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Essays on Multi-regional Firms in Domestic and Foreign Markets

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by

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Professor Benjamin Faber, Chair
Professor Andrés Rodríguez-Clare
Professor Cecile Gaubert

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Abstract

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This dissertation analyzes the decisions of firms that operate in many markets and presents new evidence on how these decisions affect economic activity within and across countries. In Chapter I, I analyze the role of multi-establishment firms' centralized decisions in shaping the propagation of local shocks across regions of the United States. In particular, I focus on retail chains pricing decisions. As retail chains do not perfectly discriminate prices across locations, local shocks affect not only local prices, but also prices in distant markets where the same retail chains operate. My main empirical finding is that county-level prices are sensitive to shocks in distant counties that happen to be served by the same retail chains. A 10% drop in house prices in other counties that are served by the same retailers leads, on average, to a 1.4% decline in the local consumer retail price index. One way of thinking about this is that I quantify how economically connected locations in the U.S. are through the networks of retail chains, above and beyond the linkages that arise from, for instance, proximity in space. In Chapter 2, I analyze the markup responses of Argentinian firms to local cost shocks. My main finding is that in response to a cost shock, a given Argentinian firm adjusts more its markups (and less its prices) in those markets where it has higher market-power. Finally, in Chapter 3, I study the behavior of global firms that operate both as exporters and as importers. I find that exporting to a new destination increases the probability of a firm to start importing from that destination (and not from others) within the lapse of one year. This effect is more likely to occur in distant markets, and in situations where importing involves non-homogeneous and rarely imported goods. Furthermore, new import activities from a new export destination continue regardless of whether the firm remains as an exporter in that market. This evidence emphasizes the influence of export experience on firms' sourcing decisions. The effect of export entry on sourcing costs has implications that go beyond qualitative insights: according to our quantitative exercise, import costs fall 53% in a given destination after export entry.

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Dissertation Introduction

This dissertation analyzes the decisions of firms that operate in many markets and presents new evidence on how these decisions affect economic activity.

In the first Chapter, I analyze the role of multi-establishment firms' centralized decisions in shaping the propagation of local shocks across regions of the United States. In particular, I study whether and how retail chains and their geographic distribution of stores contribute to the propagation of shocks across regions in the United States. Linking detailed store scanner micro-data to a county-level house price dataset for the period of the Great Recession, I investigate the spread of house-price induced local shocks through the networks of retail chains. My main empirical finding is that county-level prices are sensitive to shocks in distant counties that happen to be served by the same retail chains. A 10% drop in house prices in other counties that are served by the same retailers leads, on average, to a 1.4% decline in the local consumer retail price index. My results hold after conditioning on trade relationships due to geographic proximity. In fact, I document that once the retail chains' channel of propagation is taken into account, trade relationships due to geographic proximity play no role in propagating shocks to retail prices. I rationalize the reduced-form estimates in a model in which retail chains vary prices uniformly across their stores as a function of changes in market demand that they face at the (aggregate) chain level. I find that the calibrated model with uniform pricing can fully account for the reduced-form effects. Counterfactual analysis shows that uniform pricing and the geographic distribution of retail chains reduced cross-county dispersion of inflation by 40% during the Great Recession, benefiting consumers from low-income counties that were less exposed to drops in local house prices.

In the second chapter, I also focus on firms pricing decisions, but now focusing in the decision of exporters. In particular, with Federico Bernini, we study pricing decisions of firms located in Argentina that export to multiple countries. As most of these firms are producers selling to different countries, there is no evidence of uniform pricing in this case. Instead, I analyze how exporters differentially adjust prices in different destinations in response to cost shocks. We develop a trade model with variable markups and propose a methodology that lets us identify the within-firm, across-destinations elasticity of markup and the sensitivity of this elasticity to a firm's market power in the destination. On the empirical side, the methodology requires exogenous cost shocks in order to analyze the response of the firm across its destinations. We use a comprehensive dataset of Argentinian firms and exploit variability in the timing of import barriers imposed on Argentinian products. Not surprisingly, we find that trade barriers reduce imports for those firms that are more exposed to the policy. This, in turn, yields a considerable decline in their total exports. We then use the cost shock to uncover a novel fact: for a given firm, in a given year, the negative effect of rising import costs on exports is more prominent in markets where the firm is smaller relative to other firms in the same sector. In light of our theoretical model, this result implies that the elasticity of markup for a multi-destination exporter is increasing on its market power in the destination market. Intuitively, a multi-destination exporter decides to adjust relatively more its markups (and less their prices and export revenues) in those markets where it has higher market power.

In the third chapter, I study the behavior of global firms that are involved both in importing and exporting activities. In Importing after Exporting (w/ Facundo Albornoz), we uncover a novel fact about the relationship between exporting and importing. Using a comprehensive database of Argentine firms, we find that exporting to a new destination increases the probability of a firm beginning to import from that market within the lapse of one year. We develop a model of import and export decisions to study the effect of productivity and import costs on the intensive and extensive margins of importing. We show that "importing after exporting" implies that export entry reduces the cost of importing from that market. This effect is more likely to occur in distant markets, and in situations where importing involves non-homogeneous and rarely imported goods. Furthermore, new import activities from a new export destination continue regardless of whether the firm remains as an exporter in that market. This evidence emphasizes the influence of export experience on firms' sourcing decisions. The effect of export entry on sourcing costs has implications that go beyond qualitative insights: according to our quantitative exercise, import costs fall 53% in a given destination after export entry, and the estimated import-cost savings increase for distant markets outside the Americas.

