{\varphi}_{ij}^{-1}$, increase in external trade costs π_{ij}, and internal trade costs $\pi_i(l)$, wage rate ω_i, and the toughness of competition P_j^{-1}; but decreases with the size of the destination country Y_j. Clearly, geographical distance to the port infrastructure, measured by the magnitude of l, raises the productivity thresholds for exporters, $\tilde{\varphi}_{ij}^{-1}$.

2.2.4.2 Yearly trade flows

With the productivity thresholds defined by Eq. (20), the set of exporters is defined as those with $\varphi^{-1} \geq \tilde{\varphi}^{-1}$ for each internal distance l and destination market j, and thus aggregate yearly trade flows from country i to j. Using Eq. (14), conditional on exporting, the yearly exports of firm k with productivity φ_k from country i to j are expressed as:

$$X_{jk} = \frac{x_{jk}}{\triangle_{jk}} = A_{jk}\frac{1-\bar{\gamma}_{jk}^{R\sigma}}{R\triangle_{jk}}. \tag{21}$$

The aggregate yearly exports from country i to country j are expressed as :

$$T_{ij} = \int_0^{\tilde{\varphi}_{ij}} X_{jk} dG\left(\varphi\right), \tag{22}$$

where the productivity threshold $\tilde{\varphi}_{ij}$ is determined by Eq. (20).

2.2.5 Inferring trade costs

This section gives descriptions of the components of trade costs – per-shipment costs and variable transportation costs – from the firm choice variables and some standard trade model parameters.

2.2.5.1 Per-shipment costs

Using the optimal shipment frequency from Eq. (13) and the shipment volume from Eq. (14) to eliminate A_{ij}, the per-shipment costs are:

$$f_{ijkl} = \left[\frac{1+\frac{R(\sigma-1)}{r}\bar{\gamma}_{jk}^{r+R(\sigma-1)} - \frac{r+R(\sigma-1)}{r}\bar{\gamma}_{jk}^{R(\sigma-1)}}{\left(r+R\left(\sigma-1\right)\right)\left(1-\bar{\gamma}_{jk}^{\sigma R}\right)}\right] Rx_{jk}. \tag{23}$$

This expression depends only on transaction-level observables: the shipment frequency $\triangle_{jk}$ (through $\bar{\gamma}_{jk}$) and shipment volume x_{jk}, as well as model parameters including storage costs R, interest rate r, and the demand elasticity σ. Estimating these model parameters is beyond the scope of this paper, thus I will rely on the estimates from previous studies to impute these per-shipment costs. Other firm-level characteristics, productivity φ, and market characteristics, price level P_j and size of destination country Y_j do not enter this expression.

2.2.5.2 Variable trade costs

While it is not the focus of my estimations, it is possible to use the shipment volume from Eq. (14) to infer variable transport costs $\pi_{ij}\pi_i\left(l\right)$. Eq. (14) can be rewritten as:

$$x_{jk} = \left[(\pi_{ij} \pi_i (l)) \frac{\sigma}{\sigma - 1} \frac{w_k}{P_j} \right]^{1-\sigma} Y_j \frac{1 - \bar{\gamma}_{jk}^{R\sigma}}{R\sigma}, \tag{24}$$

which is a firm-level gravity equation augmented with optimal shipping frequency decision. Different from expression (23), firm-specific production cost w_k (hence firm productivity φ_k) and destination market characteristics, price level P_j and size of destination country Y_j, all enter expression (24) explicitly.

2.3 Data

2.3.1 Key variables and data sources

The firm-transaction level dataset is constructed using two data sources: the transaction-level data on the universe of China's international trade transactions from China Customs Office, and the firm-level data from Annual Survey of Industrial Production (ASIP) from China's National Bureau of Statistics. For the measures of internal distances to ports, I use Baidu's geocoding API to obtain precise geographic coordinates of all firm locations.[8] The baseline sample includes export transactions of Chinese manufacturing exporters in 2006, where detailed firms' addresses and 12-digit administrative region codes are available. The year 2006 is particularly suitable to study the effect of within-country trade frictions on firms' export outcomes because there were no major earthquakes in mainland China which caused disruptions to internal transportation networks.[9,10] For the ports data, I use *National Ports Layout Plan*, an official document published by China's Ministry of Transport in 2006 to identify ports which connect China and international destinations. Further details of each of these datasets are presented below.

Transaction-level Customs data. The China Customs data report the free-on-board value of firm exports (in U.S. dollars), trade regimes (e.g. processing trade or non-processing trade),

[8] Baidu Maps is one of the largest web mapping service application and technology, offering satellite imagery, street maps, and geocoded information in China.

[9] Volpe Martincus and Blyde (2013) exploit the Chilean earthquake in 2010 and find that diminished transportation infrastructure within Chile had a significant negative impact on firms' exports.

[10] According to the United States Geological Survey (USGS), there was only one major earthquake in mainland China in 2005 (M 6.3 - western Xizang, which happened on April 7, 2005, 20:04:41 UTC, URL: https://earthquake.usgs.gov/earthquakes/eventpage/usp000dmht/executive), and no major earthquake happened in mainland China in 2006. Earthquake screening criteria used on USGS: most worldwide events magnitude 4.5 and greater, from January 1, 2000 to December 31, 2010. Source: USGS, URL: https://earthquake.usgs.gov/.

destination countries, and products in the Harmonized System (HS) classification. I drop the transactions in earlier years because many private firms could only export through trade intermediaries prior to 2004 (Brandt et al., 2014). In addition, the complete 12-digit administrative region codes have not been made available until 2004. Following Djankov et al. (2010), this paper focuses on the transportation of goods to the nearest ports. The China Customs data also report the mode of transportation of each export transaction. I identify for each firm those 6-digit HS product categories which use maritime transport as the only mode of transportation in 2006 in the baseline sample.[11] The rest of HS product categories that use multiple or other modes of transportation are excluded. It ensures the identification of ports is relevant that firms ship their goods from manufacturing establishments to the nearest ports for freight transport by sea. Next, I follow Fernandes and Tang (2014) to exclude all trade transactions that are labelled as processing trade transactions, in order to focus on ordinary trade transactions. Finally, an export transaction is defined as a single shipment.

Firm-level data. While the ASIP is an industrial "firm"-level dataset, the unit of observation is a legal unit (*faren danwei*), which corresponds to the definition of "establishment" in the United States (Imbert et al., 2019). The ASIP covers all state-owned enterprises (SOEs) and all non-state manufacturing establishments with annual sales exceeding 5 million Chinese yuan (roughly 630,000 U.S. dollars in 2006). As long as physical entities establish legally, have their own names, locations and are able to take civil liability, possess and use their assets independently, they enter the dataset as individual "firms" (Brandt et al., 2014; Imbert et al., 2019). Using the same ASIP dataset, Imbert et al. (2019) also indicate these legal units almost perfectly overlap with plants in practice. I thus take each distinct legal unit as the location where managers ship their manufacturing goods to the nearest ports, and refer these legal units as individual firms.[12,13] The baseline sample covers 935

[11] I aggregate the data up to the HS 6-digit level, which I define as a product. It is because the last 2 digits of a HS 8-digit code are country-specific and may change over time (Manova and Zhang, 2012; Tang and Zhang, 2017).

[12] While some other countries sample plants or establishments, Brandt et al. (2014), which discuss the use of China's ASIP dataset, find that for most entities, the plant/firm definition coincides. Using the same ASIP dataset, Imbert et al. (2019) find that these legal units almost perfectly overlap with plants in practice. For example, 94% of plants in U.S. Census belong to single-plant firms, while the share of single-plant firms was 97% in China in 2007 (Brandt et al., 2014; Imbert et al., 2019).

[13] Taking a legal unit as a unit of observation is also particularly relevant in the study of per-shipment trade costs. Since, by definition, a legal unit can possess and use their assets independently, and are entitled to sign contracts with other entities (Brandt et al., 2014; China Statistical Yearbook, 2009), it performs the functions of obtaining trade credit, process export documents, handle inspection, clearance and logistics, which add up to per-shipment trade costs. With regard to the location of a decision-making legal unit, Antràs and Foley (2015) point out that traders would take longer transportation times into consideration because they often increase working capital

counties, and 421 manufacturing industries in 4-digit Chinese Industrial Classification (CIC) system (CIC codes 1311-4392). Each firm cell has information on employment, capital, output, assets and liabilities. For the baseline sample of firms, I follow standard practice to drop all SOEs, because they are under control of Chinese government, and not necessarily profit-maximizing (Manova et al., 2015). Firms with less than 10 employees are dropped. Lastly, I follow Ahn et al. (2011) to drop trade intermediaries which do not engage in manufacturing but serve as an import-export facilitation between domestic exporters and foreign importers.

Spatial data. To construct the spatial dimension of firms, I use the firms' addresses and detailed 12-digit administrative region codes assigned by China's Ministry of Civil Affairs that are reported in the ASIP dataset.[14] I use Baidu's geocoding API to obtain a firm's latitude and longitude with these firms' addresses and administrative region codes. Similarly, I obtain the geocoded information of each of the ports, and map each firm to its nearest port in terms of geographical distance. The distance separating a firm and its nearest port is referred to as "internal distance to the nearest port" hereafter.

Ports data. I use the *National Ports Layout Plan*, an official document published by China's Ministry of Transport in 2006 to identify ports which connect China and international destinations. This document contains information on Chinese ports, including whether they are core ports (i.e. leading ports in their corresponding geographical or economic clusters that tend to serve the surrounding provinces), their port facilities (e.g. container transport system, crude oil and coal loading and transport system, and etc.) and their corresponding geographical clusters. I use shipping information websites *Marine Traffic* and *World Port Source* to identify their unique UN/LOCODE (United Nations Code for Trade and Transport Locations) and obtain their geocoded information, including latitude and longitude. The details of all 36 ports are presented in Supplementary Appendix.[15] Similar to Coşar and Fajgelbaum (2016), I then compute the Euclidean distance

requirements. Therefore, these traders are more likely to have higher costs of obtaining external capital in order to finance transactions before the goods are loaded for shipment, which also contribute to the per-shipment trade costs.

[14]Each 12-digit administrative region code contains detailed geographic information of a firm. The first two digits correspond to the highest level of administrative division, province. The next two (3rd and 4th) digits summarize the location for the associated prefecture of city. The next two (5th and 6th) digits represent a county. The next three (7th to 9th) digits give information of the town. The last three (10th to 12th) digits refer to a village or community, the most disaggregated level of administrative divisions. For notational convenience, this paper uses "province", "city", "county", "town", and "village" to indicate these classifications accordingly.

[15]The *National Ports Layout Plan* assigns a total of 38 ports in China. I drop Hong Kong Port due to the special status of Hong Kong Special Administrative Region, and also Guangxi Coastal Port because it is not given a unique UN/LOCODE. See the UN/LOCODE List at United Nations Economic Commission for Europe (UNECE):

separating the a firm and its nearest port.[16]

2.3.2 Construction of instruments

There are potential endogeneity concerns that the distances separating port facilities and firms are correlated with the error term. First, there might be omitted variables that affect both a firm's distance to the nearest port and its monetary and time costs to arrange a shipment. Second, a firm might attempt to lower shipment costs by relocating to regions that are geographically close to the port. I then employ an instrumental variable estimation to address potential endogeneity concerns. Similar to Cai et al. (2016), Forman et al. (2008), and Fortagné et al. (2015), the primary instrument for internal distance to the nearest port is the average internal distance to the nearest port of all firms belonging to the same industry but located in other cities.[17,18,19] The intuition is that, if a firm's same-industry peers in other cities tend to locate around port regions, then this firm, which presumably operates with similar location preferences and in similar competitive environment (due to a similar cost structure of exporting or acquiring trade-specific information within the same industry, or strategic behavior to avoid congestion within a location), is also likely to locate itself in a similar fashion. Hence, these measures of internal distances satisfy the relevance condition of valid instruments. However, the industry-peer locations in other cities are unlikely to be directly correlated with the error term in the second-stage equation, conditional on the control variables, which ensure that the instrumental variables reasonably satisfy the exclusion restriction. In robustness checks, I use an alternative instrument, the average internal distances to

https://www.unece.org/cefact/locode/service/location.html/.

[16]This measure of internal distance is similar to that of Coşar and Fajgelbaum (2016). They measure the internal distance of the administrative center of a firm's prefecture to that of the nearest coastal prefecture.

[17]Cai et al. (2016) examine how the geographic location of firms affects takeover exposures and outcomes. They address endogeneity using this instrument: the proportion of firms in each firm's same industry that are located in the urban areas, where industries are defined using 2-digit SIC. The intuition is that if a high proportion of a firm's industry peers are located in urban areas, then this firm, which reasonably has the same location preferences, is also likely to be located in an urban area.

[18]Forman et al. (2008) examine the use of internal (firm) resources and external (local) resources in process innovation. The endogeneity of the numbers of programmers in the establishment and organization is addressed by instrumental variables, the numbers of programmers of other establishments and organizations in the same 2-digit NAICS industry.

[19]Fortagné et al. (2015) study the effects of the restrictive Sanitary and Phyto-Sanitary (SPS) concerns at the HS 4-digit product category level on margins of trade. They address endogeneity by using an instrumental variable which is the total number of concerns raised in a certain HS2 sector (excluding the concern raised at the product level). The intuition is that if there is an SPS on a certain product s, it is likely that an SPS concern will also be raised in products similar to s, i.e. products within the same HS2 industry.

the nearest ports of same-industry peers exporting to the same destination country, and present these additional results in Supplementary Appendix.

In the first stage, I regress the firm's internal distance to the nearest port on the same-industry-other-cities firms' average internal distance as well as on all control variables used in the second stage. I report all the first-stage results in Supplementary Appendix. The first-stage F-statistics are well above the rule-of-thumb diagnostics ($F > 10$) suggested by Staiger and Stock (1997) and significant at the 1% level. These strong first-stage results reject the null hypothesis that these instruments are weak. In the second-stage results, I use instrumented internal distances to port facilities. Their coefficient estimates are positive and significant at least at the 5% level in all empirical specifications with sizable economic magnitudes. Therefore, this evidence suggests that, after controlling for potential endogeneity in a firm's geographical location, all the main results hold.

2.4 Empirical Evidence

Before the estimations of per-shipment costs, I will first test whether Proposition 1 holds. While Proposition 1 also gives predictions on how shipment frequency changes with standard firm-level (i.e. production costs w_k), destination-level characteristics (i.e. market size Y_j, price level P_j, and iceberg transport costs π_{ij}), and good-specific demand elasticity σ, they are empirically verified in previous studies.[20] This sub-section thus focuses on how shipment frequency changes with the internal distance separating a firm and its nearest port facility, l. Figure 1 shows the distributions of shipment frequency, shipment volume and shipment value of firm-product-destination export transactions in the baseline sample. Table 1 reports the summary statistics of key variables used in Section 4.

2.4.1 Shipment frequency and internal distance

Proposition 1 states that a firm's export shipment frequency decreases with internal distance to the nearest port. To empirically examine this relationship, I use the following empirical specification:

[20]Kropf and Saure (2014) find that the shipment frequency increases with good-specific demand elasticity σ.

Figure 1: Shipment frequency, average shipment volume, and average shipment value, by firm-product-destination.

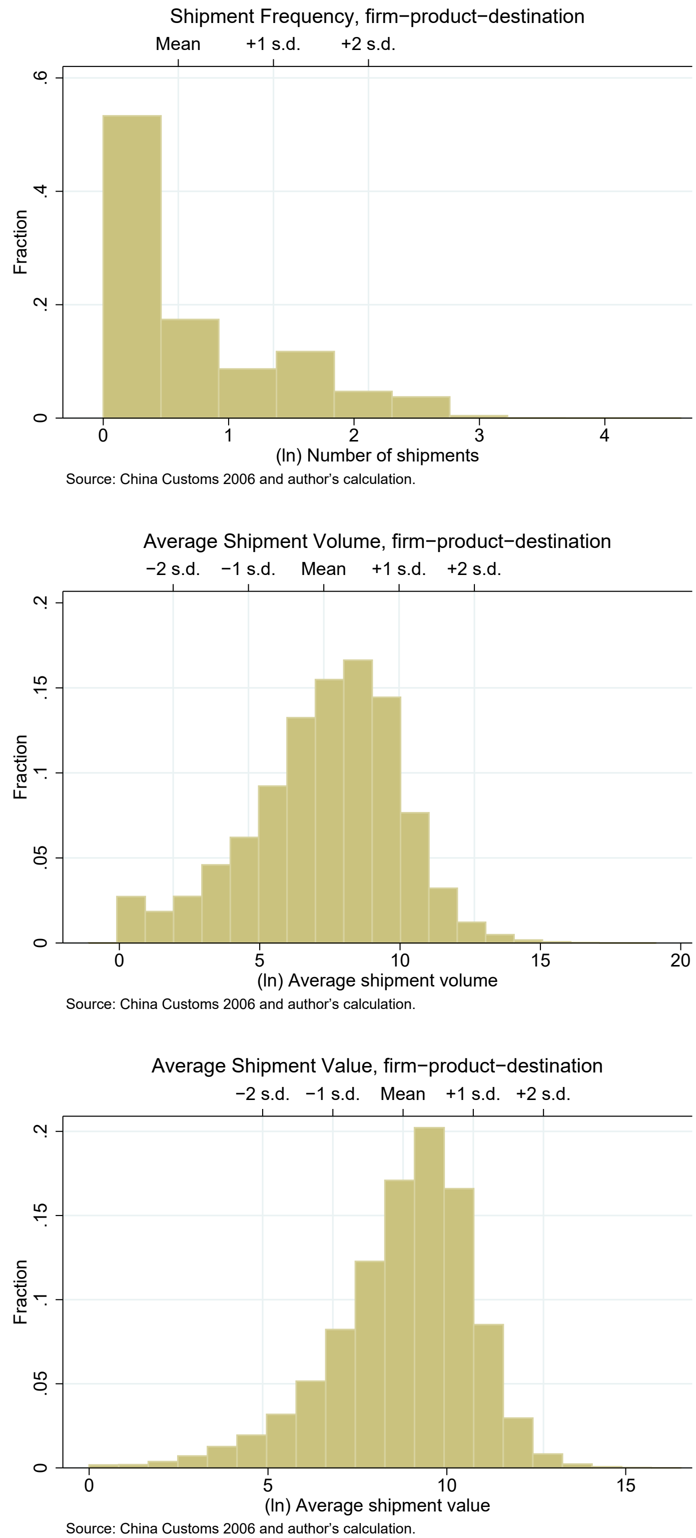

Figure 1 plots the (log) shipment frequency (top panel), average shipment volume (middle panel), and average shipment value (bottom panel) at the firm-product-destination level of Chinese manufacturing exporters in 2006. Source: China Customs 2006 and author's calculations.

Table 1: Summary statistics of key variables.

	N	Mean	Q1	Median	Q3	SD
Panel A: Internal distances to the nearest ports (km)						
Internal distances	19742	129.77	34.79	91.27	162.24	165.16
Panel B: Firm-product-destination transactions						
Shipment size, U.S. dollars (log)	248914	8.78	7.73	9.07	10.10	1.96
Shipment frequency	248914	2.59	1.00	1.00	3.00	2.82
Shipment volume (log)	248864	7.28	5.72	7.60	9.17	2.68
Panel C: Key independent variables						
Number of products	19742	4.39	1.00	2.00	5.00	6.50
Number of destinations	19742	6.79	1.00	3.00	8.00	8.93
Product-destination market share	79772	0.49	0.07	0.37	1.00	0.42
Productivity (log)	18267	1.47	1.32	1.44	1.58	0.35
Output (log)	19742	15.57	14.68	15.45	16.33	1.27
Wage (log)	19741	7.64	7.31	7.59	7.94	0.57
Employment (log)	19741	5.18	4.45	5.14	5.84	1.04

Table 1 reports the summary statistics of key variables used in Section 4. Panel A reports the firm-level internal distances to the nearest ports, in kilometers. Panel B reports the key variables of firm-product-destination export transactions. Panel C reports the key firm-level independent variables, except that the market share is defined at product-destination dimension. Source: ASIP, China Customs 2006 and author's calculations.

$$ln\,(v_{jks}) = \alpha + \beta_1 \cdot ln\,(l_k) + controls + \varepsilon_{jks}, \tag{25}$$

where v_{jks} refers to the shipment frequency of firm k, which exports its product s to country j, and l_k refers to the internal distance separating firm k and its nearest port. I include a set of fixed effects as described below. Finally, ε_{jks} is a measurement error, assumed to be normally distributed. I perform IV estimations with the instruments outlined in Section 3.2.

Table 1 reports second-stage results of the relationship between (log) shipment frequency (i.e. number of export shipments in 2006) on the internal distances to the nearest port facilities. Robust t-statistics are reported in parenthesis. Following Fortagné et al. (2015), I include HS2-destination fixed effects in all columns (1) to (5), to control for sector-country factors that may affect shipment decisions, such as business cycles, import-demand shocks, and multilateral trade resistance, as highlighted by Head and Mayer (2014). I further include product fixed effects in all columns, which are defined using SITC rev.2 4-digit level product classification codes, to control for systematic differences in trade activity across products. The inclusion of product fixed effects also absorbs the good-specific demand elasticities, such that the focus of this sub-section is on the relationship between shipment frequency and internal distances to the nearest ports.[21]

All independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if $\geq 50\%$ of the firm's capital is provided by foreign entities, and 0 otherwise. For each firm-product-destination, the average shipment size is defined as the total shipment size divided by number of shipments, while the average shipment volume is defined as the total shipment volume divided by number of shipments in 2006. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. The numbers of HS6 products exported and destination countries served are defined at the firm level. Next, I follow Fortagné et al. (2015) to include the market share of Chinese manufacturing exporters in a given HS2-destination to control for the geographical concentration of these exporters.[22] Motivated by literature on financial frictions and intensive margin of trade (Manova, 2013; Manova et al., 2015), I use (log) current liabilities (scaled

[21] The elasticities data are downloadable at: http://www.columbia.edu/~dew35/TradeElasticities/TradeElasticities.html.

[22] This proxy of market power is also used in Manova and Yu (2017). Mayer et al. (2014) use this to proxy for a sector-level competition in a destination within a HS 2-digit sector. Berry (1994) shows that the actual market share of a product is a function of product characteristics (i.e. quality) and prices. See also De Loecker et al. (2016) for the discussions of market share variables.

by firm's output) to proxy for a firm's requirement for external finance arising from short-run working capital needs, as well as (log) intangible assets (scaled by firm's output) to proxy for the holdings of non-collateralizable assets. Moreover, the natural logarithm of output, wage (scaled by number of employees), and firm size measured by number of employees are included.

Column (1) uses a specification with baseline controls. The baseline controls include (log) average shipment size, average shipment volume, and firm-level Levinsohn and Petrin (2003) productivity. In columns (2) and (3), (log) number of products exported, destinations served, product-destination market share, and county fixed effects are included. The coefficients of internal distances to the nearest ports preserve the same signs, and remain statistically significant at the 1% level in column (3). In columns (4)-(5), I additionally include port fixed effects to control for the quality of infrastructure, and a larger set of firm-level variables. The set of firm-level variables include: (log) output and average wage per employee to capture the firm's ability to overcome shipping costs, and labour costs in handling export transactions, respectively. The (log) number of employees is a proxy for firm size. The economic and statistical significance of the coefficients of internal distances remain large and significant at the 5% level. The point estimate of the column (5) specification suggests that a doubling of the internal distance to the nearest port is associated with a 26% decrease in the shipment frequency $(exp\left(-0.44 \cdot ln\left(2\right)\right)) \approx 0.74$. All coefficients of control variables give the expected signs, except (log) average wage per employee. The first-stage F-statistics are well above the 10 to reject the null hypothesis that the instrument is weak. All first-stage results are reported in Supplementary Appendix.

Table 2 provide the first preliminary evidence for the impact of internal distance on a firm's export shipment frequency. It is consistent with Proposition 1 that the shipment frequency is negatively affected by internal distance to the nearest port.

2.4.2 Shipment volume and internal distance

This sub-section examines Proposition 2, the relationship between internal distance to the nearest port and optimal shipment volume of firms. Similar to Section 4.1., I use the empirical specification Eq. (25), but replace the dependent variable with natural logarithm of the firm-product-destination shipment volume $ln\left(x_{jks}\right)$ of firm k, which exports its product s to country j. The set of control

Table 2: Shipment frequency and internal distances to the nearest ports.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: (ln) Number of shipments				
Distance to port	−0.1544***	−0.2608**	−0.3406***	−0.5096**	−0.4388**
	(−3.07)	(−2.16)	(−2.86)	(−2.52)	(−2.16)
Average shipment size	0.0834***	0.0895***	0.0105***	0.0136***	0.0141***
	(62.16)	(70.54)	(7.20)	(8.37)	(8.76)
Average shipment volume	0.0635***	0.0605***	0.0562***	0.0573***	0.0572***
	(35.16)	(55.33)	(51.35)	(47.07)	(47.46)
Productivity	0.0690***	0.0928***	0.0975***	0.0736***	0.0644***
	(5.52)	(10.09)	(10.80)	(6.21)	(5.44)
Number of products		0.0035	−0.0150***	−0.0231***	−0.0248***
		(1.54)	(−6.84)	(−10.35)	(−11.19)
Number of destinations		0.0659***	0.0603***	0.0360***	0.0394***
		(27.25)	(25.33)	(14.29)	(15.19)
Product-destination market share			0.1098***	0.1117***	0.1116***
			(120.17)	(116.01)	(116.73)
Output (lag)				0.0197***	0.0167***
				(6.60)	(5.55)
Wage scaled by employment (lag)				0.0003	−0.0013
				(0.03)	(−0.16)
Employment (lag)				0.0134***	0.0167***
				(4.40)	(5.31)
Current liabilities scaled by output (lag)					−0.0157***
					(−5.90)
Intangible assets scaled by output (lag)					0.0003
					(0.66)
Foreign ownership (lag)					0.0448***
					(6.65)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*N*	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*N*	*Y*	*Y*
Observations	232192	232067	232067	198626	197427
R^2	0.080	0.090	0.123	0.130	0.147
First-stage F	176.01	104.24	104.55	86.84	84.17

Table 2 presents results of second-stage IV estimation of Eq. (25). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is number of shipments (in natural logarithm) by firm, 6-digit product and destination country in 2006. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

variables and fixed effects are the same as Section 4.1., except that the average shipment volume is dropped as a control variable in Table 1. Again, I perform IV estimations with the instruments outlined in Section 3.2.

Table 3 reports second-stage results of the relationship between (log) shipment volume and internal distances to the nearest ports. Robust t-statistics are reported in parenthesis. The specifications are the same as Section 4.1. The economic and statistical significance of the coefficients of internal distances remain large and significant at the 1% level. Using the column (5) specification, a 1% increase in internal distance is associated with a 3.75% increase in average shipment volume. Again, the first-stage F-statistics are well above the 10 to reject the null hypothesis that the instrument is weak. All first-stage results are reported in Supplementary Appendix.

Table 3 provides strong evidence on the positive relationship between shipment volumes and internal distances to the nearest port facilities. In the next section, I will impute per-shipment trade costs, and examine the determinants of these costs.

2.4.3 Imputing per-shipment costs

This section presents the estimation results of per-shipment costs. Then I will establish the relationship between per-shipment costs and the internal distance to the nearest port. I take natural logarithm of expression (23) for the per-shipment costs in Section 2.6.1. to obtain:

$$\begin{aligned} ln\left(f_{ijkl}\right) = ln &\left[1 - \frac{r + R\left(\sigma - 1\right)}{r}\gamma_{jk}^{R(\sigma-1)} + \frac{R\left(\sigma - 1\right)}{r}\gamma_{jk}^{r+R(\sigma-1)}\right] \\ &- ln\left(r + R\left(\sigma - 1\right)\right) - ln\left(1 - \bar{\gamma}_{jk}^{R\sigma}\right) + ln\left(Rx_{jk}\right). \end{aligned} \tag{26}$$

The baseline sample consists of Chinese manufacturing exporters, thus $i = CHN$.

2.4.3.1 Basic specification

For the basic specification, I follow Kropf and Sauré (2014) and choose an annual discount rate of 5% and a storage cost of 5% ($r = R = 0.05$).[23] Naturally, the imputed per-shipment costs are

[23] This basic specification is based on empirical findings of previous literature that the non-interest storage cost R is larger than interest cost r. See Footnote 6 for details.

Table 3: Shipment volume and internal distances to the nearest ports.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: (ln) Average shipment volume				
Distance to port	1.4911***	2.3781***	2.3730***	3.8327***	3.7454***
	(10.11)	(6.76)	(6.76)	(6.42)	(6.24)
Average shipment size	0.8169***	0.8448***	0.8409***	0.8508***	0.8509***
	(125.97)	(283.59)	(233.83)	(221.09)	(224.27)
Number of shipments	0.2633***	0.2344***	0.2308***	0.2230***	0.2217***
	(39.26)	(39.80)	(38.08)	(33.12)	(33.39)
Productivity	0.0665*	−0.3533***	−0.3527***	−0.3622***	−0.3801***
	(1.80)	(−12.55)	(−12.56)	(−10.79)	(−11.20)
Number of products		−0.0864***	−0.0873***	−0.0834***	−0.0855***
		(−13.66)	(−13.89)	(−13.16)	(−13.60)
Number of destinations		0.1224***	0.1224***	0.1602***	0.1605***
		(17.88)	(17.88)	(21.59)	(20.97)
Product-destination market share			0.0058**	0.0024	0.0026
			(2.13)	(0.81)	(0.88)
Output (lag)				−0.0144	−0.0161*
				(−1.62)	(−1.78)
Wage scaled by employment (lag)				−0.0277	−0.0290
				(−1.05)	(−1.22)
Employment (lag)				−0.0514***	−0.0444***
				(−5.74)	(−4.77)
Current liabilities scaled by output (lag)					−0.0174**
					(−2.21)
Intangible assets scaled by output (lag)					−0.0058***
					(−3.92)
Foreign ownership (lag)					−0.0057
					(−0.29)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*N*	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*N*	*Y*	*Y*
Observations	232192	232067	232067	198626	197427
R^2	0.113	0.156	0.158	0.095	0.115
First-stage F	191.23	104.88	105.20	87.04	84.14

Table 3 presents results of second-stage IV estimation of Eq. (25). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is shipment volume (in natural logarithm) by firm, 6-digit product and destination country in 2006. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size is the average dollar value of shipments for a firm-product-destination observation. The number of shipments is defined at the firm level. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

relatively small because these parameter restrictions place no storage cost in addition to financial costs (annualized discount rates), and by the substitutability of both types of costs, lower annualized storage costs generate lower per-shipment costs to explain an observed shipment frequency. Hence, this imputed per-shipment cost can be seen as a conservative benchmark of the actual fixed costs. From expression (26) the only parameter left is the good-specific demand elasticity (SITC rev.2, 4-digit level), which is obtained from Broda and Weinstein (2006). In the baseline sample of Chinese exporters, the demand elasticities range from 1.10 to 108.20 with mean at 3.70 (unweighted) and at 4.90 (weighted by export shipment values). Fig. 2 plots the histogram of the imputed (log) per-shipment costs in U.S. dollars, using basic (upper left panel) specifications, as well as the histogram of the costs divided by average export shipment values at the firm-product-destination level, using basic (lower left panel) specifications. In percentage terms, the per-shipment trade costs range from 0.01% to 2.10% of average export shipment sizes. The average per-shipment cost using basic specification is approximately 0.88% (or a net present value of 211 U.S. dollars) of export shipment value.[24] In the next sub-section, I will use the further specification to impute per-shipment costs of Chinese exporters.

2.4.3.2 Further specification and related literature

Alessandria et al. (2010) parameter restrictions. Given the basic specification in Section 4.3.1., the imputed per-shipment costs are conservative by nature. To guarantee the model gives convincing imputations of per-shipment costs, I also take parameters in related literature into my estimations. In particular, I first follow Alessandria et al. (2010) to set an annualized storage cost of 35% of a firm's inventories. Fig. 2 plots the histogram of the imputed (log) per-shipment costs in U.S. dollars, using further (upper right panel) specifications, as well as the histogram of the costs in percent of average export shipment values, using basic (lower right panel) specifications. The resulting estimated average per-shipment costs are approximately 6.11% (or a net present value of 1375 U.S. dollars) of the export shipment size. Again, I follow Alessandria et al. (2010) to set all demand elasticities to $\sigma = 1.5$, the discount rate at 6%, and an annualized storage cost of 35% of

[24] In a closely related paper, Kropf and Sauré (2014) estimate a per-shipment cost ratio over average shipment size of 0.82% using Swiss exports data. My estimates of average per-shipment costs are approximately 9% larger. It is perhaps not surprising because Chinese exporters are more prone to higher per-shipment trade costs due to poorer institutional quality and more costly administrative or procedural delays passing through customs.

Figure 2: Per-shipment costs and the ratios to average shipment values, by firm-product-destination. Basic and further specifications.

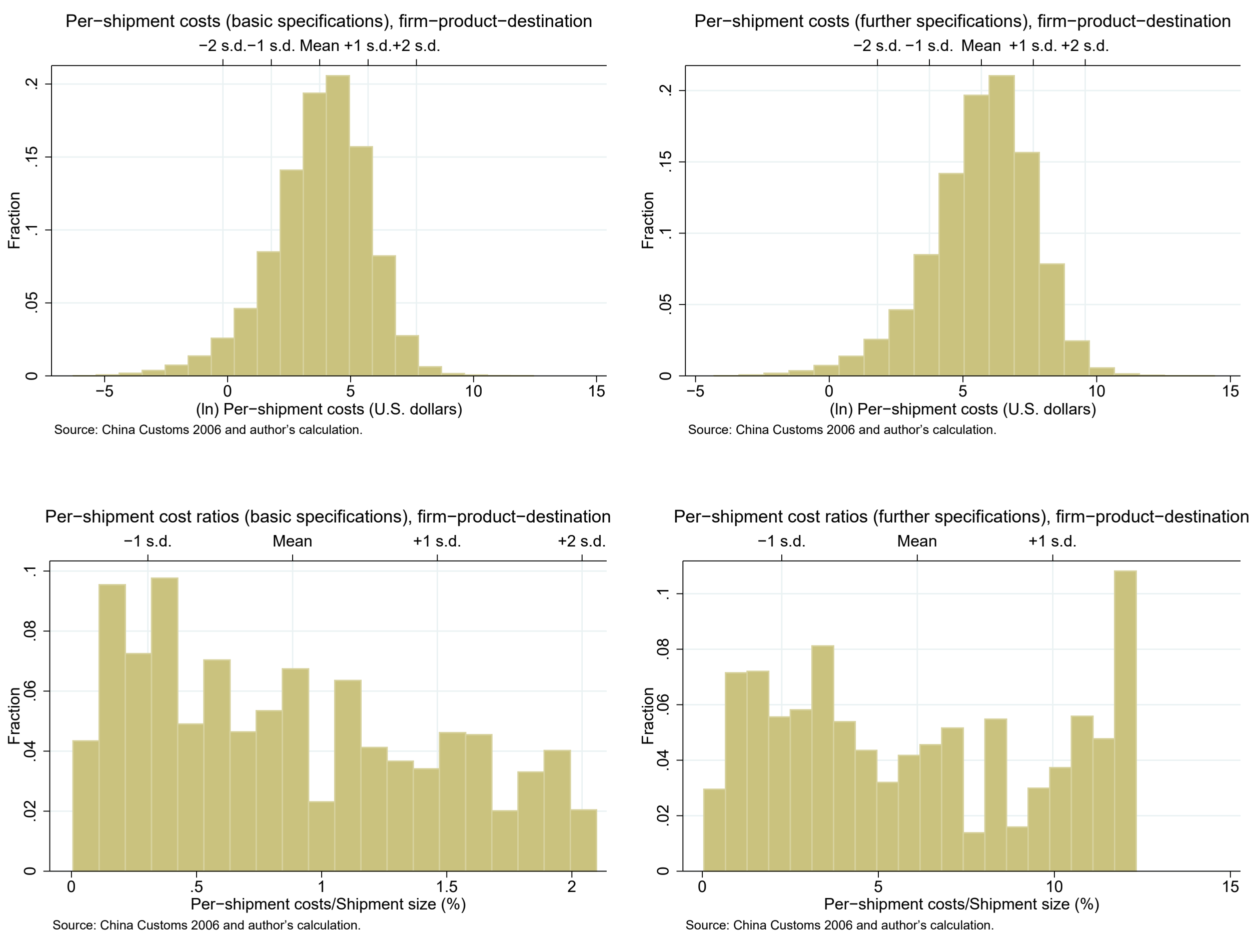

Figure 2 plots the histograms of (log) per-shipment costs (in U.S. dollars) according to Eq. (26) and the ratios to export shipment values, using basic and further specifications as described in Section 4.3.1. and 4.3.2. In basic specifications, the annualized discount rate and storage costs are set to $r = R = 0.05$, while in further specifications, the annualized discount rate and the storage costs are set to $r = 0.05$ and $R = 0.35$, respectively.

Table 4: Summary statistics. Imputed per-shipment costs and the ratios to average shipment values. Basic and further specifications.

	N	Mean	Q1	Median	Q3	SD
Panel A: Basic Specifications						
Per-shipment costs (U.S. dollars)	249191	211.01	13.83	50.80	160.68	1410.91
Per-shipment costs/Avg shipment values (%)	249191	0.88	0.39	0.84	1.36	0.58
Per-shipment costs (U.S. dollars)	248557	210.45	13.82	50.73	160.42	1410.23
Per-shipment costs/Avg shipment values (%)	248557	0.88	0.39	0.84	1.36	0.58
Panel B: Further Specifications						
Per-shipment costs (U.S. dollars)	249191	1375.11	98.76	358.58	1100.03	8413.54
Per-shipment costs/Avg shipment values (%)	249191	6.11	2.69	5.64	9.80	3.85
Per-shipment costs (U.S. dollars)	248557	1371.47	98.64	358.04	1098.16	8407.24
Per-shipment costs/Avg shipment values (%)	248557	6.10	2.69	5.64	9.80	3.85
Panel C: Alessandria et al. (2010) parameters						
Per-shipment costs (U.S. dollars)	249191	944.59	80.82	277.06	794.73	5379.16
Per-shipment costs/Avg shipment values (%)	249191	4.41	2.03	6.55	6.55	2.38
Per-shipment costs (U.S. dollars)	248557	942.57	80.74	276.61	793.48	5377.63
Per-shipment costs/Avg shipment values (%)	248557	4.41	2.03	6.55	6.55	2.38

Table 4 reports the summary statistics of imputed (log) per-shipment costs (in U.S. dollars) and the ratios to average shipment values according to Eq. (26) using the basic (Panel A) and further (Panel B) specifications as described in Section 4.3.1. and 4.3.2. In basic specifications, the annualized discount rate and storage costs are set to $r = R = 0.05$, while in further specifications, the annualized discount rate and the storage costs are set to $r = 0.05$ and $R = 0.35$, respectively. Following Alessandria et al. (2010), I set the demand elasticities $\sigma = 1.5$, annualized discount rate $r = 0.06$, storage costs $R = 0.35$ and report the results in Panel C. For each of the specifications, the full sample of firm-product-destinations is listed first, followed by the sample of firm-product-destinations with valid instruments discussed in Section 3.2.

Figure 3: Per-shipment costs, and the ratios to average shipment values, by firm-product-destination. Sorted in five quintiles of internal distances to the nearest ports. Basic and further specifications.

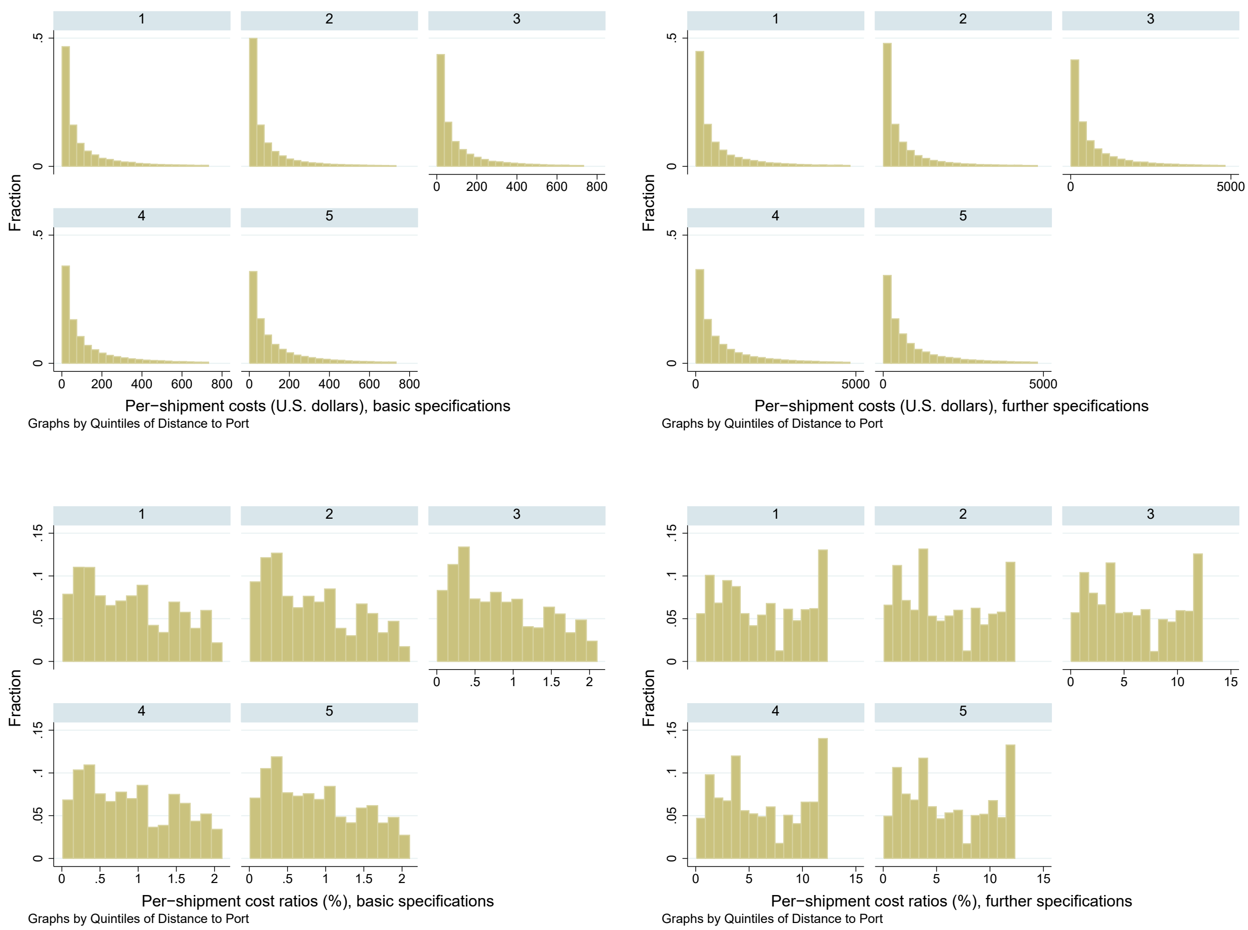

Figure 3 plots the per-shipment costs (U.S. dollars) and per-shipment trade costs divided by export shipment values (%) using both basic and further specifications. The per-shipment costs and the ratio to export shipment values are sorted in five quintiles of internal distances to the nearest port facilities. The 1st quintile (Quintile = 1) refers to firms within bottom 20% internal distances to the nearest port facilities, whereas the 5th quintile (Quintile = 5) refers to firms within top 20% internal distances to the nearest port facilities. The bottom 5% and top 5% of per-shipment costs are excluded.

a firm's inventories. The resulting average estimated per-shipment costs are then approximately 4.41% (or a net present value of 945 U.S. dollars) of the export shipment size. In percentage terms, the estimates of per-shipment costs are slightly larger than 3.60%, the number reported in Alessandria et al. (2010). I report the summary statistics of these imputed per-shipment costs in Table 3. Table 4 reports the summary statistics of per-shipment costs and the ratios to export shipment values for each of these specifications.

***World Development Indicators* cost to export (U.S. dollars per container).** The World Bank's *World Development Indicators* database records the time and costs associated with the logistical process of exporting and importing goods. In particular, I look at the cost to export (U.S. dollars per container) of Chinese exporters in 2006. The cost measures the fees levied on a 20-foot container in U.S. dollars. All the fees associated with completing the procedures to export the goods are included. These include costs for documents, administrative fees for customs clearance and so on.[25] The cost to export (U.S. dollars per container) is reported as 214.50 U.S. dollars in 2006, which is strikingly close to my estimates of per-shipment costs of 211 U.S. dollars using the basic specification. This number can be seen as a conservative estimate of per-shipment costs because it ignores some of the non-pecuniary costs.[26] It is perhaps not surprising the *World Development Indicators* cost to export is smaller than my estimates of per-shipment costs using the further specification.[27] My estimates of average per-shipment costs are 1375 U.S. dollars using the further specification, which are approximately 5 times larger than the estimates reported in *World Development Indicators*. It is still consistent with the estimates in *World Development Indicators* because they only partly account for the time costs, which are often 7-8 times more than that of monetary costs (Hornok and Koren, 2012).[28]

Random exits of exporters. In the model, it is implicitly assumed that exporters remain active in exporting. However, exporters may exit product-market(s) in the presence of random

[25] All data are downloadable from: https://datacatalog.worldbank.org/dataset/world-development-indicators. A complete definition of "cost to export" variable can be seen from: https://datacatalog.worldbank.org/cost-export-us-container-0.

[26] Hornok and Koren (2012) refer this cost to export measures the financial costs associated with an export transaction and refer it as "administrative costs".

[27] In *Doing Business 2006*, while no estimated costs in USD related to exports are reported, Chinese exporters take, on average, 6 days to process documents, 7 days to obtain necessary signatures, and additional 20 days to move goods through the borders. These amount a time cost of 33 days to export. Hornok and Koren (2012) document that welfare loss (as a percentage of GDP) from time costs is substantially larger than that from monetary costs.

[28] In the calibration results for a sample of 170 countries in Hornok and Koren (2012), they find that the median ad valorem monetary trade costs is 1.01%, while that of time costs is 9.00%.

death shocks. The imputations of per-shipment costs are affected by two ways. First, non-surviving firms will report lower shipment frequency but the same average shipment value, compared to surviving firms. By Eq. (23), a lower shipment frequency leads to a higher imputed per-shipment costs, given the same average shipment value. Second, the presence of death shocks increases the discount rate exporters use to discount future profits, which drives the imputed per-shipment costs. Using Eq. (23), I show that imputed per-shipment costs are decreasing in discount rate r (see Supplementary Appendix). To address this concern, I follow Kropf and Sauré (2014) and assume that a fraction of 5% of firm-product-destination transactions are exogenously terminated after half a year. Increasing the annualized discount rate from $r = 0.05$ to $r = 0.10$, I then impute the per-shipment cost as a weighted average of non-surviving (weight 0.05) and surviving (weight 0.95) firm-product-destination transactions. Correcting for the biases arising from random death shocks, the imputed per-shipment costs are now 0.88% (compared to the original 0.88%), and 6.10% (compared to the original 6.11%) using basic and further specifications, respectively. The previous estimations remain intact.

Low productivity firms. To further complement the bias correction for firm exits, the model assumes that lower productivity firms with low export values are going to exit product-markets. I thus drop the firm-product-destination combinations with the lowest 5% of export transaction values in 2006, and impute per-shipment costs accordingly. The per-shipment costs are 0.87% (compared to the original 0.88%) and 5.99% (compared to the original 6.11%), respectively. Again, the sample selection bias is insufficient to alter the estimation results.

Maximum shipping weights. Another concern is that shipment values may be capped by size and volume of standard containers. In addition, shipping weights of transactions are not reported in China Customs dataset. To identify transactions whose shipping weights which are likely to exceed the size and volume of standard containers, I look at the World Bank's *World Integrated Trade Solution* (WITS) Database and search for HS product categories which are often heavy in weight.[29] While Kropf and Sauré (2014) identify "water transport" as heavy product categories whose shipping weights may exceed a standard 40-feet container, I extend this identification to all general vehicles and machinery for transport purposes. I then identify nine HS 4-digit and two HS 2-digit heavy product categories (see Supplementary Appendix) and eliminate them before imputing

[29] The complete list of HS nomenclatures can be downloaded at: https://wits.worldbank.org/referencedata.html.

the per-shipment costs. The per-shipment costs are 0.90% (compared to the original 0.88%) and 6.22% (compared to the original 6.11%) using basic and further specifications, respectively. Overall, the maximum shipping weights have virtually no effects on the estimations of per-shipment costs.

Geographically dispersed importers. Chinese exporters may ship to geographically dispersed importers within a destination country. In that case, exporters may separate shipments to these importers, which may inflate the firm-product-destination shipment frequency. However, it induces a downward bias of the imputed per-shipment costs, and hence the economic significance of per-shipment costs is unaffected.

Overall, I obtain economically significant estimates of per-shipment costs which range from 0.88% to 6.11%, depending on specifications. In the next sub-section, I will examine the determinants of per-shipment costs.

2.4.4 Per-shipment costs and internal distance

I use the following empirical specification to examine the determinants of per-shipment costs:

$$ln\left(f_{jks}\right) = \alpha + \beta \cdot ln\left(l_k\right) + controls + \varepsilon_{jks}, \tag{27}$$

where f_{jks} refers to the firm-product-destination per-shipment costs imputed according to Eq. (27), l_k refers to the internal distance to the nearest port of firm k. The baseline controls are the same as those in Section 4.1., including (log) average shipment size, average shipment volume, and firm-level revenue-based Levinsohn and Petrin (2003) productivity. I additionally include number of products exported and number of destinations served in column (2), and product-destination market share in column (3). Similar to Section 4.1., I include HS2-destination and product fixed effects to capture all sector-destination (e.g. business cycles, import-demand shocks, and multilateral trade resistance) and product-specific effects in all columns (1)-(5). In columns (4)-(5), I control for a large set of firm-level characteristics, including (log) firm's output, average wage per employee, firm size (measured by number of employees), current liabilities (scaled by output), intangible assets (scaled by output), and a dummy for foreign ownership, which equals 1 if $\geq 50\%$ of a firm's capital is provided by foreign entities, and 0 otherwise. All independent variables are in natural logarithm, except the foreign ownership dummy. Finally, ε_{ijs} is a measurement error, assumed to be normally distributed. I perform IV estimations with the instruments outlined in Section 3.2., and report robust t-statistics with HS2-destination clusters.

2.4.4.1 Results

Table 5 reports the second-stage results of the relationship between per-shipment costs (U.S. dollars) and internal distances to the nearest ports. It is observed that per-shipment costs increase with internal distances, and the coefficients remain positive and statistically significant at least at the 5% level. In columns (2)-(5), I additionally include firm's export participation variables, number of products exported and number of destinations served. The former carries positive coefficients (except in column (2)), and the latter carries negative coefficients. Columns (4)-(5) include an additional set of firm-level controls. A greater variety of products is often associated with larger investment in facilitating export transactions, customizing products to different markets, and establishing overseas distribution channels, which increases per-shipment costs. Given the number of products, serving more destinations could allow economies of scale in handling export procedures, thus lowering per-shipment costs. The coefficients of product-destination market share are negative and significant, meaning that stronger firm competitiveness in product-market(s) lowers per-shipment costs. The coefficients of firm output, average wage per employee, and firm size (measured by number of employees) have expected signs, but the point estimates of average wage per employee are statistically insignificant in columns (4)-(5). Current liabilities, which captures a firm's requirement for external finance, increase per-shipment costs as expected. Intangible assets, however, do not affect per-shipment costs. In columns (4)-(5), a dummy for foreign ownership is included. The estimations in column (5) indicates that foreign majority-owned firms face smaller costs to arrange shipments. Using point estimates from Column (5), a doubling of internal distance to the nearest port is associated with a 40% increase in the per-shipment costs $(exp\,(0.49 \cdot ln\,(2))) \approx 1.40$. The first-stage F-statistics are well above the 10 to reject the null hypothesis that the instrument is weak. All first-stage results are reported in Supplementary Appendix.

These findings suggest that per-shipment costs are negatively related to within-country (internal) frictions, in addition to the cross-country (external) geographical proximity which has been extensively studied in previous literature. While distance is often used as a proxy for marginal trade costs, it can also affect per-shipment cost of exporting. Previous studies on information frictions and trade flows, e.g. Portes et al. (2001) and Portes and Rey (2005), find that geographical proximity is a good proxy for information. Exporters located closer to international port facilities have better access to trade-specific information to deal with local logistics, customs, and foreign buyers. The information flows act in a similar way as language commonalities, trade agreements, and many other trade lubricants do.

2.4.4.2 Additional results and robustness checks

The first-stage results of IV estimations. The first-stage equation estimates separate regressions of the internal distance against the primary instrument, i.e. the average internal distance to the nearest ports of firms in the same industry and located in other cities, the indicated set of variables at left, and the set of fixed effects listed at bottom of Tables 2, 3 and 5 above. The first-stage results are reported in Table 6. Regarding the first-stage results, the primary instrument is negatively correlated with the internal distance to the nearest port. All first-stage F-statistics are well above the rule-of-thumb diagnostics ($F > 10$) suggested by Staiger and Stock (1997), which reject the null hypothesis that the instruments are weak.

Robustness checks. First, average shipment values could be responsible for a significant variation of estimation results because per-shipment costs tend to increase with shipment values. I thus replace (log) per-shipment costs by (log) per-shipment costs divided by shipment values in Eq. (27), and repeat the same estimations against the same set of explanatory variables. The results are presented in Table 7. The coefficients of internal distance are slightly larger than the baseline estimations, but preserve the same level of statistical significance at the 5% level. Second, I eliminate product categories which tend to be single-unit goods by nature. Specifically, I drop all HS 6-digit product categories which always contain only one unit of the good. Intuitively, if a product category tends to be shipped as a single-unit shipment, then the shipment could be scheduled to meet seasonal or irregular foreign demands. In this case, the trade-off between per-shipment costs and storage costs may be irrelevant. The results are presented in Table 8. All the point estimates remain stable in magnitudes and are statistical significant. Third, I eliminate product categories which tend to be transacted in small shipment values because the cost trade-off

Table 5: Determinants of per-shipment costs and internal distances to the nearest ports. Further specifications. Second-stage results.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: (ln) Per-shipment costs				
Distance to port	0.1603***	0.2825**	0.3620***	0.5554**	0.4887**
	(2.69)	(2.07)	(2.67)	(2.45)	(2.16)
Average shipment size	0.9175***	0.9114***	0.9901***	0.9871***	0.9865***
	(469.19)	(478.95)	(350.22)	(324.71)	(330.13)
Average shipment volume	−0.0634***	−0.0603***	−0.0560***	−0.0572***	−0.0571***
	(−25.17)	(−34.90)	(−29.98)	(−28.62)	(−29.11)
Productivity	−0.0690***	−0.0939***	−0.0986***	−0.0772***	−0.0682***
	(−4.32)	(−8.86)	(−9.50)	(−6.07)	(−5.47)
Number of products		−0.0044	0.0140***	0.0216***	0.0232***
		(−1.21)	(4.04)	(5.94)	(6.56)
Number of destinations		−0.0650***	−0.0594***	−0.0352***	−0.0384***
		(−13.11)	(−12.88)	(−7.55)	(−8.33)
Product-destination market share			−0.1095***	−0.1112***	−0.1110***
			(−53.53)	(−51.62)	(−51.98)
Output (lag)				−0.0188***	−0.0160***
				(−5.25)	(−4.50)
Wage scaled by employment (lag)				0.0022	0.0037
				(0.22)	(0.41)
Employment (lag)				−0.0133***	−0.0164***
				(−3.48)	(−4.28)
Current liabilities scaled by output (lag)					0.0148***
					(4.52)
Intangible assets scaled by output (lag)					−0.0002
					(−0.40)
Foreign ownership (lag)					−0.0426***
					(−5.41)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*N*	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*N*	*Y*	*Y*
Observations	232192	232067	232067	198626	197427
R^2	0.820	0.812	0.818	0.809	0.813
First-stage F	73.00	64.10	64.26	45.29	43.72

Table 5 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (27) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

is less of a concern for small shipments. Thus, I drop all firm-product pairs which report average shipment values lower than its 10th percentile. The results are presented in Table 9. The coefficients of internal distance are somewhat larger than the baseline estimations. Still, all variables behave similarly as in previous tables. Fourth, I eliminate firm-product-destination combinations with only one shipment. These firm-product destinations are usually characterized by higher per-shipment costs which may overturn the estimation results. The results are presented in Table 10. The point estimates of internal distance are even larger than the baseline estimations (0.59 vs. 0.49 in the last columns). In addition, these point estimates exhibit greater statistical significance. Fifth, I eliminate firm-product-destination combinations with total shipment values below its 5th or above 95th percentiles in order to remove the effects of outliers. The results are presented in Table 11. Again, the estimation results are unaffected after excluding the shipments with small and large shipment values. Lastly, the results using an alternative instrument, i.e. the average internal distance to the nearest ports of peers in the same industry exporting to the same destination country, are presented in Table 12. While the point estimates of internal distance appear somewhat smaller in magnitudes, they preserve the statistical significance at least at the 5% level. All of these robustness checks confirm previous findings.

2.5 Conclusion

This paper examines the role of within-country trade frictions on the optimal shipping frequency, shipment volume, and per-shipment trade costs. I incorporate an explicit structure of internal geography into a heterogeneous firm model with endogenous shipping volume and frequency decisions. The micro-founded model allows structural estimation of per-shipment costs at firm-product-destination level from customs data of Chinese manufacturing exporters. My estimates suggest that per-shipment costs are economically large, ranging between 0.88% and 6.11% of the average shipment values, depending on specifications. These magnitudes are considerably larger than those which only consider monetary costs of exporting, indicating the importance of non-pecuniary components in trade costs. The internal trade frictions, measured by internal distances to the nearest port facilities, reduce shipment frequency. I also document that the per-shipment costs correlate positively with internal distances to the nearest port facilities, which raises questions concerning the estimation strategies for trade costs in the absence of an internal geography dimension.

Appendix to Chapter 2

Internal Geography, Trade Frictions, and Per-Shipment Costs

Appendix

Section 2.3.1. – Deriving the profit-maximizing frequency of exports.

I have:

$$\gamma_{jk} = e^{-\triangle_{kj}};$$
$$A_{jk} = \sigma^{-1}\left[\pi_{ij}\pi_i\left(l\right)e^{Rt'}\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{1-\sigma}Y_j.$$

By (12), I have:

$$NPV_{jk} = \frac{1}{1-\gamma_{jk}^r}\left\{A_{jk}\frac{1-\gamma_{jk}^{r+R(\sigma-1)}}{r+R\left(\sigma-1\right)} - f_{ij}f_i\left(l\right)\right\}.$$

Differentiate (12) with respect to γ_{jk}:

$$-\frac{1}{\left(1-\gamma_{jk}^r\right)^2}\left(-r\gamma_{jk}^{r-1}\right)\left[A_{jk}\frac{1}{r+R\left(\sigma-1\right)}\left(1-\gamma_{jk}^{r+R(\sigma-1)}\right) - f_{ij}f_i\left(l\right)\right]$$
$$+\frac{1}{1-\gamma_{jk}^r}\left[A_{jk}\frac{1}{r+R\left(\sigma-1\right)}\left(-\left(r+R\left(\sigma-1\right)\right)\right)\gamma_{jk}^{r+R(\sigma-1)-1}\right] = 0.$$

Simplifying and rearranging terms:

$$\frac{r\left(1-\gamma_{jk}^{r+R(\sigma-1)}\right)}{r+R\left(\sigma-1\right)} - \gamma_{jk}^{R(\sigma-1)}\left(1-\gamma_{jk}^r\right) = \frac{rf_{ij}f_i\left(l\right)}{A_{jk}}$$
$$\frac{r+R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)} - \left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}}{r+R\left(\sigma-1\right)} = \frac{rf_{ij}f_i\left(l\right)}{A_{jk}},$$

which is Eq. (13).

To show that the LHS is decreasing in γ_{jk}:

$$\frac{\partial LHS}{\partial\gamma_{jk}} = R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)-1} - R\left(\sigma-1\right)\gamma_{jk}^{R(\sigma-1)-1}$$
$$= R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)R-1}\left[1-\gamma_{jk}^{-r}\right] < 0,$$

for all $\gamma_{jk} \in (0,1)$. To see this, note that $\gamma_{jk}^{-r} > 1$ for all $\gamma_{jk} \in (0,1)$ and $\gamma_{jk}^{-r} = 1$ for $\gamma_{jk} = 0$ or $\gamma_{jk} = 1$. Hence, $\left[1-\gamma_{jk}^{-r}\right] < 0$. Also, $R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)R-1} > 0$.

For $\gamma_{jk} \to 0$, then LHS approaches to $\frac{r}{r+(\sigma-1)R} > 0$. For $\gamma_{jk} \to 1$, then LHS approaches to 0. Thus, there exists a unique $\gamma_{jk} \in (0, 1)$ which solves Eq. (13). I refer to this solution as $\bar{\gamma}_{jk}$.

Appendix

Proof of Proposition 1. To prove that γ_{jk} is decreasing in l.

LHS of (13) is independent of l, while RHS depends on l. I first evaluate $\frac{\partial\left(rf_{ij}f_i(l)/A_{jk}\right)}{\partial l}$.

$$\begin{aligned}\frac{\partial\left(rf_{ij}f_i\left(l\right)/A_{jk}\right)}{\partial l} &= rf_{ij}f_i\left(l\right)\sigma\left(\sigma-1\right)\left[\pi_{ij}\pi_i\left(l\right)e^{Rt'}\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{\sigma-2}Y_j^{-1}\pi_{ij}\pi_i^{'}\left(l\right)e^{Rt'}\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\\ &+rf_{ij}f_i^{'}\left(l\right)A_{jk}^{-1}\\ &=rf_{ij}f_i\left(l\right)\left(\sigma-1\right)A_{jk}^{-1}\frac{\pi_i^{'}\left(l\right)}{\pi_i\left(l\right)}+rf_{ij}f_i^{'}\left(l\right)A_{jk}^{-1}\\ &=rf_{ij}f_i^{'}\left(l\right)A_{jk}^{-1}\left[\left(\sigma-1\right)\frac{\pi_i^{'}\left(l\right)}{\pi_i\left(l\right)}+1\right]>0,\end{aligned}$$

because $\sigma>1$ and $\pi_i^{'}\left(l\right)>0$ by assumption. Using the proof that LHS of (13) is decreasing in γ_{jk} (see above), γ_{jk} is decreasing in l.

It completes the proof. □

Appendix

Proof of Proposition 1. To prove that γ_{jk} is increasing in σ.

$$\frac{\partial LHS}{\partial \sigma} = \frac{\left(r+R\left(\sigma-1\right)\right)\left[R\left(\sigma-1\right)R\gamma_{jk}^{r+R(\sigma-1)}ln\gamma_{jk}-\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}ln\gamma_{jk}\right]}{\left[r+\left(\sigma-1\right)R\right]^{2}}$$
$$-\frac{\left[r+R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)}-\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}\right]R}{\left[r+\left(\sigma-1\right)R\right]^{2}}.$$

Evaluate numerator:

$$\begin{aligned}
&\left(r+R\left(\sigma-1\right)\right)R\left(\sigma-1\right)R\gamma_{jk}^{r+R(\sigma-1)}ln\gamma_{jk}-\left(r+R\left(\sigma-1\right)\right)\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}ln\gamma_{jk}\\
&-rR-R\left(\sigma-1\right)R\gamma_{jk}^{r+R(\sigma-1)}+\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}\\
&=ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\left[R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)}-\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}\right]\\
&-R\left[r+R\left(\sigma-1\right)\gamma_{jk}^{r+R(\sigma-1)}-\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}\right].
\end{aligned}$$

Evaluate line 1 of numerator:

$$\begin{aligned}
&ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{r+R(\sigma-1)}\left[R\left(\sigma-1\right)\left(1-\gamma_{jk}^{-r}\right)-r\gamma_{jk}^{-r}\right]\\
&>ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{r+R(\sigma-1)}\left[-r\gamma_{jk}^{-r}\right]\\
&=ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}\left[-r\right].
\end{aligned}$$

The first inequality comes from the fact that $ln\gamma_{jk}<0$ and $\left(1-\gamma_{jk}^{-r}\right)<0$ such that the first time is positive.

Evaluate line 2 of numerator:

$$\begin{aligned}
&-R\left[r+\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{r+R(\sigma-1)}-r\gamma_{jk}^{r+R(\sigma-1)}-\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{R(\sigma-1)}\right]\\
&=-R\left[r\left(1-\gamma_{jk}^{r+R(\sigma-1)}\right)+\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{r+R(\sigma-1)}\left(1-\gamma_{jk}^{-r}\right)\right]\\
&=R\left[r\left(\gamma_{jk}^{r+R(\sigma-1)}-1\right)+\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{r+R(\sigma-1)}\left(\gamma_{jk}^{-r}-1\right)\right]\\
&>Rr\left(\gamma_{jk}^{r+R(\sigma-1)}-1\right).
\end{aligned}$$

The last inequality comes from the fact that the term $\left(r+R\left(\sigma-1\right)\right)\gamma_{jk}^{r+R(\sigma-1)}\left(\gamma_{jk}^{-r}-1\right)>0$ for all $\gamma_{jk} \in (0,1)$.

Hence, the numerator becomes a term larger than:

$$ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}\left[-r\right]+Rr\left(\gamma_{jk}^{r+R(\sigma-1)}-1\right).$$

Notice that $-ln\gamma \cdot \gamma^{\alpha}$ is minimum at $\gamma = exp\left(-\frac{1}{\alpha}\right)$. Hence, the numerator become a term larger than:

$$\begin{aligned}
&ln\gamma_{jk}\left(r+R\left(\sigma-1\right)\right)R\gamma_{jk}^{R(\sigma-1)}\left[-r\right]+Rr\left(\gamma_{jk}^{r+R(\sigma-1)}-1\right)\\
&>\frac{1}{R\left(\sigma-1\right)}\left(r+R\left(\sigma-1\right)\right)Rr+R\left[r\left(\gamma^{r+R(\sigma-1)}-1\right)\right]\\
&=Rr\left[\frac{r+R\left(\sigma-1\right)}{R\left(\sigma-1\right)}+\gamma_{jk}^{r+R(\sigma-1)}-1\right]\\
&=Rr\left[\frac{r}{R\left(\sigma-1\right)}+\gamma_{jk}^{r+R(\sigma-1)}\right]>0,
\end{aligned}$$

for all $\gamma_{jk} \in (0,1)$. It completes the proof. $\square$

Appendix

Section 2.3.2. – Deriving $\frac{d\bar{\gamma}_{jk}}{dl}$.

By (13) and Proof of Proposition (1), I have:

$$\frac{\partial LHS}{\partial l} = -\, r f_{ij} f_i^{'}\left(l\right) A_{jk}^{-1}\left[\left(\sigma-1\right)\frac{\pi_i^{'}\left(l\right)}{\pi_i\left(l\right)}+1\right].$$

By (13), I have:

$$\begin{aligned}\frac{\partial LHS}{\partial \bar{\gamma}_{jk}} &= R\left(\sigma-1\right)\bar{\gamma}_{jk}^{r+R(\sigma-1)-1} - R\left(\sigma-1\right)\bar{\gamma}_{jk}^{R(\sigma-1)-1}\\ &= R\left(\sigma-1\right)\bar{\gamma}_{jk}^{r+R(\sigma-1)-1}\left(1-\bar{\gamma}_{jk}^{-r}\right).\end{aligned}$$

Using implicit function theorem:

$$\begin{aligned}\frac{d\bar{\gamma}_{jk}}{dl} &= -\frac{\frac{\partial LHS}{\partial l}}{\frac{\partial LHS}{\partial \bar{\gamma}_{jk}}}\\ &= -\frac{-r f_{ij} f_i^{'}\left(l\right) A_{jk}^{-1}\left[\left(\sigma-1\right)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R\left(\sigma-1\right)\bar{\gamma}_{jk}^{r+R(\sigma-1)-1}\left(1-\bar{\gamma}_{jk}^{-r}\right)} < 0,\end{aligned}$$

because $\left(1-\bar{\gamma}_{jk}^{-r}\right) < 0$, and the remaining terms are positive. Hence, I show that $\frac{d\bar{\gamma}_{jk}}{dl} < 0$.

Appendix

Section 2.3.2. – Deriving $\frac{dln\left(x_{jk}\right)}{dl}$.

By (14), I have:

$$
\begin{aligned}
\frac{dx_{jk}}{dl} &= \frac{d}{dl}\frac{A_{jk}}{R}\left(1-\bar{\gamma}_{jk}^{R\sigma}\right) \\
\frac{dx_{jk}}{dl} &= \frac{1}{R}\left[\frac{\partial A_{jk}}{\partial l}\times\left(1-\bar{\gamma}_{jk}^{R\sigma}\right)+A_{jk}\times\frac{\partial\left(1-\bar{\gamma}_{jk}^{R\sigma}\right)}{\partial l}\right] \\
&= \frac{1}{R}\sigma^{-1}\left(1-\sigma\right)\left[\pi_{ij}\pi_i\left(l\right)\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\right]^{-\sigma}Y_j\pi_{ij}\pi_i^{'}\left(l\right)\frac{\sigma}{\sigma-1}\frac{w_k}{P_j}\left(1-\bar{\gamma}_{jk}^{R\sigma}\right) \\
&+ \frac{1}{R}A_{jk}\left(-R\sigma\bar{\gamma}_{jk}^{R\sigma-1}\right)\left\{\frac{rf_{ij}f_i^{'}\left(l\right)A_{jk}^{-1}\left[\left(\sigma-1\right)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R\left(\sigma-1\right)\bar{\gamma}_{jk}^{r+R(\sigma-1)-1}\left(1-\bar{\gamma}_{jk}^{-r}\right)}\right\} \\
&= \frac{1}{R}\left(1-\sigma\right)A_{jk}\frac{\pi_i^{'}\left(l\right)}{\pi_i\left(l\right)}\left(1-\bar{\gamma}_{jk}^{R\sigma}\right)-\frac{1}{R}\bar{\gamma}_{jk}^{R\sigma-1}\frac{rf_{ij}f_i^{'}\left(l\right)\left[\left(\sigma-1\right)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R\left(\sigma-1\right)\bar{\gamma}_{jk}^{r+R(\sigma-1)-1}\left(1-\bar{\gamma}_{jk}^{-r}\right)} \\
&= \left(1-\sigma\right)\frac{\pi_i^{'}\left(l\right)}{\pi_i\left(l\right)}x_{jk}-\frac{rf_{ij}f_i^{'}\left(l\right)\left[\left(\sigma-1\right)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R^2\left(\sigma-1\right)\bar{\gamma}_{jk}^{r}\left(1-\bar{\gamma}_{jk}^{-r}\right)},
\end{aligned}
$$

which is expression (17). The first term $\left(1-\sigma\right)\frac{\pi_i^{'}(l)}{\pi_i(l)}x_{jk}<0$ because I assume that $1<\sigma<+\infty$. The second term $-\frac{rf_{ij}f_i^{'}(l)\left[(\sigma-1)\frac{\pi_i^{'}(l)}{\pi_i(l)}+1\right]}{R^2(\sigma-1)\bar{\gamma}_{jk}^{r}\left(1-\bar{\gamma}_{jk}^{-r}\right)}>0$ because $\left(1-\bar{\gamma}_{jk}^{-r}\right)<0$ and everything else is positive. Intuitively, the first term refers to the negative effects of distance-induced variable trade costs on foreign demand, while the second term points to the fact that firms need to ship more at a time in order to recover the higher distance-induced per-shipment costs. Overall, $\frac{dln\left(x_{jk}\right)}{dl}$ may take a positive or negative value, depending on the relative strengths of distance effects on variable trade costs and per-shipment costs.

Appendix

Proof of Proposition 2. To prove $\frac{dln\left(\frac{1-\bar{\gamma}_{jk}^{R\sigma}}{R}\right)}{R} > 0$.

The only remaining statement concerns the dependence on R. To solve that, compute:

$$\begin{aligned}\frac{dln\left(\frac{1-\bar{\gamma}_{jk}^{R\sigma}}{R}\right)}{R} &= \frac{d}{dR}ln\left(1-\bar{\gamma}_{jk}^{R\sigma}\right) - \frac{d}{dR}lnR \\ &= \frac{1}{1-\bar{\gamma}_{jk}^{R\sigma}}\left(-\sigma\bar{\gamma}_{jk}ln\bar{\gamma}_{jk}\right) - \frac{1}{R} \\ &= -\frac{\sigma\bar{\gamma}_{jk}ln\bar{\gamma}_{jk}}{1-\bar{\gamma}_{jk}^{R\sigma}} - \frac{1}{R}.\end{aligned}$$

Note that $-\gamma^{\alpha}\cdot ln\gamma$ is minimal at $\gamma = exp\left(-\frac{1}{\alpha}\right)$ for all $\gamma \in (0,1)$. Hence,

$$\begin{aligned}\frac{dln\left(\frac{1-\bar{\gamma}_{jk}^{R\sigma}}{R}\right)}{R} &\geq \sigma\frac{\frac{1}{R\sigma}exp\left(-1\right)}{1-\bar{\gamma}_{jk}^{R\sigma}} - \frac{1}{R} \\ &\geq \frac{\frac{1}{R}}{1-\bar{\gamma}_{jk}^{R\sigma}} - \frac{1}{R} \\ &= \frac{1}{R}\left[\frac{1}{1-\bar{\gamma}_{jk}^{R\sigma}} - 1\right] \\ &= \frac{1}{R}\left[\frac{\bar{\gamma}_{jk}^{R\sigma}}{1-\bar{\gamma}_{jk}^{R\sigma}}\right] > 0.\end{aligned}$$

It completes the proof. □

Table 6: Internal distances to the nearest ports. First-stage results.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: (ln) Internal distance to the nearest port				
Same-industry distances to the nearest ports	−0.0986***	−0.0447***	−0.0448***	−0.0295***	−0.0291***
	(−13.27)	(−10.21)	(−10.22)	(−9.32)	(−9.17)
Average shipment size	0.0108***	0.0009	0.0025**	0.0014	0.0015*
	(5.56)	(0.84)	(2.01)	(1.57)	(1.76)
Average shipment volume	0.0287***	0.0011	0.0012	0.0003	−0.0001
	(17.67)	(1.17)	(1.26)	(0.48)	(−0.12)
Productivity	−0.2202***	0.0492***	0.0492***	0.0328***	0.0316***
	(−21.59)	(7.82)	(7.81)	(6.37)	(5.96)
Number of products		−0.0080***	−0.0076***	−0.0012	0.0002
		(−4.77)	(−4.55)	(−1.00)	(0.18)
Number of destinations		0.0088***	0.0089***	−0.0019	−0.0037***
		(4.97)	(5.04)	(−1.33)	(−2.59)
Product-destination market share			−0.0021***	−0.0002	−0.0002
			(−2.87)	(−0.48)	(−0.47)
Output (lag)				0.0007	−0.0013
				(0.40)	(−0.73)
Wage scaled by employment (lag)				−0.0380***	−0.0331***
				(−14.80)	(−12.71)
Employment (lag)				−0.0004	0.0026
				(−0.25)	(1.39)
Current liabilities scaled by output (lag)					−0.0075***
					(−5.80)
Intangible assets scaled by output (lag)					0.0005*
					(1.70)
Foreign ownership (lag)					−0.0238***
					(−8.92)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*N*	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*N*	*Y*	*Y*
Observations	232192	232067	232067	198626	197427
Adjusted R^2	0.120	0.735	0.736	0.886	0.885

Table 6 presents results of first-stage IV estimations of Eqs. (25) and (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is the firm-level internal distance to the nearest port. The instrument is the average internal distance to the nearest ports of the same-industry peers in other cities. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 7: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Per-shipment cost divided by average shipment value as a dependent variable.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment cost/Shipment size			
Distance to port	0.4467***	0.3787***	0.5901***	0.5256**
	(3.08)	(2.78)	(2.59)	(2.31)
Average shipment volume	−0.1157***	−0.0609***	−0.0637***	−0.0638***
	(−64.08)	(−40.55)	(−40.93)	(−41.88)
Productivity	−0.1180***	−0.1008***	−0.0798***	−0.0712***
	(−9.88)	(−9.59)	(−6.20)	(−5.63)
Number of products	0.0089**	0.0156***	0.0236***	0.0253***
	(2.14)	(4.32)	(6.20)	(6.81)
Number of destinations	−0.0618***	−0.0589***	−0.0343***	−0.0374***
	(−12.12)	(−12.90)	(−7.47)	(−8.23)
Product-destination market share		−0.1122***	−0.1146***	−0.1146***
		(−65.93)	(−62.31)	(−62.62)
Output (lag)			−0.0196***	−0.0169***
			(−5.47)	(−4.74)
Wage scaled by employment (lag)			0.0028	0.0042
			(0.28)	(0.47)
Employment (lag)			−0.0131***	−0.0161***
			(−3.40)	(−4.18)
Current liabilities scaled by output (lag)				0.0145***
				(4.37)
Intangible assets scaled by output (lag)				−0.0002
				(−0.38)
Foreign ownership (lag)				−0.0415***
				(−5.23)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
Town FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	232067	232067	198626	197427
R^2	−0.003	0.105	0.105	0.122
First-stage F	63.90	63.83	45.02	43.42

Table 7 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs divided by average export shipment size, by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 8: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Excluding per-unit basis transactions.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment costs			
Distance to port	0.2596*	0.3462***	0.5594**	0.4924**
	(1.95)	(2.62)	(2.45)	(2.16)
Average shipment size	0.9083***	0.9890***	0.9859***	0.9854***
	(436.62)	(331.76)	(305.20)	(310.21)
Average shipment volume	−0.0580***	−0.0539***	−0.0554***	−0.0553***
	(−32.15)	(−27.80)	(−26.06)	(−26.57)
Productivity	−0.0927***	−0.0980***	−0.0779***	−0.0690***
	(−8.75)	(−9.39)	(−5.96)	(−5.39)
Number of products	−0.0049	0.0140***	0.0223***	0.0239***
	(−1.36)	(4.07)	(6.07)	(6.68)
Number of destinations	−0.0645***	−0.0590***	−0.0349***	−0.0381***
	(−12.85)	(−12.64)	(−7.44)	(−8.22)
Product-destination market share		−0.1116***	−0.1130***	−0.1128***
		(−54.19)	(−51.97)	(−52.31)
Output (lag)			−0.0189***	−0.0163***
			(−5.23)	(−4.52)
Wage scaled by employment (lag)			0.0008	0.0025
			(0.08)	(0.28)
Employment (lag)			−0.0134***	−0.0164***
			(−3.46)	(−4.21)
Current liabilities scaled by output (lag)				0.0146***
				(4.39)
Intangible assets scaled by output (lag)				−0.0003
				(−0.47)
Foreign ownership (lag)				−0.0430***
				(−5.51)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	228310	228310	195710	194517
R^2	0.810	0.816	0.806	0.809
First-stage F	68.98	69.16	45.93	44.54

Table 8 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 9: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Excluding firm-product pairs with average shipment values below the 10th percentile.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment costs			
Distance to port	0.2425*	0.2809**	0.6025***	0.5516**
	(1.90)	(2.24)	(2.66)	(2.46)
Average shipment size	0.9027***	0.9923***	0.9885***	0.9879***
	(461.42)	(338.37)	(312.15)	(317.36)
Average shipment volume	−0.0607***	−0.0548***	−0.0559***	−0.0557***
	(−33.18)	(−27.74)	(−26.42)	(−26.80)
Productivity	−0.0983***	−0.1015***	−0.0934***	−0.0862***
	(−9.50)	(−10.02)	(−7.19)	(−6.70)
Number of products	−0.0027	0.0129***	0.0203***	0.0217***
	(−0.75)	(3.80)	(5.25)	(5.71)
Number of destinations	−0.0682***	−0.0589***	−0.0366***	−0.0394***
	(−13.52)	(−12.70)	(−7.63)	(−8.28)
Product-destination market share		−0.1186***	−0.1203***	−0.1202***
		(−52.33)	(−48.94)	(−49.23)
Output (lag)			−0.0147***	−0.0120***
			(−3.79)	(−3.16)
Wage scaled by employment (lag)			0.0039	0.0062
			(0.40)	(0.70)
Employment (lag)			−0.0151***	−0.0184***
			(−3.56)	(−4.46)
Current liabilities scaled by output (lag)				0.0137***
				(4.18)
Intangible assets scaled by output (lag)				0.0000
				(0.00)
Foreign ownership (lag)				−0.0404***
				(−4.87)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	208372	208372	178344	177260
R^2	0.797	0.809	0.790	0.793
First-stage F	77.56	77.63	51.44	50.65

Table 9 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 10: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Excluding firm-product-destination combinations with only one shipment.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment costs			
Distance to port	0.4961***	0.5813***	0.6391**	0.5878**
	(2.74)	(3.17)	(2.48)	(2.32)
Average shipment size	0.9180***	0.9861***	0.9817***	0.9809***
	(361.36)	(295.94)	(279.60)	(285.19)
Average shipment volume	−0.0459***	−0.0421***	−0.0423***	−0.0421***
	(−24.18)	(−20.87)	(−21.22)	(−21.45)
Productivity	−0.0905***	−0.1000***	−0.0743***	−0.0639***
	(−5.99)	(−6.40)	(−4.19)	(−3.70)
Number of products	−0.0107***	0.0036	0.0085**	0.0094***
	(−2.86)	(0.94)	(2.40)	(2.72)
Number of destinations	−0.0276***	−0.0244***	−0.0005	−0.0028
	(−5.48)	(−4.99)	(−0.10)	(−0.60)
Product-destination market share		−0.1003***	−0.1023***	−0.1021***
		(−45.52)	(−45.35)	(−45.86)
Output (lag)			−0.0148***	−0.0124***
			(−3.23)	(−2.80)
Wage scaled by employment (lag)			0.0008	0.0014
			(0.07)	(0.13)
Employment (lag)			−0.0167***	−0.0197***
			(−3.61)	(−4.43)
Current liabilities scaled by output (lag)				0.0156***
				(4.08)
Intangible assets scaled by output (lag)				−0.0006
				(−0.89)
Foreign ownership (lag)				−0.0312***
				(−3.68)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	107934	107934	93619	93067
R^2	0.812	0.807	0.821	0.826
First-stage F	31.78	31.87	31.03	31.13

Table 10 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 11: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Excluding firm-product-destination combinations with total shipment values below 5th or above 95th percentiles.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment costs			
Distance to port	0.4015**	0.4150**	0.5980**	0.5355**
	(2.39)	(2.54)	(2.39)	(2.15)
Average shipment size	0.8828***	0.9688***	0.9660***	0.9655***
	(410.52)	(325.45)	(304.67)	(308.57)
Average shipment volume	−0.0542***	−0.0499***	−0.0506***	−0.0504***
	(−30.18)	(−25.92)	(−24.96)	(−25.27)
Productivity	−0.0861***	−0.0878***	−0.0806***	−0.0716***
	(−6.74)	(−7.19)	(−5.44)	(−4.91)
Number of products	−0.0080**	0.0106***	0.0158***	0.0172***
	(−2.12)	(3.05)	(4.25)	(4.67)
Number of destinations	−0.0629***	−0.0560***	−0.0353***	−0.0382***
	(−12.42)	(−11.96)	(−7.48)	(−8.18)
Product-destination market share		−0.1194***	−0.1208***	−0.1207***
		(−56.37)	(−53.82)	(−54.20)
Output (lag)			−0.0081**	−0.0052
			(−2.15)	(−1.37)
Wage scaled by employment (lag)			−0.0007	0.0007
			(−0.07)	(0.08)
Employment (lag)			−0.0181***	−0.0214***
			(−4.64)	(−5.46)
Current liabilities scaled by output (lag)				0.0151***
				(4.25)
Intangible assets scaled by output (lag)				−0.0006
				(−0.96)
Foreign ownership (lag)				−0.0381***
				(−4.55)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	208589	208589	178942	177872
R^2	0.711	0.728	0.724	0.729
First-stage F	46.28	46.29	38.64	37.29

Table 11 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 4-digit Chinese Industrial Classification) and located in other cities (defined as 4-digit administrative regions) instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics with HS2-destination clusters are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 12: Per-shipment costs and internal distances to the nearest ports. Second-stage results. Alternative instruments.

	(1)	(2)	(3)	(4)
	Dependent variable: (ln) Per-shipment costs			
Distance to port	0.4654***	0.4874***	0.3113**	0.3061**
	(3.34)	(3.54)	(2.31)	(2.28)
Average shipment size	0.9115***	0.9903***	0.9877***	0.9870***
	(673.25)	(646.89)	(623.14)	(621.19)
Average shipment volume	−0.0608***	−0.0564***	−0.0572***	−0.0572***
	(−51.71)	(−48.43)	(−47.49)	(−47.45)
Productivity	−0.1025***	−0.1045***	−0.0688***	−0.0619***
	(−9.96)	(−10.45)	(−6.52)	(−5.81)
Number of products	−0.0027	0.0151***	0.0215***	0.0234***
	(−1.14)	(6.44)	(9.78)	(10.63)
Number of destinations	−0.0666***	−0.0605***	−0.0356***	−0.0391***
	(−25.89)	(−23.97)	(−14.53)	(−15.59)
Product-destination market share		−0.1093***	−0.1113***	−0.1111***
		(−113.37)	(−117.73)	(−117.35)
Output (lag)			−0.0187***	−0.0164***
			(−6.43)	(−5.52)
Wage scaled by employment (lag)			−0.0072	−0.0024
			(−1.09)	(−0.39)
Employment (lag)			−0.0133***	−0.0158***
			(−4.44)	(−5.12)
Current liabilities scaled by output (lag)				0.0136***
				(5.74)
Intangible assets scaled by output (lag)				−0.0001
				(−0.25)
Foreign ownership (lag)				−0.0475***
				(−8.60)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Port FE	*N*	*N*	*Y*	*Y*
Observations	231831	231831	198448	197253
R^2	0.797	0.806	0.820	0.821
First-stage F	77.80	77.86	162.81	162.71

Table 12 presents results of second-stage IV estimation of Eq. (27). Exports with state-owned enterprises (SOEs), and trade intermediaries defined in Ahn, Khandelwal, and Wei (2011) are excluded. Only ordinary trade transactions are included in the sample. The average internal distances to the nearest ports of firms in the same industry (defined as 2-digit Chinese Industrial Classification) exporting to the same destination country instrument for the firm's internal distance to its nearest port. The first-stage equation estimates separate regressions of the internal distance against instrument, the indicated set of variables listed at left, and the set of fixed effects listed at bottom. The dependent variable is per-shipment costs (in natural logarithm) by firm, 6-digit product and destination country in 2006 imputed according to Eq. (26) using further specifications. The explanatory variables are internal distances separating firms and their nearest ports listed in National Ports Layout Plan 2006. All the independent variables are in natural logarithm, except that foreign ownership is a dummy which equals 1 if 50% or more of the firm's capital is provided by foreign entities, and 0 otherwise. The average shipment size and volume are the average dollar value of shipments and the average quantity of shipments for a firm-product-destination observation, respectively. Firm-level productivity is computed using revenue-based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Number of products exported and number of destinations served are computed at the firm level. Product-destination market share refers to the dollar values of shipments contributed by a firm-product-destination observation divided by the total dollar values of all shipments of a product-destination observation. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 13: List of all sample ports.

Port Name	Cluster	Port Name	Cluster
Cangzhou-Huanghua Port	Bohai Economic Rim	Fuzhou Port	Southeast Coastal Area
Dalian Port	Bohai Economic Rim	Ningde Port	Southeast Coastal Area
Dandong Port	Bohai Economic Rim	Putian Port	Southeast Coastal Area
Jinzhou Port	Bohai Economic Rim	Quanzhou Port	Southeast Coastal Area
Qingdao Port	Bohai Economic Rim	Xiamen Port	Southeast Coastal Area
Qinhuangdao Port	Bohai Economic Rim	Zhangzhou Port	Southeast Coastal Area
Rizhao Port	Bohai Economic Rim	Basuo Port	Southwest Coastal Area
Tangshan-Jingtang Port	Bohai Economic Rim	Fangcheng Port	Southwest Coastal Area
Tianjin Port	Bohai Economic Rim	Haikou Port	Southwest Coastal Area
Yantai Port	Bohai Economic Rim	Sanya Port	Southwest Coastal Area
Yingkou Port	Bohai Economic Rim	Zhanjiang Port	Southwest Coastal Area
Dongguan Port	Pearl River Delta	Lianyungang Port	Yangtze River Delta
Guangzhou Port	Pearl River Delta	Nanjing Port	Yangtze River Delta
Huizhou Port	Pearl River Delta	Nantong Port	Yangtze River Delta
Shantou Port	Pearl River Delta	Ningbo-Zhoushan Port	Yangtze River Delta
Shenzhen Port	Pearl River Delta	Shanghai Port	Yangtze River Delta
Zhongshan Port	Pearl River Delta	Suzhou Port	Yangtze River Delta
Zhuhai Port	Pearl River Delta	Zhenjiang Port	Yangtze River Delta

Source: National Ports Layout Plan 2006, China's Ministry of Transport.

Table 14: List of HS 6-digit product categories in robustness checks for maximum shipping weights.

HS code (4-digit)	Descriptions
8701	Tractors (other than tractors of heading 87.09).
8702	Motor vehicles for the transport of ten or more persons, including the driver.
8703	Motor cars and other motor vehicles principally designed for the transport of persons (other than those of heading 87.02), including station wagons and racing cars.
8704	Motor vehicles for the transport of goods.
8705	Special purpose motor vehicles, other than those principally designed for the transport of persons or goods (for example, breakdown lorries, crane lorries, fire fighting vehicles, concrete- mixer lorries, road sweeper lorries, spraying lorries, mobile workshops, mobile radiological units)
8706	Chassis fitted with engines, for the motor vehicles of headings 87.01 to 87.05.
8707	Bodies (including cabs), for the motor vehicles of headings 87.01 to 87.05.
8709	Works trucks, self-propelled, not fitted with lifting or handling equipment, of the type used in factories, warehouses, dock areas or airports for short distance transport of goods; tractors of the type used on railway station platforms; parts of the foregoing vehicles
8710	Tanks and other armoured fighting vehicles, motorised, whether or not fitted with weapons, and parts of such vehicles.

HS code (2-digit)	Descriptions
88	Aircraft, spacecraft, and parts thereof
89	Ships, boats and floating structures

Source: The World Bank's List of HS nomenclatures.

Chapter 3

Spatial Frictions, Quality Differentiation, and Export Prices

Abstract

This paper examines the role of within-country trade frictions on the price-setting behavior of exporters. Using Chinese geospatial and firm-transaction level data on exports by product and destination country, I find that free-on-board export unit price decreases systematically with internal distance to the nearest port infrastructure, and the effect is stronger in shipments of differentiated or knowledge-intensive products, and in non-core products of exporters. Within product categories, higher-productivity exporters ship products at higher unit prices, and the negative effect of internal distance on unit prices is significantly weakened compared to their lower-productivity counterparts. All these empirical findings are robust after controlling for a large set of fixed effects, firm-level characteristics, and alternative productivity measures. These results suggest not only quality sorting across space, but also within-firm variations of unit prices across products and destinations. I present a simple theoretical framework extending Melitz and Ottaviano (2008) that features quality differentiation across space to rationalize these empirical patterns.

JEL Classifications: F10, O18, R32

Keywords: export price, quality differentiation, internal geography, trade frictions

3.1 Introduction

Exporters exhibit substantial heterogeneity in price-setting behavior. Previous literature find that export unit prices, defined as the ratio of export value to quantity at the firm-product-destination level, vary with destination-level characteristics, e.g. distance, market size, income per capita, trade liberalization, as well as firm-product level variables including firm's productivity, worldwide export revenue, degree of product differentiation, and R&D intensity. Yet, the relationship between export unit prices and within-country trade frictions is relatively under-explored. This paper studies how export unit prices vary systematically with a firm's geographical proximity to the nearest trade infrastructure, and how the unit prices differ across firm- and product-specific attributes using a sample of Chinese manufacturing exporters.

A number of studies in heterogeneous firms have provided enormous contributions in explaining the empirical patterns related to export prices. The seminal paper of Melitz and Ottaviano (2008) (hereafter abbreviated as MO) construct a theoretical model matching empirically observed relationships between export prices, firm productivity, and transportation costs. More recently, new variants of MO introduce additional dimensions of firm behavior, including production of non-core products (Mayer et al., 2014), idiosyncratic tastes and quality differentiation (Foster et al., 2008; Antoniades, 2015), in order to explain even richer empirical patterns in price-setting behavior in the context of international trade.

In this paper, I develop a new line of studies on the relationship between export unit prices and within-country trade frictions, and propose a simple MO-based model that is consistent with my empirical findings. The within-country trade friction is measured by the internal distance separating a firm and its nearest port infrastructure. I construct a large geospatial and firm-transaction level dataset of the universe of Chinese manufacturing exporters in 2006. Using precise latitude and longitude data, I map each firm's location to its nearest port connecting China and international destinations according to an official document published by China's Ministry of Transport. Then I examine the relationship between export unit prices at the firm-production-destination level and the firm's internal distance to the nearest port, controlling for a large set of fixed effects and firm-level characteristics. In addition, I relate export prices to industry- and product-level characteristics, including R&D intensity and distance to the core product.

This paper documents robust evidence on the systematic variation in export prices across firms. While the standard MO framework predicts that export prices increase in geographical distance between exporting and importing countries, I find that (a) exporters charge lower export unit prices when they are geographically distant from the nearest port infrastructure; (b) exporters charge lower export unit prices when the product is differentiated according to Rauch (1999) classification and the exporters are geographically distant from the nearest port; (c) exporters charge lower export unit prices when the industry has a high knowledge and advertising intensity and the exporters are geographically distant from the nearest port; (d) exporters charge lower export unit prices when the product is one of the top two products in terms of yearly export sales across all destinations, higher export unit prices when the product rank or product distance increases (i.e. the product is further away from the firm's core competency), and that the unit prices are depressed less significantly when the product is close to the firm's core competency for geographically distant firms; (e) higher productivity exporters charge higher export unit prices, and their unit prices are less affected by the internal distance than their lower productivity counterparts; and (f) exports with higher export unit prices are less significantly affected by the internal distance, both within and across HS 8-digit product categories. These empirical findings are robust using the relative price measure, which is defined as the ratio of unit price of a HS 8-digit product shipped from a firm to a destination country to the average unit price of the same HS 8-digit product across firms and destination countries.

Admittedly, the price-setting behavior of exporters involves potentially multiple mechanisms other than distance and quality differentiation, such as market toughness (Johnson, 2012), skill and capital intensity (Schott, 2004; Ma et al., 2014; Harrigan et al., 2015), and financial frictions (Crinò and Ogliari, 2017; Choi and Lugovskyy, 2019), which could be not readily observable and straightforward to quantify. To address this concern, I draw on a vast literature and take the previously documented key determinants of export unit prices in all empirical specifications. All results remain intact after controlling for an exhaustive set of fixed effects and firm-level characteristics.

To explain the empirical patterns, I incorporate spatial frictions and quality dimensions in the MO model which allow for location-specific heterogeneity in domestic transportation and innovation costs. Building on Foster et al. (2008) and Antoniades (2015) which consider variety-specific idiosyncratic tastes and scope for quality differentiation as a variant of MO theoretical framework, I extend their work by incorporating an explicit spatial structure à la Coşar and Fajgelbaum

(2016) to allow for an additional spatial dimension of domestic locations within the exporting country. Apart from the determinants of export prices in standard MO-based models, the internal distance also plays a role in price-setting. While domestic transportation costs associated with longer internal distance drive up export prices as in MO; the geographically distant firms optimally choose lower levels of quality of products because of higher cost of innovation associated with their locational disadvantages, which translates to lower unit prices. The transportation cost and quality differentiation mechanisms give rise to two opposing effects, thus the export unit prices could be ambiguous with the internal distance. The empirical findings show that export unit prices decrease with internal distance, which support the notion that quality differentiation effect dominates.

More broadly, I also find robust evidence that contributes to a better understanding of the internal geography of export unit prices and spatial heterogeneity of price-setting behavior. In particular, I examine how exporters of varying geographical proximity to the nearest port infrastructure, through cost and quality differentiation mechanisms, differentially set export unit prices based on unit of measurement, product differentiation, knowledge and advertising intensity, as well as product rank/distance relative to the core competency. The interactions between internal distance, firm- and product-specific attributes receive considerably less attention in economic geography literature (where the latter focus on characteristics of importing countries) because of the lack of precise geocoded information of firm locations and trade infrastructure. This paper fills the gap of literature on how firms' export pricing could be affected by location-specific heterogeneity in trade costs, which is defined as the firm's geographical proximity to the nearest port infrastructure.

Literature. This paper is related to the literature on role of gravity on systematic heterogeneity in the export prices charged for the same narrowly-defined products. Baldwin and Harrigan (2011) find that disaggregated export unit prices are positively related to cross-country distance, and negatively related to the market size and income per capita of the importing countries, using the U.S. export unit values in 2005. Harrigan et al. (2015) find that highly productive firms and skill-intensive firms charger higher prices and that U.S. firms exhibit strong positive price-distance effects, using U.S. firm-level export data in 2002. Manova and Zhang (2012) use detailed customs data on the universe of Chinese export flows and find that across destinations within a firm-product, exporters charge higher prices in bilaterally more distant importing countries. While these studies provide compelling empirical evidence on positive price-distance effects, they focus on cross-country distance between exporting and importing countries. I take an alternative perspective to study how exporters' location within the country and ease of access of trade infrastructure could shape price-setting behavior.

This paper is also related to the line of research regarding the role of spatial quality differentiation and innovation in exporting. Lugovskyy and Skiba (2015) establish the relationship between the quality of product-level bilateral trade flows and the geographic position of the exporters, and they find that the quality increases in transportation costs as well as preferences for quality of the destinations. Kneller and Yu (2016) find that the average unit values of the majority of Chinese exports increase with both cross-country distance and market size, but mixed evidence is also found in a few factors. The authors explain these patterns with price discrimination and quality selection effects. Anderson et al. (2019) use a dataset of Indian manufacturing exporters and document that export prices are negatively associated with cross-country distance. They propose that Indian exporters tend to produce with a smaller scope for quality differentiation in response to high domestic innovation costs, causing the negative relationship between firm productivity and export unit prices. Fontaine et al. (2020) study the cross-sectional dispersion of export prices to the European Economic and Monetary Union (EMU) members from French exporters, and document that the export prices are highly dispersed within the EU, within the euro area, and within EMU countries, and the dispersion is more prevalent among the more differentiated products. These results indicate that product and quality differentiation are potential candidates for explaining substantial heterogeneity in export unit prices in narrowly-defined products. Unlike these studies which focus on cross-country distance, this paper attempts to establish the link between within-country geographical (dis)advantages and the scope for quality differentiation, and its implications on export unit prices.

This paper also complements previous studies on multi-product firm behavior, product varieties, and economic geography. Eckel and Neary (2010) present a model of multi-product firms and predict that increased competition across destinations induces multi-product firms to focus on their core competencies, and the relatively high-cost varieties may be discontinued or produced in lower volumes as an adjustment in intra-firm extensive margin. Eckel et al. (2015) develop a model that firms must invest to improve both the quality of each product and of their brand, and find robust confirmation that prices fall with distance from core competencies in differentiated good sectors. Mayer et al. (2014) build a theoretical model which consider multi-product firms' exported product range and product mix, and find strong empirical confirmation that tougher competition in an importing country induces an exporter to skew its export sales toward its top-selling core products. Moreover, the firm-level productivity increases as a response to the change in firm's product mix, indicating that firms tend to produce relative more better-performing products in tougher markets, which raise measured firm productivity. Cardoso-Vargas (2017) finds that longer distance to the core product considerably lowers the probability of the new product-destination match, and even further to destinations with high purchasing power. All these empirical findings point to the fact that firms compete not only in productivity, but also in quality via the choice of investment in innovation. I provide one of the earliest evidence on how internal distance affects product prices of varying distances relative to the core products within multi-product exporters.

The remainder of the paper is organized as follows. Section 2 describes the data and construction of key variables. Section 3 presents data patterns and estimation results. Section 4 provides the theoretical framework, and discusses the role of internal geography and quality differentiation, as well as their implications on price-setting behavior of exporters. Section 5 concludes. Robustness checks and additional results are presented in the Supplementary Appendix.

3.2 Data

In this study, I analyze export transaction data of manufacturing firms in China, the largest exporter of goods in the world. The firm-transaction level dataset is ideal for this exercise because the data are available at a highly disaggregated level and its product and industry coverage are exceptionally wide. The observation in the dataset is the export unit price of a Harmonized System (HS) 8-digit level product by an exporter to a destination country in a year. The detailed descriptions of dataset and construction of key variables are presented below.

3.2.1 Key variables and data sources

The firm-transaction level dataset is constructed using three primary data sources: (1) the transaction-level customs data on the universe of China's international trade transactions from China Customs

Office, (2) the firm-level data from Annual Survey of Industrial Production (ASIP) from China's National Bureau of Statistics, and (3) the ports data from *National Ports Layout Plan*, an official document published by China's Ministry of Transport in 2006 to identify ports which connect China and international destinations. For the spatial dimension of the dataset, I use Baidu's geocoding API to obtain obtain precise geographic coordinates of firm and port locations.[1] The baseline sample includes export transactions of Chinese manufacturing exporters with full firm addresses and their 12-digit administrative region codes (i.e. the most disaggregated code for location) in 2006. Moreover, I focus on the export transactions in 2006 because no major earthquakes occurred in mainland China which caused disruptions to internal transportation networks, making this year particularly suitable to study the effect of within-country trade frictions on firms' export unit prices. This treatment is to isolate any negative impact on firms' exports because of diminished transportation infrastructure within the country.[2,3]

Transaction-level customs data. The China Customs data report the free-on-board value of firm exports (in U.S. dollars), trade regimes (e.g. processing trade or non-processing trade), destination countries, units of measurement (see Section 2.2. for details), mode of transportation, and products in the Harmonized System (HS) classification. The provision of export transaction values and units of measurement make construction of export unit values possible. I follow Djankov et al. (2010) to focus on the transportation of goods to the nearest ports. I thus identify for each firm those HS 8-digit product categories which use maritime transport as the only mode of transportation in 2006 in the baseline sample. The remaining product categories that use multiple or other modes of transportation are excluded. It ensures that firms ship products to the nearest ports for freight transport by sea. Next, I follow Fernandes and Tang (2014) to keep only ordinary trade transactions. Finally, I aggregate the export transaction values and volumes to a yearly basis, such that all export unit values can be constructed at the firm-product-destination level in a year. This treatment removes seasonality and lumpiness in the monthly transaction data (Manova and

[1]Baidu Maps is one of the largest web mapping service application and technology in China. It works like Google Maps and offers satellite imagery, street maps, and geocoded information of Chinese locations.

[2]Volpe Martincus and Blyde (2013) exploit the Chilean earthquake in 2010 as a natural experiment and document that diminished transportation infrastructure within Chile had a significant negative impact on firms' exports.

[3]According to the United States Geological Survey (USGS), only one major earthquake was recorded in mainland China in 2005 (M 6.3 - western Xizang, which happened on April 7, 2005, 20:04:41 UTC, URL: https://earthquake.usgs.gov/earthquakes/eventpage/usp000dmht/executive), and no major earthquake occurred in mainland China in 2006. Earthquake screening criteria used on USGS: most worldwide events magnitude 4.5 and greater, from January 1, 2000 to December 31, 2010. Source: USGS, URL: https://earthquake.usgs.gov/.

Zhang, 2012).

Firm-level data. While the ASIP is regarded as an industrial "firm"-level dataset, the unit of observation is a legal unit, which corresponds to the definition of "establishment" in the United States (Imbert et al., 2019). Each firm cell has rich information on employment, wage, capital, output, assets, liabilities, and etc. The ASIP covers all state-owned enterprises (SOEs) and all non-state-owned manufacturing establishments with annual sales exceeding 5 million Chinese yuan (roughly 630,000 U.S. dollars in 2006). As long as physical entities establish legally, have their own names, locations and are able to take civil liability, possess and use their assets independently, they enter the dataset as individual "firms" (Brandt et al., 2014; Imbert et al., 2019). Using the same ASIP dataset, Imbert et al. (2019) find that these legal units almost perfectly overlap with plants in practice.[4] I thus take each distinct legal unit as the location where managers ship manufactured goods to the nearest ports, and refer a legal unit as an individual firm. For the baseline sample, I follow standard practice to drop all SOEs, because they are under control of Chinese government, and not necessarily profit-maximizing (Manova et al., 2015). Firms with less than 10 employees are excluded. Next, I follow Ahn et al. (2011) to drop trade intermediaries and wholesalers which do not engage in manufacturing but serve as an import-export facilitation between domestic exporters and foreign importers. Finally, the baseline sample covers 935 counties, and 421 manufacturing industries in 4-digit Chinese Industrial Classification (CIC) system (CIC codes 1311-4392).

Spatial data. To construct the spatial dimension of this dataset, I use the firms' addresses and detailed 12-digit administrative region codes assigned by China's Ministry of Civil Affairs that are reported in the ASIP dataset.[5] I use Baidu's geocoding API to obtain firms' latitude and longitude values with these firms' addresses and administrative region codes. Similarly, I obtain the geocoded information of all ports, and map each firm to its nearest port in terms of geographical distance. The geographical distance separating a firm and its nearest port is referred to as "internal distance

[4]While some other countries sample plants or establishments, Brandt et al. (2014), which discuss the use of China's ASIP dataset, find that for most entities, the plant/firm definition coincides. Using the same ASIP dataset, Imbert et al. (2019) also indicate that these legal units almost perfectly overlap with plants in practice. For example, 94% of plants in U.S. Census belong to single-plant firms, while the share of single-plant firms was 97% in China in 2007 (Brandt et al., 2014; Imbert et al., 2019).

[5]Each 12-digit administrative region code contains detailed geographic information of a firm. The first two digits correspond to the highest level of administrative division, province. The next two (3rd and 4th) digits summarize the location for the associated prefecture of city. The next two (5th and 6th) digits represent a county. The next three (7th to 9th) digits give information of the town. The last three (10th to 12th) digits refer to a village or community, the most disaggregated level of administrative divisions.

to the nearest port" hereafter. Following Coşar and Fajgelbaum (2016), I compute the Euclidean distance separating the firm and its nearest port.[6]

Ports data. I use the *National Ports Layout Plan*, an official document published by China's Ministry of Transport in 2006 to identify ports which connect China and international destinations. This document contains information on Chinese ports, including their primary port functions and their port facilities. I use shipping information websites *Marine Traffic* and *World Port Source* to identify their unique UN/LOCODE (United Nations Code for Trade and Transport Locations) and obtain their geocoded information, including latitude and longitude values. The details of all 36 ports are presented in Supplementary Appendix.[7]

3.2.2 Construction of variables

Throughout this paper, a product is defined as a Harmonized System (HS) 8-digit code (hereafter HS8), and a destination is defined as the importing country. Manova and Zhang (2012) indicate that the number of distinct Chinese HS8 product codes is comparable to that of the U.S. HS 10-digit product codes. This disaggregated nature of product data makes it possible to study export unit prices within narrowly defined categories, mitigating the concern of small intrinsic differences across products. The export unit price and number of observations under each table are defined at the firm-product-destination level. The details of construction of key variables are described below.

Units of measurement. There are several units of measurement for different HS8 product categories in the Chinese customs data. To ensure the consistency of units of measurement, I standardize and group them into the following base units: meter (length), and kilogram (mass), according to the International System of Units (SI, or *Système International d'unités*), the international standard of metric system.[8] The other non-SI units of measurements used in the dataset are converted to cubic metre or 1,000 litre (volume), square metre (area), piece or set (quantity).

[6]This measure of internal distance is similar to that of Coşar and Fajgelbaum (2016). They measure the internal distance of the administrative center of a firm's prefecture to that of the nearest coastal prefecture.

[7]The *National Ports Layout Plan* assigns a total of 38 ports in China. I drop Hong Kong Port due to the special status of Hong Kong Special Administrative Region, and also Guangxi Coastal Port because it is not given a unique UN/LOCODE. See the UN/LOCODE List at United Nations Economic Commission for Europe (UNECE): https://www.unece.org/cefact/locode/service/location.html/.

[8]The seven base units in the International System of Units (SI) are: the metre (length), kilogram (mass), second (time), ampere (electric current), Kelvin (temperature), mole (quantity), and candela (brightness). Only the first two units of measurement are used in the China Customs dataset. For other units of measurements, I standardize them into non-SI base units to ensure consistency.

The construction of consistent units of measurements is essential to compare unit prices of HS8 products, as well as study the price-setting behavior across goods, e.g. comparing mass-based and non-mass-based goods. Bastos and Silva (2010b) find that unit prices of mass-based goods measured in kilos are *not* more sensitive to distance compared to goods measured in other metric units.[9] I adopt the same approach and report separately the full sample and mass-based goods (measured in kilograms) to examine if unit prices of mass-based goods behave differently from all manufactured goods in general. I follow Manova and Zhang (2012) to include product fixed effects in all specifications to account for the different units of measurement across products.

Unit prices and relative prices. For each firm-product-destination, the export unit price is defined as the total export transaction amount (in U.S. dollars) divided by total quantities transacted (Manova and Zhang, 2012; Görg et al., 2017). Following Cardoso-Vargas (2017), I also construct the relative price as an alternative measure of price. It is defined as the export unit price divided by the average export unit price of the same HS8 product across all firm-product-destinations. The construction of HS8 relative price is to compare prices within the same HS8 product to minimize systematic differences in cost and quality. It is also noted that the product quality is measured by the average unit price of exports within industries in standard trade literature, e.g. Manova and Zhang (2012) and Brambilla and Porto (2016).

Knowledge and advertising intensity. Motivated by Keller and Yeaple (2013), the cost of obtaining the composite intermediate could be driven by the knowledge intensity of a final good. The mechanism of acquiring knowledge-intensive composite intermediates is beyond the scope of this paper. Still, I follow Keller and Yeaple (2013) to identify, for each 4-digit Chinese Industrial Classification (CIC) industry, the ratio of total R&D expenditures to total employment, in order to capture the unobserved knowledge intensity of an industry. In addition, the industry-level ratio of advertising expenditures to sale is commonly used as a proxy for product differentiation (Bagwell, 2007). Taken these together, for each industry I also construct the ratio of the sum of R&D and advertising expenditures to employment, as in Kugler and Verhoogen (2012). These measures serve as proxies for degree of product differentiation.

Dummy for differentiated goods. Following Bastos and Silva (2010a, 2010b), I use both the "conservative" and "liberal" classification of differentiated and homogeneous goods of Rauch

[9]See Table 7 of Bastos and Silva (2010).

(1999) using the Standard International Trade Classification system (SITC) Rev. 2 commodities as measures of vertical differentiation of products.[10] Rauch (1999) classifies commodities into three categories: goods traded on organized exchange (the most homogeneous), referenced priced, and differentiated. I concord the original SITC 4-digit codes to HS 8-digit codes, and merge them with the Chinese customs transaction-level data. Using firm-level data on export unit values, Bastos and Silva (2010a) find that Rauch (1999) classification is well suited for capturing quality differentiation. Manova and Zhang (2012) also find that the variation identified by the Rauch dummies is of a quality nature, and use them to proxy for the scope for quality differentiation. I then follow Bastos and Silva (2010b) to construct a dummy variable which equals 1 if the product category is classified as differentiated, and 0 otherwise.

Rank of products, core product and distance to the core. Following Mayer et al. (2014) and Eckel et al. (2015), I compute the rank of all HS8 products exported by a firm, and the HS8 product with the highest total export sales across destinations is defined as the core product of a firm.[11] Next, I follow Eckel and Neary (2010) to construct a dummy for an exporter's top 2 products in terms of yearly export sales. In addition, I follow Cardoso-Vargas (2017) to construct the distance of each product with respect to the core product ("distance to the core" hereafter). The natural logarithm of distance to the core is defined as:

$$ln\ (distance\,to\,the\,core_{it}^{n}) = ln\left[101 - \left(\frac{export\,sales_{it}^{n}}{export\,sales_{it}^{core}} \times 100\right)\right],$$

where $export\,sales_{it}^{n}$ refers to the export sales of product n by firm i in year t, while $export\,sales_{it}^{core}$ represents export sales of the core product of firm i, which has the product rank of 1. Thus, the distance to the core measures the difference between core product and all non-core products in terms of yearly export sales across all destinations, and is standardized to a scale of 1 to 101. Clearly, a core product has a distance of 1, and a non-core product with negligible export sales relative to the core product has a maximum distance of 101. I use these measures to capture the diminished product quality and appeal as the firm is pulled away from its core competency, as described in Mayer et al. (2014).

[10]The product classification data can be downloaded at: https://econweb.ucsd.edu/~jrauch/rauch_classification.html.

[11]If two HS8 products have the highest export sales, then both their ranks are rounded down towards the nearest integer, meaning that neither is classified as a core product.

3.3 Empirical Evidence

Figure 1 shows the distributions of export unit prices at the firm-product-destination level, internal distance to the nearest port, and revenue based Levinsohn and Petrin (2003) productivity at the firm level in the baseline sample. Table 1 reports the summary statistics of key variables used in Section 3.

3.3.1 Unit price and internal distance

In this section, I examine the variation in export unit prices at the firm-product-destination level. I use the following estimating equation similar to that in Manova and Zhang (2012):

$$log\ (unit\,price_{fpd}) = \alpha + \beta \cdot (internal\,distance_f) + controls + \{FEs\} + \varepsilon_{fpd}, \tag{1}$$

where the $unit\,price_{fpd}$ refers to the free-on-board export unit prices of a product p charged by firm f to a foreign destination d, defined in Section 2.2., and $internal\,distance_f$ refers to the firm's internal distance to its nearest port, respectively. Finally, ε_{fpd} is a measurement error, assumed to be normally distributed. OLS estimations with robust t-statistics in parenthesis are presented below. An extensive set of fixed effects, namely HS2-destination, port, county, industry, and product-fixed effects are included in this empirical specification. Following Fortagné et al. (2015), I include HS2-destination fixed effects to account for sector-country factors that may affect export prices, such as business cycles, market toughness, importer-demand shocks, and multilateral trade resistance, as highlighted by Head and Mayer (2014). I also follow Manova and Zhang (2012) to include product fixed effects to account for the differences in products' natural units of measurements, average value and quality, import restrictions, distribution costs, the need for specialized labor or equipment in production processes. Port fixed effects are included to control for the port heterogeneity, e.g. level of shipping port automation. As in standard trade literature, county and industry (defined as a 4-digit Chinese Industrial Classification code) fixed effects account for local infrastructure and congestion, and cross-industry differences in comparative advantages and financial vulnerability in exporting, respectively.

All independent variables are in natural logarithms, except that the foreign ownership variable is a dummy which equals 1 if 50% or more of the firm's capital was provided by foreign entities,

Figure 1: Distributions of export unit prices, internal distance, and firm productivity.

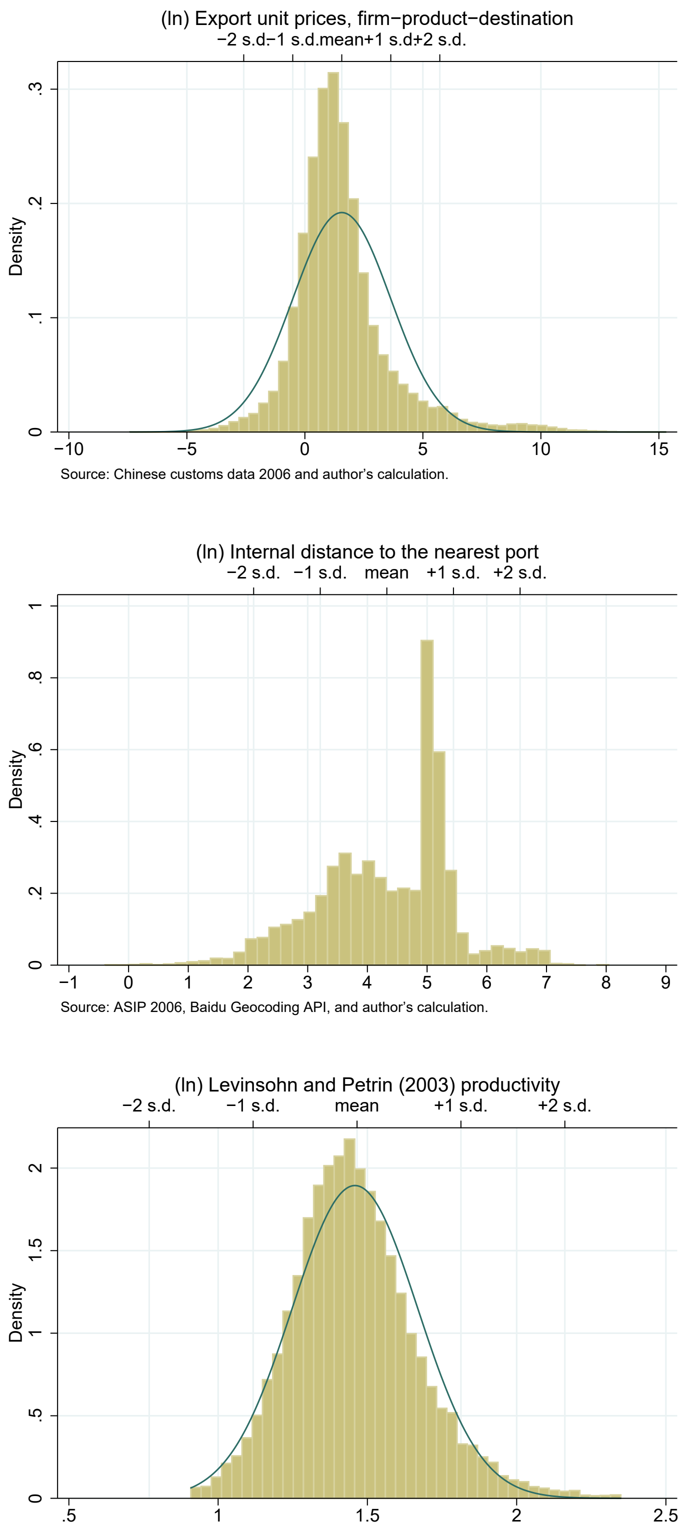

Figure 1 plots the natural logarithms of export unit prices at the firm-product-destination level (top panel), internal distance to the nearest port at the firm level (middle panel), and revenue based Levinsohn and Petrin (2003) estimator of productivity (bottom panel) of Chinese manufacturing exporters in 2006. The top and bottom 1% of firm-level productivity are excluded. Source: China Customs 2006, ASIP 2006, Baidu Geocoding API, and author's calculations.

Table 1: Summary statistics of key variables.

	N	Mean	Q1	Median	Q3	SD
Panel A: Export prices (log)						
Unit prices	279,146	1.56	0.41	1.25	2.25	2.08
Relative prices		0.36	−0.21	0.20	0.80	1.11
Panel B: Internal distances to the nearest ports (km)						
Internal distances	20,548	131.32	34.97	92.86	162.59	168.53
Panel C: Productivity measures (log)						
Revenue based productivity	19,006	1.47	1.32	1.44	1.58	0.35
Panel D: Key independent variables						
Average shipment size (log)	279,146	8.78	7.74	9.07	10.10	1.95
Number of shipments		2.58	1.00	1.00	3.00	2.73
Product-destination market share	96,052	0.50	0.08	0.40	1.00	0.42
Number of destinations	20,548	6.92	1.00	3.00	9.00	9.02
Number of products		4.80	1.00	3.00	6.00	6.99
Output (log)		15.56	14.67	15.44	16.32	1.27
Wage (log)		7.64	7.30	7.59	7.94	0.58
Employment (log)		5.17	4.45	5.12	5.83	1.04
Foreign ownership (dummy)	20,514	0.26	0.00	0.00	1.00	0.44

Table 1 reports the summary statistics of key variables used in Section 3. Panel A reports export unit prices and relative prices at firm-product-destination level. Panel B reports the firm-level internal distances to the nearest ports. Panel C reports the revenue based Levinsohn and Petrin (2003) estimator of productivity. Panel D reports the key firm-level independent variables, except that the average shipment size is defined at firm-product-destination level, and the market share is defined at product-destination level. Source: China Customs 2006, ASIP 2006, Baidu Geocoding API, and author's calculations.

and 0 otherwise. A shipment is defined as an export transaction in Chinese customs dataset. The average shipment size is defined at the total export value divided by number of shipments at the firm-product-destination level. The number of destinations and HS8 products are defined at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator.[12] Next, I follow Fortagné et al. (2015) to include the product-destination market share of exporters in a given HS2-destination to control for the geographical concentration of these exporters.[13] Motivated by literature on financial vulnerability and export performance (Manova, 2013; Manova et al., 2015; Crinò and Ogliari, 2017), I use (log) current liabilities (scaled by firm's output) to proxy for a firm's requirement for external finance arising from short-run working capital needs. I then use (log) intangible assets (scaled by firm's output) to proxy for the use of software and intellectual property in a firm's production.[14] Moreover, the natural logarithm of output and firm size measured by number of employees are included. Finally, I include the (log) wage (scaled by number of employees) to capture the intensity of use of higher-wage skilled labor, as suggested by Brambilla and Porto (2016).[15]

3.3.1.1 Unit price, unit of measurement, and internal distance

Now I turn to the baseline estimation of the relationship between export unit price and internal distance. In all columns (1) to (6), a full set of fixed effects (e.g. HS2-destination, port, county, industry, and product) and controls are included. These fixed effects absorb characteristics of importing country (e.g. distance from China, income per capita, market toughness, and etc.), and help establish a conditional correlation between export price and internal distance.

Columns (1) to (3) report the results using the full baseline sample, and columns (4) to (6) report results using only mass-based products, which use kilograms as the natural unit of measurement. Columns (1) and (4) show results with continuous measure of internal distance, using full sample, and mass-based products, respectively. The coefficients of internal distances are negative and

[12] Results are similar if value added based Levinsohn and Petrin (2003) estimator is used.

[13] This proxy of market power is also used in Manova and Yu (2017). Mayer et al. (2014) use this to proxy for a sector-level competition in a destination within a HS 2-digit sector.

[14] The intangible assets are associated with market power and productivity gains. See Crouzet and Eberly (2019) for their discussions.

[15] Brambilla and Porto (2016) find that the quality provision is costly and requires more intensive use of higher-wage skilled labor in modifying the production process. In addition, the production of high quality products at the industry level creates a wage premium in that industry.

Table 2: Unit price, unit of measurement, and internal distance.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Mass-based		
	Dependent variable: (ln) Unit price					
Distance to port	-0.0376^{***} (−6.47)			-0.0361^{***} (−5.32)		
Distance - Group 1		-0.1310^{***} (−4.79)	-0.1310^{***} (−4.79)		-0.2967^{***} (−8.94)	-0.2962^{***} (−8.93)
Distance - Group 2		-0.1186^{***} (−3.98)	-0.1187^{***} (−3.98)		-0.2248^{***} (−6.32)	-0.2245^{***} (−6.31)
Distance - Group 3		-0.1779^{***} (−5.76)	-0.1780^{***} (−5.76)		-0.2728^{***} (−7.34)	-0.2725^{***} (−7.34)
Distance - Group 4		-0.2412^{***} (−5.70)	-0.2452^{***} (−5.18)		-0.2453^{***} (−5.03)	-0.1950^{***} (−3.65)
Distance - Group 5			-0.2345^{***} (−3.94)			-0.3650^{***} (−5.18)
Average shipment size	0.0896^{***} (44.43)	0.0897^{***} (44.44)	0.0897^{***} (44.44)	0.0688^{***} (29.25)	0.0690^{***} (29.36)	0.0690^{***} (29.36)
Number of shipments	-0.1096^{***} (−36.57)	-0.1096^{***} (−36.56)	-0.1096^{***} (−36.56)	-0.0992^{***} (−30.22)	-0.0989^{***} (−30.14)	-0.0989^{***} (−30.14)
Number of destinations	-0.0937^{***} (−25.57)	-0.0939^{***} (−25.61)	-0.0939^{***} (−25.60)	-0.1052^{***} (−25.63)	-0.1056^{***} (−25.71)	-0.1058^{***} (−25.74)
Number of products	0.0605^{***} (18.60)	0.0603^{***} (18.54)	0.0603^{***} (18.54)	0.1125^{***} (31.51)	0.1122^{***} (31.45)	0.1123^{***} (31.48)
Market share	0.0101^{***} (5.84)	0.0100^{***} (5.82)	0.0100^{***} (5.82)	0.0153^{***} (7.53)	0.0151^{***} (7.42)	0.0151^{***} (7.42)
Productivity	0.0803^{***} (6.49)	0.0791^{***} (6.39)	0.0791^{***} (6.39)	0.1077^{***} (7.79)	0.1066^{***} (7.68)	0.1068^{***} (7.69)
Output	-0.0177^{***} (−3.94)	-0.0174^{***} (−3.88)	-0.0174^{***} (−3.88)	-0.0947^{***} (−18.13)	-0.0952^{***} (−18.20)	-0.0952^{***} (−18.20)
Wage	0.1621^{***} (28.02)	0.1607^{***} (27.77)	0.1607^{***} (27.76)	0.1343^{***} (20.47)	0.1318^{***} (20.11)	0.1319^{***} (20.12)
Employment	0.0614^{***} (14.29)	0.0613^{***} (14.24)	0.0613^{***} (14.24)	0.1201^{***} (23.63)	0.1211^{***} (23.81)	0.1210^{***} (23.79)
Current liabilities	0.0193^{***} (6.86)	0.0194^{***} (6.91)	0.0194^{***} (6.91)	-0.0079^{**} (−2.40)	-0.0084^{**} (−2.55)	-0.0083^{**} (−2.52)
Intangible assets	0.0048^{***} (6.86)	0.0048^{***} (6.86)	0.0048^{***} (6.86)	0.0054^{***} (6.66)	0.0054^{***} (6.60)	0.0054^{***} (6.60)
Foreign ownership	0.0872^{***} (14.06)	0.0875^{***} (14.11)	0.0875^{***} (14.11)	0.0839^{***} (11.66)	0.0841^{***} (11.70)	0.0840^{***} (11.68)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	258357	258357	258357	142709	142709	142709
Adjusted R^2	0.794	0.794	0.794	0.543	0.543	0.543

Table 2 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. Mass-based products are HS8 products with kilograms as the natural unit of measurement. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

statistically significant at the 1% level. The point estimate of the column (1) specification suggests that a 10% increase in the internal distance to the nearest port is associated with a 0.38% decrease in export unit prices. The unit prices of mass-based exports do not exhibit greater responsiveness to the internal distances: a 10% increase in the internal distance is associated with a 0.36% decrease in export unit prices accordingly. In the rest of columns, I sort exporters according to their internal distances into 4 or 5 geographic groups. The omitted group (Group 0) consists of exporters located within 5 kilometres to their nearest ports in baseline sample. Group 1 refers to exporters with internal distances $5.0 < l \leq 131.3 \times \frac{1}{2}$ kilometres to their nearest ports, where the average internal distance to the nearest port is 131.3 kilometres in the baseline sample. Similarly, Group 2 exporters have internal distances $131.3 \times \frac{1}{2} < l \leq 131.3$ kilometres. Groups 3 to 5 have internal distances $131.3 < l \leq 131.3 \times 2$, $131.3 \times 2 < l \leq 131.3 \times 4$, and $l > 131.3 \times 4$ kilometres to the nearest ports, respectively. Columns (2) and (5) report the coefficients of internal distances using 4 geographic groups, while columns (3) and (6) report those using 5 geographic groups. The coefficients are negative and remain statistically significant at the 1% level in column (2). Compared to the regions within 5 kilometres of the port infrastructure, exporters set lower export unit prices when they are further away from the ports. Similar patterns are also found in mass-based products, as seen from columns (5) and (6). Notably, the coefficients of internal distances are almost doubled of that reported in columns (2) and (3), indicating that exporters of mass-based products, once left the regions within 5 kilometres of the ports, charge considerably lower unit prices. These could suggest that exporters of mass-based products absorb part of the local transportation costs when exporting to foreign markets.

I next turn to the key independent variables. Starting with the firm-level productivity measure, I observe that the coefficients are positive and statistically significant at the 1% level across all columns. Columns (1) and (4) show that a 10% increase of productivity is associated with a 0.80% (for all products) and 1.08% (for mass-based products only) increase in export unit prices. Note that in MO and its variants, the productivity parameter is also taken as the inverse of a firm's marginal cost of production. These results indicate that a higher marginal cost (i.e. lower productivity) is associated with a lower export unit price. This is inconsistent with the original MO framework without quality differentiation, which predicts that export price is increasing in both marginal cost of production and iceberg transportation cost (see Eq. (20) of MO). In other words, the standard MO cost component might not be sufficient in explaining these findings, and introducing a quality dimension into the model could serve as a natural solution to reconcile with these seemingly contradictory empirical patterns.

The rest of variables have the predicted signs. In terms of shipment-related variables, the export unit prices are positively related to the average shipment size and number of products, but negatively related to number of shipments and destinations. A larger average shipment size suggests that exporters tend to ship products of higher unit values in general, and that the number of products has a positive relationship with unit prices because it incurs customization cost to introduce additional varieties for a multi-product firm, consistent with Mayer et al. (2014). Larger number of shipments and destination market served suggest that exporters benefit from lower administrative and shipping expenses that are common to the same set of exported products. The product-destination market share serves as a proxy for the market power of an exporter, which likely increases unit prices via the channel of markups. Regarding the firm-level characteristics, the export unit prices are positively related to wage, employment, intangible assets, foreign ownership dummy, but negatively related to firm output. Consistent with Brambilla and Porto (2016), quality provision is costly and requires the use of higher-wage skilled labor in production process, thus the positive coefficients on wage indicate the strong positive relationship between export prices and product quality. It is well established that firm size (proxied by number of employees) has strong positive correlation with output prices (Rodrigue and Tan, 2019). Intangible assets scaled by firm's output proxy for the use of software and intellectual property in production, which could increase the export prices through the channel of productivity gains. Output captures firms' economies of scale, and firms operating at higher capacities are more efficient to save production costs, thus charging lower unit prices. The last variable, current liabilities scaled by output, does not show consistent patterns on unit prices across full sample and mass-based products.

Overall, Table 2 presents robust evidence that firms being geographically distant from the nearest ports set lower export unit prices even within narrowly defined products across destination markets. This relationship is highly statistically significant.

3.3.1.2 Unit price, product differentiation, and internal distance

In this sub-section, I examine if the relationship between unit prices and internal distance varies across industries of different scopes for quality differentiation. Tables 3 and 4 present the OLS estimation results using two measures of product differentiation commonly used in trade literature. The first measure of product differentiation comes directly from Rauch (1999), who classifies SITC Rev.2 commodities into the following categories: (i) goods traded on organized exchange, (ii) referenced priced, and (iii) differentiated products, where type (i) refers to the most homogeneous products. The construction of the second measure of product differentiation is motivated by Keller and Yeaple (2013), who study the effect of knowledge intensity of production on import sourcing decisions, and use industry-level R&D expenditures as a measure of the technological knowledge which is highly non-codified. The R&D derived technological knowledge is shown to drive product differentiation within an industry.[16] To generate comparable results, I also include a full set of fixed effects as in Section 3.1.1., which absorb the product- and industry-level differences in product differentiation in export unit prices. My unreported results show that Rauch (1999) product-level dummies and industry-level knowledge and advertising intensity measures alone have positive effects on export unit prices, providing robust evidence in line with several previous studies on export prices and quality differentiation.

Table 3 reports the results using both Rauch (1999) conservative and liberal classifications of product differentiation, as well as full sample and mass-based products. The differentiation dummy is defined as 1 if the product is classified as differentiated, and 0 otherwise. Columns (1) and (3) show that geographically distant firms set lower unit prices when exporting differentiated products. However, the coefficient is only statistically significant at the 5% level in conservative classification, but is insignificant in liberal classification. Columns (2) and (4) show that geographically distant exporters of mass-based products tend to set lower unit prices when the products are differentiated. Interestingly, unit prices of mass-based products are lowered more significantly than all exported products as a whole. Under the assumption that differentiated goods require costly quality upgrading production processes, these results suggest that export units prices are adversely affected through the quality upgrading channel associated with within-country distance-induced frictions.

[16] Hoberg and Phillips (2016) also find evidence that firm R&D and advertising are associated with subsequent product differentiation from competitors.

Table 3: Unit price, Rauch (1999) product differentiation, and internal distance.

	(1)	(2)	(3)	(4)
	Conservative classification		Liberal classification	
	Full sample	Mass-based	Full sample	Mass-based
	Dependent variable: (ln) Unit price			
Distance to port	−0.0295***	−0.0247***	−0.0346***	−0.0283***
	(−4.19)	(−3.17)	(−4.93)	(−3.67)
Distance to port × Differentiated	−0.0105**	−0.0168***	−0.0040	−0.0120**
	(−1.97)	(−2.90)	(−0.75)	(−2.09)
Average shipment size	0.0896***	0.0687***	0.0896***	0.0687***
	(44.42)	(29.23)	(44.43)	(29.23)
Number of shipments	−0.1096***	−0.0992***	−0.1096***	−0.0992***
	(−36.57)	(−30.23)	(−36.57)	(−30.23)
Number of destinations	−0.0938***	−0.1052***	−0.0937***	−0.1052***
	(−25.58)	(−25.62)	(−25.57)	(−25.62)
Number of products	0.0606***	0.1125***	0.0606***	0.1125***
	(18.63)	(31.51)	(18.61)	(31.51)
Market share	0.0101***	0.0153***	0.0101***	0.0153***
	(5.86)	(7.55)	(5.85)	(7.54)
Productivity	0.0800***	0.1071***	0.0802***	0.1072***
	(6.46)	(7.74)	(6.47)	(7.75)
Output	−0.0178***	−0.0946***	−0.0177***	−0.0946***
	(−3.95)	(−18.11)	(−3.94)	(−18.11)
Wage	0.1622***	0.1341***	0.1621***	0.1341***
	(28.02)	(20.44)	(28.02)	(20.45)
Employment	0.0615***	0.1200***	0.0614***	0.1200***
	(14.29)	(23.60)	(14.29)	(23.60)
Current liabilities	0.0192***	−0.0080**	0.0193***	−0.0080**
	(6.83)	(−2.43)	(6.85)	(−2.42)
Intangible assets	0.0048***	0.0055***	0.0048***	0.0055***
	(6.90)	(6.70)	(6.87)	(6.69)
Foreign ownership	0.0872***	0.0839***	0.0872***	0.0840***
	(14.06)	(11.66)	(14.06)	(11.67)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
Observations	258357	142709	258357	142709
Adjusted R^2	0.794	0.543	0.794	0.543

Table 3 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. Mass-based products are HS8 products with kilograms as the natural unit of measurement. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

The rest of variables preserve the same signs as those reported in Table 2. Lastly, the coefficients on distance to port remain negative and stable in magnitudes, lending support to the negative relationship between export unit prices and internal distances.

Table 4 presents evidence on the relationship between unit prices, product differentiation, and internal distance to complement the findings in Table 3. The same set of fixed effects and controls are included. The industry-level knowledge intensity measures are given by R&D expenditures divided by employment, and the sum of R&D and advertising expenditures divided by employment. Columns (1) and (3) show that geographically distant firms charge lower unit prices when they export knowledge-intensive products. Columns (2) and (4) show similar results, except that the coefficients are slightly larger in magnitudes, indicating that unit prices are more adversely affected in mass-based products when they are exported by geographically distant exporters and more differentiated. Again, all other variables preserve the same signs and fairly stable magnitudes as reported in Table 2.

Taken Tables 3 and 4 together, I find robust evidence that firms charge lower export unit prices when they are geographically distant from the nearest ports and the products are differentiated. Export unit price is decreasing in the interaction term between scope for quality differentiation and internal distance. These findings suggest that within-country transportation costs measured by the internal distance to the nearest port, work jointly with product differentiation to affect price-setting behavior of exporters.

3.3.1.3 Unit price, product rank, and internal distance

In this sub-section, I examine if the relationship between unit prices and internal distance varies across core and non-core products within an exporter. Mayer et al. (2014) develop a multi-product version of MO, and predict theoretically that the price is increasing in competency augmented variable cost.[17] Tougher market competition induces multi-product firms to skew production toward their better performing products which are closer to their core competency. I take a slightly different perspective to study if the better performing products are charged different unit prices if the firms

[17]Mayer et al. (2014) denote the marginal cost for product of rank m produced by a firm whose core ($m = 0$) marginal cost equals c by $v(m, c) = \omega^{-m}c$ with $\omega \in (0, 1)$. When a firm's production is moving away from its core competency, the variable cost increases geometrically.

Table 4: Unit price, industry-level knowledge and advertising intensity, and internal distance.

	(1)	(2)	(3)	(4)
	Full sample	Mass-based	Full sample	Mass-based
	Dependent variable: (ln) Unit price			
Distance to port	−0.0521***	−0.0499***	−0.0406***	−0.0390***
	(−8.26)	(−6.91)	(−6.92)	(−5.70)
Distance to port × RD/employment	−0.0173***	−0.0194***		
	(−8.19)	(−7.62)		
Distance to port × (RD+AD)/employment			−0.0158***	−0.0180***
			(−6.50)	(−6.35)
Average shipment size	0.0895***	0.0688***	0.0895***	0.0688***
	(44.36)	(29.28)	(44.37)	(29.26)
Number of shipments	−0.1097***	−0.0993***	−0.1096***	−0.0992***
	(−36.58)	(−30.25)	(−36.56)	(−30.22)
Number of destinations	−0.0940***	−0.1051***	−0.0940***	−0.1052***
	(−25.64)	(−25.59)	(−25.63)	(−25.62)
Number of products	0.0607***	0.1126***	0.0606***	0.1125***
	(18.67)	(31.55)	(18.64)	(31.53)
Product-destination market share	0.0101***	0.0153***	0.0100***	0.0152***
	(5.85)	(7.51)	(5.83)	(7.48)
Productivity	0.0790***	0.1077***	0.0800***	0.1080***
	(6.39)	(7.81)	(6.46)	(7.83)
Output	−0.0185***	−0.0960***	−0.0181***	−0.0954***
	(−4.12)	(−18.39)	(−4.03)	(−18.27)
Wage	0.1620***	0.1342***	0.1618***	0.1339***
	(28.00)	(20.48)	(27.97)	(20.42)
Employment	0.0622***	0.1217***	0.0619***	0.1211***
	(14.48)	(23.95)	(14.40)	(23.83)
Current liabilities scaled by output	0.0191***	−0.0076**	0.0194***	−0.0074**
	(6.79)	(−2.30)	(6.91)	(−2.26)
Intangible assets scaled by output	0.0047***	0.0054***	0.0048***	0.0054***
	(6.85)	(6.62)	(6.88)	(6.57)
Foreign ownership	0.0868***	0.0832***	0.0868***	0.0828***
	(14.00)	(11.57)	(14.00)	(11.50)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
Observations	258357	142709	258357	142709
Adjusted R^2	0.794	0.543	0.794	0.543

Table 4 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. Mass-based products are HS8 products with kilograms as the natural unit of measurement. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

are geographically distant from their nearest ports. To measure the performance of products within firms, I use the total yearly export sales of that product across all destinations to compute each product's rank. Thus, the product with the highest yearly export sales is regarded as the core product in the multi-product framework of Mayer et al. (2014). There are three distinct measures of product ranks. First, the product rank dummy (Top 2) equals 1 if the product belongs to the top 2 best performing products of a firm, and 0 otherwise. Second, the product rank (HS8 Rank) refers to the within-firm rank of products according to their total yearly export sales across all destinations. Lastly, the distance to the core product (HS8 Dist) is defined in Section 2. Longer distance to the core product means the firm is pulled away further from its core competency in manufacturing the non-core product.

The coefficients of product ranks give expected signs which are consistent with Mayer et al. (2014). Exporting top 2 performing products is associated with a 0.15% decrease in unit prices, while HS8 Rank and HS8 Dist carry positive coefficients because rising competency augmented variable costs are passed onto the higher unit prices. In addition, the interaction terms between internal distances and product rank measures indicate that core products from geographically distant firms are charged higher unit prices than non-core products. The key variables of interests have the same signs and comparable magnitudes in mass-based products.

Table 5 provides an interesting result on asymmetric responses of export unit prices of core and non-core products. Exporters manage to pass larger proportions of internal transportation costs onto unit prices of core products.

3.3.2 High vs. low productivity firms and alternative productivity measures

This section studies if certain productivity groups and alternative productivity measures could possibly overturn the main empirical findings in Section 3.1. Recall that in MO, the marginal cost of production is seen as the inverse of productivity. On the cost aspect of pricing, it is possible that higher productivity firms are more capable to overcome the internal transportation cost, such that the export unit prices are less affected by within-country trade frictions. On the quality differentiation aspect of pricing, it is possible that high productivity (i.e. low marginal cost) firms are more competent to prioritize resources for quality upgrading. The cost and quality differenti-

Table 5: Unit prices, product ranks, and internal distances.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			Mass-based		
	Dependent variable: (ln) Unit price					
Distance to port	-0.0547^{***} (−8.65)	-0.0236^{***} (−4.01)	-0.0223^{***} (−3.52)	-0.0570^{***} (−7.56)	-0.0251^{***} (−3.68)	-0.0205^{***} (−2.86)
Top 2	-0.1491^{***} (−7.63)			-0.2144^{***} (−9.42)		
Distance to port × Top 2	0.0317^{***} (7.36)			0.0371^{***} (7.36)		
HS8 Rank		0.0078^{***} (12.74)			0.0071^{***} (11.21)	
Distance to port × HS8 Rank		-0.0025^{***} (−13.76)			-0.0020^{***} (−9.52)	
HS8 Dist			0.0255^{***} (5.57)			0.0337^{***} (6.71)
Distance to port × HS8 Dist			-0.0055^{***} (−5.52)			-0.0056^{***} (−5.07)
Average shipment size	0.0905^{***} (44.50)	0.0888^{***} (43.59)	0.0901^{***} (44.45)	0.0714^{***} (30.08)	0.0696^{***} (29.29)	0.0705^{***} (29.80)
Number of shipments	-0.1088^{***} (−36.13)	-0.1119^{***} (−37.24)	-0.1092^{***} (−36.17)	-0.0950^{***} (−28.80)	-0.1000^{***} (−30.37)	-0.0957^{***} (−28.93)
Number of destinations	-0.0929^{***} (−25.32)	-0.0936^{***} (−25.55)	-0.0932^{***} (−25.40)	-0.1038^{***} (−25.29)	-0.1043^{***} (−25.42)	-0.1043^{***} (−25.41)
Number of products	0.0568^{***} (16.58)	0.0667^{***} (19.55)	0.0586^{***} (17.22)	0.0986^{***} (26.29)	0.1123^{***} (30.48)	0.1032^{***} (27.41)
Market share	0.0102^{***} (5.94)	0.0093^{***} (5.43)	0.0101^{***} (5.89)	0.0158^{***} (7.77)	0.0145^{***} (7.15)	0.0157^{***} (7.71)
Productivity	0.0808^{***} (6.52)	0.0812^{***} (6.55)	0.0807^{***} (6.52)	0.1082^{***} (7.80)	0.1080^{***} (7.78)	0.1083^{***} (7.81)
Output	-0.0181^{***} (−4.01)	-0.0157^{***} (−3.49)	-0.0180^{***} (−4.01)	-0.0955^{***} (−18.28)	-0.0936^{***} (−17.89)	-0.0954^{***} (−18.25)
Wage	0.1626^{***} (28.11)	0.1612^{***} (27.89)	0.1626^{***} (28.10)	0.1350^{***} (20.58)	0.1334^{***} (20.38)	0.1350^{***} (20.57)
Employment	0.0615^{***} (14.31)	0.0600^{***} (13.94)	0.0616^{***} (14.32)	0.1205^{***} (23.72)	0.1194^{***} (23.46)	0.1206^{***} (23.72)
Current liabilities	0.0192^{***} (6.84)	0.0192^{***} (6.84)	0.0193^{***} (6.87)	-0.0082^{**} (−2.49)	-0.0081^{**} (−2.48)	-0.0080^{**} (−2.43)
Intangible assets	0.0048^{***} (6.86)	0.0046^{***} (6.66)	0.0047^{***} (6.85)	0.0053^{***} (6.49)	0.0052^{***} (6.34)	0.0054^{***} (6.60)
Foreign ownership	0.0875^{***} (14.12)	0.0875^{***} (14.12)	0.0872^{***} (14.07)	0.0841^{***} (11.69)	0.0852^{***} (11.84)	0.0838^{***} (11.65)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	258357	258357	258357	142709	142709	142709
Adjusted R^2	0.794	0.794	0.794	0.544	0.544	0.543

Table 5 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. Mass-based products are HS8 products with kilograms as the natural unit of measurement. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

ation mechanisms point to different predictions on the price-setting behavior of high productivity firms: compared to low productivity firms, internal distance-induced transportation costs lower unit prices, while quality upgrading processes increase unit prices. Thus, the combined effects on unit prices charged by high vs. low productivity firms are ambiguous, and depend on the relative strengths of the cost and quality differentiation forces.

Table 6 presents estimation results of Eq. (1) using both revenue (Columns (1) and (2)) and value added based (Columns (3) and (4)) productivity measures. Columns (1) and (3) columns refer to those firm-product-destination export prices charged by below-median productivity firms, while columns (2) and (4) refer to those charged by above-median productivity firms. There are two main observations: (i) export prices charged by higher productivity firms are less responsive to internal distance, regardless of productivity measures used, and (ii) for above- (below-) median productivity firms, higher productivity is associated with higher (lower) unit prices if revenue based productivity measure is used; unit prices become unresponsive to productivity for below-median productivity firms if value added based productivity measure is used. The former gives a negative correlation between export price and productivity, while the latter gives a positive correlation between export price and marginal cost.[18]

Overall, Table 6 provides new empirical evidence on how export unit prices vary across different productivity groups, and how the firm productivity affects relative strengths of cost and quality differentiation forces, thus the sign of conditional correlation between export prices and firm productivity. Consistent with previous estimations, the internal distance is negatively correlated with the export prices, regardless of productivity groups and measured used.

3.3.3 High vs. low unit prices within and across HS8 products

This section studies if the relationship between export unit prices and internal distance exhibits different empirical patterns across price groups. There are two classifications of unit price groups: (i) within a HS8 product, and (ii) within a HS6 product. In the first classification I compute the median unit price for each HS8 product, above (below) which forms above- (below-) median price groups. Similarly, in the second classification I compute the median unit price within a HS6

[18]Anderson et al. (2019) find a negative association between firm productivity and export prices, while Bastos and Silva (2010b) find a positive association.

Table 6: Unit prices, productivity groups, and internal distances.

	(1)	(2)	(3)	(4)
	Revenue based productivity		Value added based productivity	
	Below median	Above median	Below median	Above median
	Dependent variable: (ln) Unit price			
Distance to port	-0.0446^{***}	-0.0184^{**}	-0.0443^{***}	-0.0310^{***}
	(-4.69)	(-1.96)	(-4.70)	(-3.21)
Revenue based productivity	-0.1014^{***}	0.0800^{***}		
	(-2.83)	(4.39)		
Value added based productivity			0.0021	0.0195^{**}
			(0.57)	(2.15)
Average shipment size	0.0811^{***}	0.0977^{***}	0.0816^{***}	0.0987^{***}
	(27.83)	(34.08)	(27.51)	(34.84)
Number of shipments	-0.0979^{***}	-0.1048^{***}	-0.1007^{***}	-0.1052^{***}
	(-23.05)	(-24.75)	(-23.26)	(-25.23)
Number of destinations	-0.0753^{***}	-0.0961^{***}	-0.0785^{***}	-0.0907^{***}
	(-14.12)	(-16.00)	(-14.92)	(-14.73)
Number of products	0.0542^{***}	0.0629^{***}	0.0643^{***}	0.0486^{***}
	(11.22)	(11.48)	(13.48)	(8.67)
Product-destination market share	0.0114^{***}	0.0090^{***}	0.0108^{***}	0.0087^{***}
	(4.66)	(3.75)	(4.33)	(3.67)
Output	-0.0086	0.0063	-0.0495^{***}	0.0092
	(-1.06)	(0.91)	(-6.67)	(1.14)
Wage	0.1672^{***}	0.1316^{***}	0.1753^{***}	0.1336^{***}
	(16.34)	(15.32)	(18.19)	(15.17)
Employment	0.0581^{***}	0.0450^{***}	0.0859^{***}	0.0393^{***}
	(7.43)	(7.05)	(12.18)	(5.71)
Current liabilities scaled by output	0.0150^{***}	0.0270^{***}	0.0166^{***}	0.0278^{***}
	(3.69)	(5.44)	(4.03)	(5.54)
Intangible assets scaled by output	0.0023^{**}	0.0054^{***}	0.0027^{***}	0.0073^{***}
	(2.22)	(4.65)	(2.62)	(6.21)
Foreign ownership	0.0760^{***}	0.0825^{***}	0.0855^{***}	0.0795^{***}
	(8.14)	(8.26)	(9.22)	(7.90)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
Observations	127739	128094	127604	128218
Adjusted R^2	0.786	0.821	0.788	0.820

Table 6 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. The baseline sample is divided into two (above- and below-median) sub-samples by revenue and value added based productivity measures. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

product, and define the corresponding price groups. Columns (1) and (2) report results using within HS8 price groups. It is observed that unit prices of above-median price group are less sensitive to internal distance, average shipment size, and firm size measured in number of employees than the below-median counterparts. More strikingly, a few variables including number of shipments, number of products, productivity, firm output, and current liabilities change signs and foreign ownership dummy is significantly more positively correlated with unit prices in above-median price group than in below-median price group. If export price is a good proxy for product quality, these results show that higher quality products are less adversely affected by the within-country trade frictions, and the chosen levels of quality are increasing with firm productivity only in above-median price group. It indicates that quality upgrading is more concentrated in higher quality products, and the quality differentiation is minimal in lower quality products. Not surprisingly, output and wage show stronger positive relationship with unit prices in above-median price group, indicating that larger firms equipped with skilled workers are more able to export products with greater scope for product differentiation. Finally, the negative association between unit prices and internal distance remains robust and is not overturned by different classifications of price groups.

In summary, Table 7 presents strong evidence that higher quality products are less adversely affected by within-country trade frictions, and that the export prices of higher quality products are positively correlated with firm productivity.

3.3.4 Additional results and further discussion

Relative price. I construct the relative price, for each firm-product-destination, the ratio of export unit price to within HS8 average unit price (Columns (1) and (2)), as well as the corresponding relative price but as a ratio to within HS6 average unit price (Columns (3) and (4)).[19] Both serve as alternative measures of export unit price. The advantage of using relative prices is to compare products within narrowly defined categories, mitigating the concern of small intrinsic differences in cost and quality across products. I present the results in Table 8 of Supplementary Appendix. The relative prices are negatively related to the internal distance, and their coefficients preserve

[19] Manova and Zhang (2012) indicate that product classification is consistent across destinations at the HS 6-digit level.

Table 7: Unit price, price groups within HS8 and HS6 products, and internal distance.

	(1)	(2)	(3)	(4)
	Within HS8 unit prices		Within HS6 unit prices	
	Below median	Above median	Below median	Above median
	Dependent variable: (ln) Unit price			
Distance to port	−0.0166***	−0.0109*	−0.0193***	−0.0094
	(−3.14)	(−1.75)	(−3.65)	(−1.52)
Average shipment size	0.0751***	0.0152***	0.0741***	0.0165***
	(41.45)	(7.29)	(40.71)	(7.89)
Number of shipments	0.0085***	−0.1228***	0.0070***	−0.1219***
	(3.39)	(−38.11)	(2.79)	(−37.78)
Number of destinations	0.0295***	−0.1234***	0.0279***	−0.1185***
	(9.43)	(−30.76)	(8.90)	(−29.66)
Number of products	−0.0010	0.0405***	0.0016	0.0387***
	(−0.36)	(11.63)	(0.57)	(11.10)
Product-destination market share	0.0059***	0.0066***	0.0066***	0.0069***
	(3.74)	(3.77)	(4.18)	(3.97)
Productivity	−0.0009	0.0620***	−0.0052	0.0525***
	(−0.08)	(4.75)	(−0.51)	(4.04)
Output	−0.0201***	0.0216***	−0.0193***	0.0240***
	(−5.07)	(4.51)	(−4.87)	(5.04)
Wage	0.0456***	0.0811***	0.0441***	0.0803***
	(9.19)	(12.90)	(8.84)	(12.80)
Employment	0.0293***	0.0104**	0.0293***	0.0099**
	(7.56)	(2.31)	(7.56)	(2.20)
Current liabilities scaled by output	−0.0078***	0.0237***	−0.0085***	0.0228***
	(−3.22)	(7.81)	(−3.47)	(7.43)
Intangible assets scaled by output	0.0020***	0.0030***	0.0022***	0.0033***
	(3.21)	(4.13)	(3.51)	(4.56)
Foreign ownership	0.0046	0.0741***	0.0023	0.0786***
	(0.82)	(11.57)	(0.41)	(12.30)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*Y*	*Y*
Observations	128492	126814	128314	127109
Adjusted R^2	0.909	0.890	0.907	0.890

Table 7 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. The baseline sample is divided into two (above- and below-median) sub-samples by HS8 and HS6 product unit prices. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust *t*-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

the negative signs and stable magnitudes. Similarly, the relative prices are positively related to firm productivity.

Alternative productivity measure. With Stata command *levpet* developed by Petrin et al. (2004), I construct the value added based Levinsohn and Petrin (2003) estimator of productivity. I perform the same estimation as in Table 2 using both unit price and relative price, and present the results in Table 9 of Supplementary Appendix. All variables preserve the same signs and statistical significance. Both price measures are negatively related to internal distance, and positively related to firm productivity. While the coefficients of firm productivity appear somewhat smaller than Table 2, it is noted that the mean of value added based productivity is greater than that of revenue based productivity (4.34 vs. 1.47) in baseline sample. Hence, the differences in conditional correlations between these two productivity measures are minimal, lending strong support to the previously documented empirical patterns this section. Overall, all the main empirical findings remain intact.

3.4 Theoretical Framework

In this section, I propose a simple Melitz and Ottaviano (2008) heterogeneous firm trade model (hereafter abbreviated as MO) with endogenous quality choice and an explicit spatial structure of the exporting country. The consumer preferences for quality allows for firms' quality differentiation, and the spatial structure allows for location-specific heterogeneity in both iceberg transportation costs and costs of innovation or quality enhancing of products. Consider a world economy with two countries, Home (H) and Foreign (F), each producing and consuming both a homogeneous good sold on perfectly competitive markets and manufactured goods sold on monopolistically competitive markets. The manufactured good is both horizontally and vertically differentiated in a continuum of varieties indexed by $i \in \Omega$. For simplicity, I focus on Home exporters exporting to Foreign consumers, and do not explicitly model Home exporters serving domestic markets.

3.4.1 Consumption

Following Antoniades (2015), I introduce a quality dimension into the standard MO model. The consumer preferences are expressed as:

$$U = q_0^c + \alpha \int_{i \in \Omega} q_i^c di + \beta \int_{i \in \Omega} z_i q_i^c di - \frac{1}{2}\gamma \int_{i \in \Omega} (q_i^c)^2 \, di - \frac{1}{2}\eta \left\{ \int_{i \in \Omega} q_i^c di \right\}^2, \tag{2}$$

where q_0^c and q_i^c refer to the consumption of the homogeneous (numeraire) good and each variety i of the differentiated manufactured goods, respectively. Consumers value the quality of a variety z_i and the demand is increasing in quality. When all firms choose zero quality for each variety, i.e. $z_i = 0$, then Eq. (2) is reduced to the standard MO consumption preferences. The parameters α and η capture the degree of substitution between the homogeneous good and each variety of the differentiated goods, and the parameter γ captures the degree of differentiation among varieties, respectively. The taste parameter β determines how consumers value quality of varieties, which could vary across countries and/or industries. All these parameters are assumed to be positive.

The inverse demand for each variety can be written as:

$$p_i = \alpha - \gamma q_i^c + \beta z_i - \eta Q^c, \tag{3}$$

where $Q^c = \int_{i \in \Omega} (q_i^c) \, di$. The inverse demand is a function of quantity of variety i, consumption of differentiated good, and parameters. Inverting Eq. (3) gives the linear demand for each variety of the manufactured goods in a country of market size L:

$$q_i = L q_i^c = \frac{\alpha L}{\eta N + \gamma} - \frac{L}{\gamma} p_i + \frac{L\beta}{\gamma} z_i + \frac{\eta N L}{\eta N + \gamma} \bar{p} - \frac{\eta N L \beta}{\eta N + \gamma} \bar{z}, \tag{4}$$

where N is the number of varieties consumed in the market, $\bar{p} = \frac{1}{N} \int_{i \in \Omega^*} p_i di$ is the average price, $\bar{z} = \frac{1}{N} \int_{i \in \Omega^*} z_i di$ is the average quality, and $\Omega^* \subset \Omega$ indicates the subset of varieties consumed in the market. Similarly, when quality differentiation dimension is absent (by setting $z_i = 0 = \bar{z}$), Eq. (4) is reduced to the original MO demand system. A key feature is that the resulting demand for variety i is linear in price and quality. There exists a choke price p_i^{max} that is the highest possible price that firms can charge while the demand remains positive. Setting demand $q_i = 0$, the choke price p^{max} is then:

$$p_i < \frac{1}{\eta N + \gamma} \left[\alpha\gamma + (\eta N + \gamma) \beta z_i + \eta N \gamma \bar{p} - \eta N \beta \gamma \bar{z} \right] \equiv p_i^{max}, \tag{5}$$

where p_i is the unit price of variety i characterized by quality level z_i, exclusive of delivery cost.

3.4.2 Spatial structure of exporting country

I incorporate Coşar and Fajgelbaum (2016) internal geography framework into the model, in order to generate spatial heterogeneity in transportation costs and fixed costs of quality upgrading. The exporting country consists of a set of firm locations arbitrarily arranged on a map. Assume that only some of these locations are equipped with trade infrastructure that can trade directly with the rest of the world. I index locations by l, and assume without loss of generality that l represents the geographical distance separating each location l and its nearest port, and denote all ports by $l = 0$. All goods must pass through a domestic port before getting shipped to a foreign destination. Given this spatial structure, a location indexed $l = 0$ can be interpreted as a seaport, airport, or location equipped with technology for international trade for firms in each location l. Let the maximum distance separating a location within an exporting country and its nearest port be $\bar{l}$. Firms take this internal distance l into the export entry decisions (via transportation costs), as well as optimal quality upgrading decisions (via a change in scope for quality differentiation). Firms pay location- and destination-specific iceberg transportation costs to ship their goods first from location $l \geq 0$ to location $l = 0$ (i.e. the nearest port), and subsequently from location $l = 0$ to a foreign market.[20] The transportation costs are multiplicative and given by: $t_{lF} = t_l t_{HF} > 1$, such that t_{lF} units of goods must be shipped from location $l \geq 0$ for each unit goods to arrive in a foreign market F. Assume the standard iceberg external (cross-country) transportation costs $t_{HF} > 1$, the internal (within-country) transportation costs $t_l \geq 1$, and that $t_l^{'}(l) > 0$, $t_l^{''}(l) \geq 0$, with $t_l(0) = 1$.

3.4.3 Production

Both the homogeneous and manufactured goods are produced with labor as the only factor of production. Labor is inelastically supplied in a competitive market. While the homogeneous good is produced under constant returns to scale using one unit of labor per unit of output at unit cost, the manufactured good is produced under increasing returns to scale.

[20]While Bellone et al. (2016) consider local areas segmented by infra-national iceberg costs, they assume that all domestic firms share the same cost of delivering goods to a foreign market regardless of their within-country locations.

3.4.3.1 Hallak and Sivadasan (2013) process and product productivity

A firm needs to pay a fixed cost of entry, f_E, to enter local market, and then it will draw a process productivity parameter which determines its marginal cost c, and a product productivity which determines its incremental marginal cost relative to the core variety ξ to maintain the same level of quality. Following Hallak and Sivadasan (2013), both are drawn from a bivariate distribution $v(c, \xi)$ with support on $[0, \bar{c}] \times \left[0, \bar{\xi}\right]$. The process productivity (or simply "productivity") is the ability of a firm to produce a unit of output at lower variable cost, while the product productivity captures the differences in marginal costs of different varieties to achieve a specific level of quality within a firm, and is assumed to be increasing with the distance to the core variety. For each firm, I index by m the variety produced in an ascending order of distance from the firm's core variety, $m = 0$. A firm moving away from the core variety suffers from lower product productivity to maintain the same quality or product appeal given the same level of investment for quality upgrading. I assume that $\xi(m) > 0$, $\xi_m > 0$, $\xi_{mm} > 0$. Intuitively, it involves additional costs of quality upgrading and implementing quality control systems to minimize item defects when a variety whose required production technology is out of the firm's depth.

3.4.3.2 Fixed cost of quality upgrading

In addition, firms pay product- and location-specific fixed cost of quality upgrading, which is increasing in internal distance, but invariant to output. This is intuitive: quality upgrading comes from innovation which requires specific upfront investment in acquisition of technological knowledge and industrial equipment that customize outputs to satisfy the demand from Foreign consumers. Firms further away from international port facilities have poorer access to agents that have adopted the innovation technology and imported industrial equipment that improve quality or product appeal to Foreign consumers. A recent study, Xiao et al. (2021), find that inventor-firm spatial proximity improves the inventor productivity.[21,22] In addition, the fixed cost of quality upgrading

[21] This assumption also mirrors Comin et al. (2013) that "even when a technology has arrived in a country, it takes years and even decades before it has diffused to the point of having a significant impact on productivity".

[22] An alternative way to model the cost of quality upgrading is to follow Stokey (2020) and assume cost of technological adoption is decreasing in penetration rate, i.e. the share of producers using the same technology within a region. The intuition is that producers can learn to adopt new technologies through direct communication between firm managers or by poaching the workers of earlier adopters. Due to data limitations on technological adoption, I

is also assumed to be increasing and convex to the level of quality.[23] The higher knowledge intensity of the production, the higher fixed cost of quality upgrading the firms face. In other words, it takes a higher cost to upgrade an output of quality z to $z + \triangle z$ in an industry with higher knowledge intensity.[24] Intuitively, the search cost for appropriate skilled labor, industrial equipment, imported materials, and technological knowledge is increasing in the knowledge intensity of outputs. Denote the industry-level knowledge intensity by ϕ with $\phi \geq 0$. The product- and location-specific fixed cost of quality upgrading is expressed as: $\theta\left(l, \phi\right) z^2$, and assumed to have the following properties: $\theta > 0$, $\theta_l > 0$, $\theta_{ll} \geq 0$, $\theta_\phi > 0$, $\theta_{\phi\phi} \geq 0$, $\theta_{l\phi} = \theta_{\phi l} > 0$, and $\theta\left(l, 0\right) = 0 = \theta\left(0, \phi\right)$. Overall, these assumptions are major departures from (i) Antoniades (2015) and Bellone et al. (2016) which use a simplifying assumption that θ is common to all firms operating in the same exporting country and all products produced within a firm; and (ii) all studies which use a single dimension of process productivity that cannot account for differences in unit prices for core and non-core varieties conditioning on internal distance and process productivity.

3.4.3.3 Total cost function

Firms maximize profits by taking, for each destination country, the number of competitors N, the average price $\bar{p}$, and the average level of quality $\bar{z}$ as given. Firms also choose the optimal level of quality for each destination country. The cost function of a firm characterized by process productivity c_i and product productivity ξ_i with quality level z_i is given by:

$$TC_i = c_i q_i + \xi_i\left(m\right) z_i q_i + \theta\left(l, \phi\right) z_i^2. \tag{6}$$

The first term is identical to MO and captures the variable cost of production. The second term accounts for the differences in marginal costs in achieving a specific level of quality for each unit of

simplify the idea by assuming that the fixed cost of innovation is decreasing in internal distance. The intuition is similar: firm managers can acquire technological knowledge in quality upgrading from other agents at the transportation hubs.

[23] Antoniades (2015) interprets this country- and industry-specific parameter θ (as a part of fixed cost of quality upgrading) as the cost of innovation (inverse of ability to innovate). The cost of innovation is low when the ability of a country is high.

[24] It is consistent with Keller and Yeaple (2013) who predict that the average knowledge intensity of trade between countries is increasing in distance between them (see Section D). I further generalize this idea to take the overall trade frictions (combined within-country and cross-country distances) into consideration. The main point is that firms face stronger distance-induced frictions to establish import-export relationships, more so when the production of variety in an industry involves sophisticated and knowledge-intensive inputs.

between core and non-core varieties. The third term captures the fixed cost of quality upgrading that does not vary with output. The parameter θ captures variety- and location-specific differences in the ability to innovate.

3.4.4 Performance measures

Let c_X be the marginal cost cut-off between the firms that export to a foreign market ($c < c_X$) and the firms that do not export ($c \geq c_X$). The firm with marginal cost c_X earns zero profits and its demand $q(c_X)$ is driven to 0. The cut-off rule is given by:

$$c_X = sup\left\{c : \pi_{lF} > 0\right\} = \frac{p_F^{max}}{t_{lF}}, \tag{7}$$

where π_{lF} refers to the profit of a firm characterized with process productivity c, product productivity ξ and quality level z at location l exporting to a foreign market, and p_F^{max} refers to the choke price for a foreign market defined similarly as in Eq. (5). Clearly, geographically distant firms characterized by high t_{lF} need higher productivity (i.e. lower marginal cost) draws to start exporting to a foreign market. The subscript for firm i is omitted for notational simplicity. I express all performance measures, price p, quantity q, markup μ, and profit π, as functions of marginal cost c, export cut-off c_X, and level of quality z:

$$p(c,z) = \frac{1}{2}t_{lF}(c_X + c) + \frac{1}{2}(\beta + \xi(m))z; \tag{8}$$

$$q(c,z) = \frac{L}{2\gamma}t_{lF}(c_X - c) + \frac{L}{2\gamma}(\beta - \xi(m))z; \tag{9}$$

$$\mu(c,z) = \frac{1}{2}t_{lF}(c_X - c) + \frac{1}{2}(\beta - \xi(m))z; \tag{10}$$

$$\pi(c,z) = \frac{L}{4\gamma}\left[t_{lF}(c_X - c) + (\beta - \xi(m))z\right]^2 - \theta(l,\phi)z^2, \tag{11}$$

where L is the market size.

Optimal level of quality. The firm chooses the optimal quality by maximizing the profit function Eq. (11). The optimal quality z^* is:

$$z^* = t_{lF}\lambda(c_X - c), \tag{12}$$

where $\lambda = \frac{L(\beta - \xi(m))}{4\theta(l,\phi)\gamma - L(\beta - \xi(m))^2}$ is the scope for quality differentiation. To ensure positive levels of quality z, I assume that $\lambda > 0$ or equivalently $\beta > \xi(m)$ and $4\theta(l,\phi)\gamma > L(\beta - \xi(m))^2$. The optimal level of quality is increasing in (i) transportation cost t_{lF}, (ii) scope for quality differentiation λ, (iii) the difference between export cut-off c_X and marginal cost c. The scope for quality differentiation λ is increasing in market size L, the taste parameter for quality β, but decreasing in incremental marginal cost of quality upgrading ξ (which in turn increases as index of variety m increases), degree of substitutability among varieties γ, and the cost of innovation θ (which in turn increases with internal distance l and knowledge intensity ϕ). By construction, a geographically distant firm characterized by high l optimally chooses a lower level of quality z through a lower λ; the quality z is even lower when it participates in production of knowledge-intensive (i.e. high ϕ) outputs. Intuitively, it is harder to recoup the higher fixed cost of innovation driven by geographical disadvantages and high knowledge intensity of products, thus firms optimally choose lower levels of quality to serve a foreign market. I re-write Eqs. (8) to (11) by substituting the optimal quality z^* from Eq. (12), which are given by:

$$p = \frac{1}{2}t_{lF}(c_X + c) + \frac{1}{2}(\beta + \xi)t_{lF}\lambda(c_X - c); \tag{13}$$

$$q = \frac{L}{2\gamma}t_{lF}(1 + (\beta - \xi)\lambda)(c_X - c); \tag{14}$$

$$\mu = \frac{1}{2}t_{lF}(1 + (\beta - \xi)\lambda)(c_X - c); \tag{15}$$

$$\pi = \frac{L}{4\gamma}t_{lF}^2(1 + (\beta - \xi)\lambda)(c_X - c)^2. \tag{16}$$

In this modified setting with endogenous quality upgrading and spatial heterogeneity in cost of innovation, the internal distance to the nearest port drives down the scope for quality differentiation to serve a foreign market, and the effect is more significant when the exporters produce knowledge-intensive varieties or the varieties are further away from their own core competencies. These determinants of scope for quality differentiation differ across varieties, firms, and industries. The product productivity term operates through two channels: (i) the incremental cost of achieving a specific level of quality increases the unit price of a non-core variety, more so if the variety is further away from the firm's core competency, and (ii) the incremental cost drives down the scope for quality differentiation because the marginal cost of increasing the quality of a non-core variety is higher. Lastly, Eq. (13) represents the delivered cost-insurance-freight (c.i.f.) price of a firm characterized by inverse of process productivity c, inverse of product productivity $\xi(m)$, location l, knowledge intensity ϕ shipped to a foreign market. The corresponding free-on-board (f.o.b.) price is:

$$p_{fob} = \frac{1}{2}(c_X + c) + \frac{1}{2}(\beta + \xi)\lambda(c_X - c). \tag{17}$$

Other than the characteristics of importing countries, e.g. market size L and geographical distance from China, that are well documented, Eq. (17) sheds light on how geographical proximity to trade infrastructure, product differentiation and knowledge components of varieties, and distance to the core variety play a crucial role in price-setting behavior of firms through the change in scope for quality differentiation.

3.4.5 Linking theory and empirical evidence

In Section 3, I present empirical findings on the relationship between export prices, internal distance, industry characteristics, and non-core varieties of varying distances to a firm's core competency. This section is a summary of how the model can explain the fact that unit prices are negatively related with the internal distance, as well as rich empirical patterns including the effects of industry characteristics and multi-variety strategies on export prices.

Absorption of domestic transportation costs vs. quality differentiation. Practically speaking, it is hard to distinguish whether the negative correlations between export prices and internal distance are caused by geographically distant firms absorbing part of the domestic transportation costs, or by optimally choosing lower levels of quality.[25] Therefore, the focus of this paper is not to identify the mechanism(s) on how internal distance affects the export prices, but to build a channel how internal distance and quality differentiation or upgrading jointly affect the

[25] According to the Incoterms (also known as the International Commercial Terms) standard published by the International Chamber of Commerce, the free-on-board (f.o.b.) prices mean that the seller pays for transportation of goods to the port of shipment and loading costs. Once the goods have been loaded on board, risk transfers to the buyer who bears all costs thereafter. In theory, the f.o.b. definition does not rule out the possibility that firms could absorb part of the domestic transportation costs because of their locational disadvantages. The f.o.b. prices exclude international transportation costs, insurance costs, and customs duties. See Görg et al. (2010) for their discussions.

export prices. I follow Hallak and Sivadasan (2013) to introduce a quality iceberg transportation cost which assumes the standard iceberg cost is decreasing in quality of a variety. It can be written as: $t^{'}(z) < 0$. Intuitively, in the presence of per-unit charges, transportation costs share a smaller proportion of export prices for higher quality varieties. If the investment in quality differentiation of upgrading improves the quality of a variety, and that exporters tend to absorb internal transportation costs, then the interaction terms of internal distance and differentiated dummy or knowledge intensity should give positive coefficients because given the same internal distance, higher quality varieties are less sensitive to the quality iceberg transportation costs. The negative coefficients of these interaction terms in Section 3 indicate that longer internal distance plays a role in the quality adjustment with a narrower scope for quality differentiation.

Internal distance, product differentiation and knowledge intensity. Longer internal distance to the nearest port hurts the firm's ability to innovate or in the technology of innovation. Firms further away from ports could face more within-country frictions to search for appropriate skilled labor, industrial equipment, imported materials and technological knowledge. The implication is that geographically disadvantaged firms optimally choose lower levels of quality and charge lower unit prices, via a decrease in scope for quality differentiation λ. Building on the search cost explanation, firms incur higher fixed cost of quality upgrading if they produce highly differentiated and knowledge-intensive varieties. Firms are typically less effective in generating and implementing innovation for highly differentiated and knowledge-intensive varieties, due to the fact that these varieties require specific inputs and technological knowledge which a few producers manage to rapidly translate quality innovation into a distinguished variety. This is modelled by an increase by an increase in $\theta(l, \phi)$ with the assumption that $\theta_{l\phi} = \theta_{\phi l} > 0$. Geographically disadvantaged firms sort themselves into producing lower quality varieties because it is harder to recoup the fixed cost of quality upgrading.

Core and non-core varieties. When a firm produces a variety further away from its core competency, it faces a higher incremental cost of quality upgrading $\xi(m)$, where $m = 0$ refers to the core variety and m increases when a variety moves away from a firm's core competency. Intuitively, the quality upgrading is more costly when a variety whose required production technology is out of the firm's expertise. This marginal cost of quality upgrading operates through two channels in price-setting. First, the firm passes the marginal cost of quality upgrading on to the consumers, leading to higher unit prices. Second, the higher cost of quality upgrading for a non-core variety also drives down the scope for quality differentiation compared to the core variety within the same firm. Overall, the empirical findings are in favor of the dominance of cost-price channel.

Relationship between (process) productivity and export prices. Consistent with Khandelwal (2010) and Anderson et al. (2019), when the scope for quality differentiation is high (low), which satisfies $1 < (>) \, (\beta + \xi) \, \lambda$, then export prices serve as a good (poor) proxy for quality and the quality ladders are long (short). While the baseline estimation in Table 2 shows strong positive correlations between process productivity and export prices, it is also observed that the correlations from below-median price groups are either negative or close-to-zero, depending on productivity measures. Here, the below-median price groups potentially include those products and/or industries that have limited scope for quality differentiation, hence the markups do not rise as fast to offset their lower marginal costs.

3.5 Conclusion

I document rich empirical patterns about the relationship between within-country trade frictions, export prices of narrowly defined product categories, and a large set of firm-product characteristics. These results contribute to a new line of research on economic geography and price-setting behavior of exporters. I construct a geospatial firm-product dataset of the universe of Chinese manufacturing exporters in 2006, and find systematic variation in export unit prices across firms and products. There are several key empirical findings: (a) exporters charge lower unit prices when they are geographically distant from the nearest port facility; (b) geographically distant exporters charge lower unit prices for differentiated, knowledge intensive, and non-core products; (c) high productivity exporters charge higher unit prices, and their unit prices are less affected by the internal distance; and (d) products with high unit prices are less significantly affected by the internal distance, both within and across HS8 products. I propose a simple quality augmented MO framework with an explicit spatial structure of the exporting country and the distinction between process and product productivity to explain these empirical findings. The theoretical framework generates marginal cost and quality differentiation effects, which act as two opposing forces on export prices. In addition to the standard marginal cost effect, exporters of varying geographical proximity to port facilities sort themselves into different levels of quality differentiation, which is determined by (i) internal distance; (ii) knowledge intensity; and (iii) distance to the core variety. Both internal distance and knowledge intensity increase the cost of quality upgrading, and that the distance to the core variety lowers product productivity. Exporters optimally adjust their scope for quality differentiation by taking these firm-product characteristics into consideration.

The cost of quality upgrading or innovation does not necessarily have a monotonic relationship with internal distance. In fact, previous studies make different assumptions on the cost of innovation. Most notably, Comin et al. (2013) assume the probability of technology adoption depends positively on the fraction of agents who have adopted it before, and a parameter which governs the frequency of meetings of these agents. Desmet and Rossi-Hansberg (2014) assume a location's technology depends positively on other locations' technology but negatively on the distance between these locations. Stokey (2020) assumes the cost of technological adoption depends positively on the share of producers or industry capacity that has already adopted the new technology. Therefore, the geographic patterns in export prices could be driven by density of producers possessing the common technological knowledge and equipment for quality upgrading. Due to data limitations on firm-level technological adoption, I leave it for further scrutiny in future research.

Appendix to Chapter 3

Spatial Frictions, Quality Differentiation, and Export Prices

Table 8: Relative price and internal distance.

	(1)	(2)	(3)	(4)
	Within HS8 products		Within HS6 products	
	Full sample	Mass-based	Full sample	Mass-based
	Dependent variable: (ln) Relative price			
Distance to port	−0.0307***	−0.0334***	−0.0293***	−0.0356***
	(−5.15)	(−4.96)	(−4.82)	(−5.25)
Average shipment size	0.0838***	0.0789***	0.0854***	0.0776***
	(45.55)	(36.67)	(45.37)	(35.74)
Number of shipments	−0.0730***	−0.0739***	−0.0847***	−0.0787***
	(−24.54)	(−23.12)	(−27.77)	(−24.28)
Number of destinations	−0.0822***	−0.0877***	−0.0866***	−0.0906***
	(−22.54)	(−22.12)	(−23.36)	(−22.74)
Number of products	0.0477***	0.0870***	0.0553***	0.0867***
	(15.42)	(26.40)	(17.55)	(26.03)
Product-destination market share	−0.0163***	−0.0086***	−0.0097***	−0.0052***
	(−11.63)	(−5.27)	(−6.77)	(−3.17)
Productivity	0.0674***	0.1056***	0.0702***	0.1104***
	(5.29)	(8.06)	(5.39)	(8.27)
Output	−0.0282***	−0.0921***	−0.0249***	−0.0958***
	(−6.33)	(−18.78)	(−5.48)	(−19.33)
Wage	0.1481***	0.1267***	0.1489***	0.1284***
	(25.18)	(19.91)	(24.80)	(20.05)
Employment	0.0670***	0.1142***	0.0658***	0.1212***
	(15.59)	(23.50)	(15.03)	(24.71)
Current liabilities scaled by output	0.0096***	−0.0116***	0.0122***	−0.0101***
	(3.37)	(−3.56)	(4.18)	(−3.08)
Intangible assets scaled by output	0.0039***	0.0043***	0.0042***	0.0041***
	(5.51)	(5.38)	(5.85)	(5.05)
Foreign ownership	0.0834***	0.0767***	0.0866***	0.0752***
	(13.02)	(10.69)	(13.26)	(10.37)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Observations	259037	143197	259037	143197
Adjusted R^2	0.147	0.166	0.157	0.175

Table 8 presents OLS estimation of Eq. (1). The dependent variables are the natural logarithm of the ratios of export unit price to within HS8 and HS6 average unit prices, respectively. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using revenue based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust t-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 9: Unit price, value added based productivity and internal distance.

	(1)	(2)	(3)	(4)
	Dependent variable:			
	(ln) Unit price		(ln) Relative price	
	Full sample	Mass-based	Full sample	Mass-based
Distance to port	−0.0369***	−0.0353***	−0.0301***	−0.0329***
	(−6.34)	(−5.20)	(−5.06)	(−4.88)
Average shipment size	0.0896***	0.0688***	0.0837***	0.0789***
	(44.40)	(29.25)	(45.53)	(36.64)
Number of shipments	−0.1095***	−0.0989***	−0.0729***	−0.0736***
	(−36.52)	(−30.11)	(−24.50)	(−23.03)
Number of destinations	−0.0940***	−0.1059***	−0.0825***	−0.0883***
	(−25.64)	(−25.80)	(−22.61)	(−22.28)
Number of products	0.0611***	0.1133***	0.0480***	0.0876***
	(18.76)	(31.73)	(15.54)	(26.57)
Product-destination market share	0.0101***	0.0152***	−0.0163***	−0.0086***
	(5.84)	(7.49)	(−11.61)	(−5.26)
Productivity	0.0124***	0.0225***	0.0095***	0.0204***
	(4.56)	(7.67)	(3.49)	(7.26)
Output	−0.0145***	−0.0941***	−0.0249***	−0.0905***
	(−3.17)	(−18.05)	(−5.50)	(−18.45)
Wage	0.1636***	0.1361***	0.1493***	0.1283***
	(28.30)	(20.74)	(25.40)	(20.14)
Employment	0.0571***	0.1153***	0.0632***	0.1093***
	(13.49)	(23.15)	(14.94)	(22.93)
Current liabilities scaled by output	0.0195***	−0.0062*	0.0096***	−0.0103***
	(6.87)	(−1.87)	(3.34)	(−3.15)
Intangible assets scaled by output	0.0048***	0.0056***	0.0039***	0.0044***
	(6.88)	(6.88)	(5.48)	(5.51)
Foreign ownership	0.0875***	0.0856***	0.0834***	0.0780***
	(14.11)	(11.89)	(13.03)	(10.87)
HS2-Destination FE	*Y*	*Y*	*Y*	*Y*
Port FE	*Y*	*Y*	*Y*	*Y*
County FE	*Y*	*Y*	*Y*	*Y*
Industry FE	*Y*	*Y*	*Y*	*Y*
Product FE	*Y*	*Y*	*N*	*N*
Observations	258357	142709	259037	143197
Adjusted R^2	0.794	0.543	0.147	0.166

Table 9 presents OLS estimation of Eq. (1). The dependent variable is the natural logarithm of export unit price by firm, HS8 product and destination country in 2006. Mass-based products are HS8 products with kilograms as the natural unit of measurement. All independent variables are in natural logarithm except the foreign ownership dummy. Distance to port is the internal distance separating a firm and its nearest port listed in National Ports Layout Plan 2006. Average shipment size is the average dollar value of shipments at the firm-product-destination level. A single shipment is defined as an export transaction. Number of destinations and number of products exported are computed at the firm level. Firm-level productivity is computed using value added based Levinsohn and Petrin (2003) estimator. See Petrin et al. (2004) for details. Product-destination market share is calculated as the ratio of a firm's export sales in a product-destination to the total sales of all firms in the same product-destination. Wage, current liabilities, and intangible assets are scaled by the firm's output. Foreign ownership dummy equals 1 if 50% or more of the capital was provided by foreign entities, and 0 otherwise. Robust *t*-statistics are reported in parenthesis. ***, **, * represent significance levels at 1%, 5%, and 10%, respectively.

Table 10: List of all sample ports.

Port Name	Cluster	Port Name	Cluster
Cangzhou-Huanghua Port	Bohai Economic Rim	Fuzhou Port	Southeast Coastal Area
Dalian Port	Bohai Economic Rim	Ningde Port	Southeast Coastal Area
Dandong Port	Bohai Economic Rim	Putian Port	Southeast Coastal Area
Jinzhou Port	Bohai Economic Rim	Quanzhou Port	Southeast Coastal Area
Qingdao Port	Bohai Economic Rim	Xiamen Port	Southeast Coastal Area
Qinhuangdao Port	Bohai Economic Rim	Zhangzhou Port	Southeast Coastal Area
Rizhao Port	Bohai Economic Rim	Basuo Port	Southwest Coastal Area
Tangshan-Jingtang Port	Bohai Economic Rim	Fangcheng Port	Southwest Coastal Area
Tianjin Port	Bohai Economic Rim	Haikou Port	Southwest Coastal Area
Yantai Port	Bohai Economic Rim	Sanya Port	Southwest Coastal Area
Yingkou Port	Bohai Economic Rim	Zhanjiang Port	Southwest Coastal Area
Dongguan Port	Pearl River Delta	Lianyungang Port	Yangtze River Delta
Guangzhou Port	Pearl River Delta	Nanjing Port	Yangtze River Delta
Huizhou Port	Pearl River Delta	Nantong Port	Yangtze River Delta
Shantou Port	Pearl River Delta	Ningbo-Zhoushan Port	Yangtze River Delta
Shenzhen Port	Pearl River Delta	Shanghai Port	Yangtze River Delta
Zhongshan Port	Pearl River Delta	Suzhou Port	Yangtze River Delta
Zhuhai Port	Pearl River Delta	Zhenjiang Port	Yangtze River Delta

Source: National Ports Layout Plan 2006, China's Ministry of Transport.

Conclusion

The thesis builds a complete and coherent picture on the role of within-country spatial frictions in multiple dimensions of export behavior. While economic geography is primarily concerned with geographical characteristics between exporting and importing countries, internal geographical characteristics, e.g., domestic spatial networks among firms, and geographical distance to the nearest trade infrastructure, are relatively under-explored. This thesis aims to fill the gap in the literature on economic geography and international trade.

The first chapter develops a Bayesian learning model to formalize the relationship between within-country spatial frictions in firms' learning environment and extensive margin of trade. Firms learn from exporting neighbors and their revealed information in different spatial networks to reduce uncertainty about a foreign market's demand, which affects the likelihood of market entry. The empirical evidence suggests that firms value geographically close neighbors and their signals substantially more than the distant ones, and the knowledge diffusion decays fast in space. The learning effects are stronger when there are more geographical neighbors in a firm's spatial networks, precision or strength of signal increases, and when the firm starts exporting to a market dissimilar from its previously served markets. The observed heterogeneous knowledge diffusion effects across space confirm the necessity of introducing within-country spatial frictions in firms' learning environment at fine resolution.

The second chapter builds on the literature on internal trade barriers, shipment costs, and optimal shipment decisions. Using a heterogeneous firm trade model with endogenous shipment frequency and internal geography dimension, this chapter structurally estimates the shipment costs of Chinese manufacturing exporters at the firm-product-destination level. In addition, shipment costs are positively related to within-country spatial frictions, measured by the internal distance separating a firm and its nearest port infrastructure, and thus geographically disadvantaged firms favour large and infrequent shipments. These empirical findings indicate that the internal geography dimension of shipment costs has significant impact on firms' export behavior.

The third chapter studies the the role of within-country spatial frictions on quality differentiation and price-setting behavior of exporters. Empirical evidence suggests that the free-on-board export unit price decreases systematically with internal distance to the nearest port infrastructure, and the effect is stronger in shipments of differentiated or knowledge-intensive products, and in non-core product of multi-product exporters. These results indicate not only quality sorting across space, but also substantial within-firm variations of unit prices across products and destinations. Finally, this chapter proposes a theoretical framework extending Melitz and Ottaviano (2008) with a spatial quality differentiation component to rationalize these empirical findings.

Bibliography

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N. (2015). The economics of density: evidence from the Berlin Wall. *Econometrica 83*(6), 2127-2189.

Ahn, J.B., Khandelwal, A., Wei, S.-J. (2011). The role of intermediaries in facilitating trade. *Journal of International Economics 84*, 73-85.

Albornoz, F., Calvo-Pardo, H., Corcos, G., Ornelas, E. (2012). Sequential exporting. *Journal of International Economics 88*(1), 17-31.

Albornoz, F., Fanelli, S., Hallak, J.C. (2016). Survival in export markets. *Journal of International Economics 102*, 262-281.

Alessandria, G., Kaboski, J.P., Midrigan, V. (2010). Inventories, lumpy trade, and large devaluations. *American Economic Review 100*(5), 2304-2339.

Allen, T. (2014). Information frictions in trade. *Econometrica 82*(6), 2041-2083.

Anderson, M.A., Davies, M.H., Signoret, J.E., Smith, S.L.S. (2019). Firm heterogeneity and export pricing in India. *Southern Economic Journal 85*(3), 985-1004.

Antoniades, A. (2015). Heterogeneous firms, quality, and trade. *Journal of International Economics 95*(2), 263-273.

Antràs, P., Foley, C. F. (2015). Poultry in motion: a study of international trade finance practices. *Journal of Political Economy 123*(4), 853-901.

Arzaghi, M., Henderson, J.V. (2008). Networking off Madison Avenue. *Review of Economic Studies 75*(4), 1011-1038.

Atkin, D., Donaldson, D. (2015). Who's getting globalized? The size and implications of intra-national trade costs. Available at: `https://www.mit.edu/~atkin/`. (Accessed: January 1, 2020)

Bagwell, K. (2007). The economic analysis of advertising. In M. Armstrong, R. Porter (Eds.), *Handbook of Industrial Organization* (pp. 1701-1844). Elsevier.

Baldwin, R., Harrigan, J. (2011). Zeros, quality, and space: trade theory and trade evidence. *American Economic Journal: Microeconomics 3*(2), 60-88.

Bandiera, O., Barankay, I., Rasul, I. (2005). Social preferences and the response to incentives: evidence from personnel data. *Quarterly Journal of Economics 120*(3), 917-962.

Bastos, P., Silva, J. (2010). Identifying vertically differentiated products. *Economics Letters 106*(1), 32-34.

Bastos, P., Silva, J. (2010). The quality of a firm's exports: where you export to matters. *Journal of International Economics 82*(2), 99-111.

Baum-Snow, N., Gendron-Carrier, N., Pavan, R. (2020). Local productivity spillovers. Available at: `https://sites.google.com/site/baumsnow/research`. (Accessed: July 1, 2020)

Békés, G., Fontagné, L., Muraközy, B. (2012). Temporary trade and heterogeneous firms. *Journal of International Economics 87*(2), 232-246.

Békés, G., Fontagné, L., Muraközy, B., Vicard, V. (2017). Shipment frequency of exporters and demand uncertainty. *Review of World Economics 153*, 779-807.

Bellone, F., Musso, P., Nesta, L., Warzynski, F. (2016). International trade and firm-level markups when location and quality matter. *Journal of Economic Geography 16*, 67-91.

Benkovskis, K., Masso, J., Tkacevs, O., Vahter, P., Yashiro, N. (2017). Export and productivity in global value chains: comparative evidence from Latvia and Estonia. OECD Economics Department Working Papers No. 1448. Available at: `https://www.oecd-ilibrary.org/economics/export-and-productivity-in-global-value-chains_cd5710c4-en`. (Accessed: July 1, 2019)

Bernard, A.B., Jensen, J.B. (2004). Why some firms export. *Review of Economics and Statistics 86*(2), 561-569.

Bernard, A.B., Redding, S., Schott, P. (2010). Multiple-product firms and product switching. *American Economic Review 100*(1), 70-97.

Bisztray, M., Koren, M., Szeidl, A. (2018). Learning to import from your peers. *Journal of International Economics 115*, 242-258.

Blum, B.S., Claro, S., Horstmann, I.J. (2013). Occasional and perennial exporters. *Journal of International Economics 90*(1), 65-74.

Brambilla, I., Porto, G.G. (2016). High-income export destinations, quality and wages. *Journal of International Economics 98*, 21-35.

Brandt, L., van Biesebroeck, J., Zhang, Y. (2012). Creative accounting or creative destruction: firm level productivity growth in Chinese manufacturing. *Journal of Development Economics 97*(2), 339-351.

Brandt, L., van Biesebroeck, J., Zhang, Y. (2014). Challenges of working with the Chinese NBS firm-level data. *China Economic Review 30*, 339-352.

Broda, C., Weinstein, D.E. (2006). Globalization and the gains from variety. *Quarterly Journal of Economics 121*(2), 541-585.

Bullock, J.G. (2007). *Experiments on partisanship and public opinion: party cues, false beliefs, and Bayesian updating* [Doctoral dissertation, Stanford University]. Stanford SearchWorks. Available at: `https://searchworks.stanford.edu/view/6970436`. (Accessed: July 1, 2019)

Cai, J., Szeidl, A. (2018). Interfirm relationships and business performance. *Quarterly Journal of Economics 133*(3), 1229-1982.

Cai, Y., Tian, X., Xia, H. (2016). Location, proximity, and M&A transactions. *Journal of Economics and Management Strategy 25*(3), 688-719.

Cao, S.S., Ma, G., Tucker, J., Wan, C. (2018). Technological peer pressure and product disclosure. *The Accounting Review 93*(6), 95-126.

Cardoso-Vargas, C.E. (2017). Distance to the core, productivity and selection of export products-destinations. Available at: `https://mpra.ub.uni-muenchen.de/77192/`. (Accessed: March 1, 2021)

Chaney, T. (2014). Networks in international trade. *American Economic Review 104*(11), 3600-3634.

Choi, B., Lugovskyy, V. (2019). Asymmetric effects of financial development on export price and quality across countries. *Review of International Economics 27*(2), 594-642.

Clerides, S., Lach, S., Tybout, J.R. (1998). Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco. *Quarterly Journal of Economics 113*(3), 903-947.

Comin, D., Dmitriev, M., Rossi-Hansberg, E. (2013). The spatial diffusion of technology. Available at: `https://www.princeton.edu/~erossi/SDT.pdf`. (Accessed: May 1, 2021)

Coşar, A.K., Demir, B. (2016). Domestic road infrastructure and international trade: evidence from Turkey. *Journal of Development Economics 118*, 232-244.

Coşar, A.K., Fajgelbaum, P.D. (2016). Internal geography, international trade, and regional specialization. *American Economic Journal: Microeconomics 8*(1), 24-56.

Crinò, R., Ogliari, L. (2017). Financial imperfections, product quality, and international trade. *Journal of International Economics 104*, 63-84.

Crouzet, N., Eberly, J. (2019). Understanding weak capital investment: the role of market concentration and intangibles. *Proceedings of the 2018 Jackson Hole Symposium*, 87-148.

Das, S., Roberts, M.J., Tybout, J.R. (2007). Market entry costs, producer heterogeneity, and export dynamics. *Econometrica 75*(3), 837-873.

De Loecker, J., Goldberg, P.K., Khandelwal, A.K., Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica 84*(2), 445-510.

Desmet, K., Rossi-Hansberg, E. (2014). Spatial development. *American Economic Review 104*(4), 1211-1243.

Djankov, S., Freund, C., Pham, C.S. (2010). Trading on time. *Review of Economics and Statistics 92*(1), 166-173.

Duranton, G., Morrow, P.M., Turner, M.A. (2014). Roads and trade: evidence from the US. *Review of Economic Studies 81*(2), 681-724.

Eaton, J., Eslava, M., Kugler, M., Tybout, J. (2007). Export dynamics in Colombia: firm-level evidence. NBER Working Paper No. 13531. Available at: `https://www.nber.org/papers/w13531`.

Eckel, C., Iacovone, L., Javorcik, B., Neary, J.P. (2015). Multi-product firms at home and away: cost- versus quality-based competence. *Journal of International Economics 95*(2), 216-232.

Eckel, C., Neary, J.P. (2010). Multi-product firms and flexible manufacturing in the global economy. *Review of Economic Studies 77*(1), 188-217.

Ellison, G., Glaeser, E.L. (1997). Geographic concentration in U.S. manufacturing industries: a dartboard approach. *Journal of Political Economy 105*(5), 889-927.

Fafchamps, M., Quinn, S. (2018). Networks and manufacturing firms in Africa: results from a randomized field experiment. *World Bank Economic Review 32*(3), 656-675.

Fernandes, A.P., Tang, H. (2014). Learning to export from neighbors. *Journal of International Economics 94*(1), 67-84.

Fontagné, L., Orefice, G., Piermartini, R., Rocha, N. (2015). Product standards and margins of trade: firm-level evidence. *Journal of International Economics 97*(1), 29-44.

Fontaine, F., Martin, J., Mejean, I. (2020). Price discrimination within and across EMU markets: evidence from French exporters. *Journal of International Economics 124*, 103300.

Forman, C., Goldfarb, A., Greenstein, S. (2008). Understanding inputs into innovation: do cities substitute for internal firm resources? *Journal of Economics and Management Strategy 17*(2), 295-316.

Foster, L., Haltiwanger, J., Syverson, C. (2008). Reallocation, firm turnover and efficiency: selection on productivity or profitability. *American Economic Review 98*(1), 394-425.

Gerber, A., Green, D. (1999). Misperceptions about perceptual bias. *Annual Review of Political Science 2*(1), 189-210.

Görg, H., Halpern, L., Muraközy, B. (2010, March 14). *Shipping the premium beer farther away.* VoxEU. Available at: `https://voxeu.org/article/shipping-out-best-beer-why-export-prices-increase-distance`. (Accessed: May 1, 2021)

Görg, H., Halpern, L., Muraközy, B. (2017). Why do within-firm-product export prices differ across markets? Evidence from Hungary. *World Economy 40*(6), 1233-1246.

Hallak, J.C., Sivadasan, J. (2013). Product and process productivity: implications for quality choice and conditional export premia. *Journal of International Economics 91*(1), 53-67.

Hamano, M., Vermeulen, W.N. (2020). Natural disasters and trade: the mitigating impact of port substitution. *Journal of Economic Geography 20*(3), 809-856.

Harrigan, J., Ma, X., Shlychkov, V. (2015). Export prices of U.S. firms. *Journal of International Economics 97*(1), 100-111.

He, Z., Dai, M. (2017). The causal effect of firm-level market-specific imports on exports. Available at: `http://www.columbia.edu/~zh2178/Learning%20by%20Importing.pdf`. (Accessed: July 1, 2019)

Head, K., Mayer, T. (2014). Gravity equations: workhorse, toolkit, cookbook. In G. Gopinath, E. Helpman, K. Rogoff (Eds.), *Handbook of International Economics* (pp. 131-195). Elsevier.

Hoberg, G., Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy 124*(5), 1423-1465.

Hornok, C., Koren M. (2012). Welfare effects of administrative barriers to trade. EFIGE Working Paper 51. Available at: `https://www.bruegel.org/wp-content/uploads/2015/09/efige_wp51_0708121.pdf`. (Accessed: December 1, 2019)

Hornok, C., Koren, M. (2015). Administrative barriers to trade. *Journal of International Economics 96*, 110-122.

Hornok, C., Koren, M. (2015). Per-shipment costs and the lumpiness of international trade. *Review of Economics and Statistics 97*(2), 525-530.

Hottman, C., Redding, S.J., Weinstein, D.E. (2016). Quantifying the sources of firm heterogeneity. *Quarterly Journal of Economics 131*(3), 1291-1364.

Huang, Y., Xiong, W. (2018). Geographic distribution of firm productivity and production: a "market access" approach. Available at: `https://scholar.harvard.edu/wxiong/jmp/geo-prod`. (Accessed: November 1, 2019)

Imbert, C., Seror, M., Zhang, Y., Zylberberg, Y. (2019). Migrants and firms: evidence from China. Available at: `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3338794`. (Accessed: December 1, 2019)

Johnson, R.C. (2012). Trade and prices with heterogeneous firms. *Journal of International Economics 86*(1), 43-56.

Kamal, F., Sundaram, A. (2016). Buyer-seller relationships in international trade: do your neighbors matter? *Journal of International Economics 102*, 128-140.

Keller, W., Yeaple, S.R. (2013). The gravity of knowledge. *American Economic Review 103*(4), 1414-1444.

Khandelwal, A. (2010). The long and short (of) quality ladders. *Review of Economic Studies 77*(4), 1450-1476.

Kneller, R., Yu, Z. (2016). Quality selection, sectoral heterogeneity and Chinese exports. *Review of International Economics 24*(4), 857-874.

Koenig, P., Mayneris, F., Poncet, S. (2010). Local export spillovers in France. *European Economic Review 54*(4), 622-641.

Kropf, A., Sauré, P. (2014). Fixed costs per shipment. *Journal of International Economics 92*, 166-184.

Krugman, P. (1979). A model of technology transfer, and the world distribution of income. *Journal of Political Economy 87*(2), 253-266.

Kugler, M., Verhoogen, E. (2012). Prices, plant size, and product quality. *Review of Economic Studies 79*(1), 307-339.

Levchenko, A. (2007). Institutional quality and international trade. *Review of Economic Studies 74*(3), 791-819.

Levinsohn, J., Petrin, A. (2003). Estimating production function using inputs to control for unobservables. *Review of Economic Studies 70*(2), 317-342.

Lu, J., Tao, Z. (2009). Trends and determinants of China's industrial agglomeration. *Journal of Urban Economics 65*, 167-180.

Lu, Y., Wang, J., Zhu, L. (2019). Place-based policies, creation, and agglomeration economies: evidence from China's Economic Zone Program. *American Economic Journal: Economic Policy 11*(3), 325-360.

Lugovskyy, V., Skiba, A. (2015). How geography affects quality. *Journal of Development Economics 115*, 156-180.

Lynch, S.M. (2007). *Introduction to Applied Bayesian Statistics and Estimation for Social Scientists*. Springer-Verlag New York.

Ma, Y., Tang, H., Zhang, Y. (2014). Factor intensity, product switching, and productivity: evidence from Chinese exporters. *Journal of International Economics 92*(2), 349-362.

Manova, K. (2013). Credit constraints, heterogeneous firms, and international trade. *Review of Economic Studies 80*(2), 711-744.

Manova, K., Wei, S-J., Zhang, Z. (2015). Firm exports and multinational activity under credit constraints. *Review of Economics and Statistics 97*(3), 574-588.

Manova, K., Yu, Z. (2017). Multi-product firms and product quality. *Journal of International Economics 109*, 116-137.

Manova, K., Zhang, Z. (2012). Export prices across firms and destinations. *Quarterly Journal of Economics 127*(1), 379-436.

Manski, C.F. (1993). Identification of endogenous social effects: the reflection problem. *Review of Economic Studies 60*(3), 531-542.

Mayer, J. (2001). Technology diffusion, human capital and economic growth in developing countries. UNCTAD Discussion Papers 154. Available at: `https://econpapers.repec.org/paper/uncdispap/154.htm`. (Accessed: April 1, 2019)

Mayer, T., Melitz, M.J., Ottaviano, G.I.P. (2014). Market size, competition, and the product mix of exporters. *American Economic Review 104*(2), 495-536.

Mayneris, F., Poncet, S. (2015). Chinese firms' entry to export markets: the role of foreign export spillovers. *World Bank Economic Review 29*(1), 150-179.

Melitz, M.J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695-172.

Melitz, M.J., Ottaviano, G.I.P. (2008). Market size, trade, and productivity. *Review of Economic Studies 75*(1), 295-316.

Mion, G., Opromolla, L.D. (2014). Managers' mobility, trade performance, and wages. *Journal of International Economics 94*(1), 85-101.

Mion, G., Opromolla, L.D., Sforza, A. (2016). The diffusion of knowledge via managers' mobility. CEPR Discussion Paper 11706. Available at: `https://cepr.org/active/publications/discussion_papers/dp.php?dpno=11706`. (Accessed: March 1, 2020)

Morales, E., Sheu, G., Zahler, A. (2019). Extended gravity. *Review of Economic Studies*, *86*(6), 2668-2712.

Moxnes, A. (2010). Are sunk costs in exporting country specific? *Canadian Journal of Economics 43*(2), 467-493.

Petrin, A., Poi, B.P., Levinsohn J. (2004). Production function estimation in Stata using inputs to control for unobservables. *The Stata Journal 4*(2), 113-123.

Portes, R., Rey, H. (2005). The determinants of cross-border equity flows. *Journal of International Economics 65*(2), 269-296.

Portes, R., Rey, H., Oh, Y. (2001). Information and capital flows: the determinants of transactions in financial assets. *European Economic Review 54*(4), 783-796.

Pupato, G. (2010). Non-market interactions and entry into export markets. Available at: `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1777327`. (Accessed: July 1, 2020)

Rauch, J.E. (1999). Networks versus markets in international trade. *Journal of International Economics 48*(1), 7-35.

Rauch, J.E., Watson, J. (2003). Starting small in an unfamiliar environment. *International Journal of Industrial Organization 21*(7), 1021-1042.

Roberts, M.J., Tybout, J.R. (1997). The decision to export in Colombia: an empirical model of entry with sunk costs. *American Economic Review 87*(4), 545-564.

Rodrigue, J., Tan, Y. (2019). Price, product quality, and exporter dynamics: evidence from China. *International Economic Review 60*(4), 1911-1955.

Rossi-Hansberg, E., Sarte, P.-D., Owens, R. (2010). Housing externalities. *Journal of Political Economy 118*(3), 485-535.

Schott, P.K. (2004). Across-product versus within-product specialization in international trade. *Quarterly Journal of Economics 119*(2), 647-678.

Shimamoto, D., Kim, Y.R., Todo, Y. (2019). The effect of social interactions on exporting activities: evidence from micro, small, and medium-sized enterprises in rural Vietnam. The Research Institute of Economy, Trade and Industry (RIETI) Discussion Paper Series 19-E-020. Available at: https://www.rieti.go.jp/jp/publications/dp/19e020.pdf. (Accessed: July 1, 2020)

Staiger, D., Stock, J.H. (1997). Instrumental variables regression with weak instruments. *Econometrica 65*(3), 557-586.

Stokey, N.L. (2020). Technology diffusion. *Review of Economic Dynamics*. Advance online publication. https://doi.org/10.1016/j.red.2020.09.008.

Tang, H., Zhang, Y. (2017). Quality differentiation and trade intermediation. Available at https://teacher.econ.cuhk.edu.hk/~yfzhang/pdf/intermediary.pdf. (Accessed: March 1, 2020)

Van Leemput, E. (2021). A passage to India: quantifying internal and external barriers to trade. *Journal of International Economics 131*, 103473.

Volpe Martincus, C., Blyde, J. (2013). Shaky roads and trembling exports: assessing the trade effects of domestic infrastructure using a natural experiment. *Journal of International Economics 90*(1), 148-161.

Wang, J. (2013). The economic impact of Special Economic Zones: evidence from Chinese municipalities. *Journal of Development Economics 101*, 133-147.

Xiao, H., Wu, A., Kim, J. (2021). Commuting and innovation: are closer inventors more productive? *Journal of Urban Economics 121*, 103300.