Chapter 1

Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail

1.1 Introduction

The propagation of local shocks through the economy has been a central topic in macroeconomics. The most common way economists have been thinking of how shocks propagate across space is through inter-regional trade. Shocks to a particular location will affect prices and production in other locations through input-output linkages (e.g. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012); Acemoglu, Akcigit, and Kerr (2016), and Caliendo, Parro, Rossi-Hansberg, and Sarte (2017)). How does our understanding change if we take into account the propagation of shocks across establishments of multi-regional firms?

If the various establishments of multi-regional firms operate as independent business units, these firms will play no additional role in propagating shocks across regions. However, some characteristics of these firms can create inter-dependencies between their establishments. For example, if firms have a common pricing strategy across their establishments, then shocks in one region will affect prices in all their locations.[1] There are reasons to think that this phenomenon occurs for an important sector of the US economy: retail trade -i.e. grocery, drugstore and mass merchandise stores.[2] Given that the distribution of retail chains across regions in the U.S is far from uniform, it is natural to think that their networks of stores might affect how economic shocks are propagated across the economy. Yet, surprisingly, the existing literature in trade and urban economics has so far paid relatively little

[1] Another example is technology transfer from the parent company to their affiliates, which can generate co-movement in the sales growth of multinationals across countries (Cravino and Levchenko (2017)).

[2] DellaVigna and Gentzkow (2019) show that most US food, drugstore, and mass merchandise chains charge nearly-uniform prices across stores, despite wide variation in consumer demographics and competition. Nakamura (2008) shows that retail chains' fixed effects explain a substantial share of price variation.

attention to how the spatial networks of retail chains stores shape the propagation of shocks across regions.

In this paper, I fill this gap. I study whether and how local demand shocks propagate to consumer prices in distant regions through retail chain networks. Exploiting regional variation in local consumer demand from the collapse in house prices during the Great Recession, I find that the local consumer price index depends not only on local demand conditions, but also on shocks in distant regions that happen to be served by the same retail chains.

My main analysis is based on store-level scanner data from the Nielsen-Kilts retail panel. The data includes sales and prices in more than 35,000 participating grocery, drug and mass merchandise stores in more than 2,000 counties. In addition, it provides the location of each store and a unique identifier for the retail chain that is the ultimate owner of the store. I combine this with data on county-level changes in house prices during the Great Recession (2007-2011) from the Federal Housing Finance Agency (FHFA).

In order to identify the role of retail chains in propagating shocks across counties in the U.S., I use the Nielsen data to construct a spatial network of the retail chains' stores. Given that retail chains are unevenly distributed in space, their spatial network naturally creates linkages between counties. At the center of my analysis is a new measure of connectedness that characterizes the exposure between each pair of counties. The bilateral exposure of county c to county k is a weighted average of the share of each retail chain's national sales that take place in county k, where the weights are given by the market share of each retail chain in county c.[3] Intuitively, a county c will be more exposed to county k if county k is an important market for retail chains that are dominant in county c.[4] I then use these bilateral measures in order to compute a county's exposure to house price changes in other counties. The exposure of county c to house price changes elsewhere is the network-weighted percentage change in house prices, where the weights are given by the bilateral exposure of county c to each county k.[5]

My main empirical finding is that county-level prices are sensitive to house price-induced local shocks in distant counties that are linked by retail chain networks. In order to deal with endogeneity of house price changes, I follow the identification strategy in Mian and Sufi (2011) and use the local housing supply elasticity to instrument for local house price changes. More importantly, I also use the network-weighted housing supply elasticity to instrument for network-weighted house price changes in other counties.[6] Across a variety of

[3] Formally, exposure of county c to county k is given by: $\omega_{ck} = \sum_r l_{rc} S_{rk}$. S_{rk} denotes the share of retail chain r's national sales that take place in market k. l_{rc} denotes the share of a county's sales that correspond to retail chain r (See Equation 1.4). Note that, unlike bilateral distance, this measure of connectedness is intrinsically asymmetric.

[4] This paper is the first to characterize the bilateral linkages between counties in the retail chains dimension. I make the matrix that contains the bilateral linkages accessible to members of the broader research community.

[5] County $\Delta \log HP(others)_c = \sum_{k \neq c} \omega_{ck} \Delta \log HP_k$, where HP denotes house price index (See equation 1.3).

[6] Several papers have used this instrument for changes in local house prices (Mian and Sufi (2011), Adelino, Schoar, and Severino (2015), Stroebel and Vavra (2019), among others).

empirical specifications, I find a positive elasticity of local prices to house price movements in other counties, linked by the retail chains' networks. Specifically, a ten percent drop in house prices in distant counties linked by the network of retail chains leads, on average, to a 1.4 percent decline in county-level consumer prices.

My identification strategy faces several challenges. Since retail chains are not placed randomly across space, the most important challenge is that it is hard to distinguish propagation of shocks through the network of retail chains from common shocks in the regions in which the retail chains operate. Notably, to minimize transportation costs, retail chains might locate their stores in nearby counties, where wages and prices co-move due to, for example, integrated labor markets or trade relationships. In a series of empirical exercises, I show that common shocks to regions linked by the network of retail chains do not explain my results.

First, I document that my results hold after conditioning on trade relationships due to geographic proximity. In fact, once the retail chains' channel of propagation is taken into account, trade relationships due to geographic proximity play no role in propagating shocks to retail prices. Furthermore, I exclude counties within the same state and show that the shocks also spread to distant regions located outside the state. Second, I do not observe co-movement in wages between counties that are linked by the retail chains' networks. Finally, and more importantly, in a complementary empirical strategy, I turn to more granular data at the store-by-county level. This allows me to include county-by-time fixed effects, which absorb any common variation within a county that is due to a regional shock, regardless of whether the shock is specific to that county or correlated with shocks in other counties.[7] Using variation in price changes across stores within a given county, I find an elasticity of store-level prices with respect to house price movements in other counties of 0.12-0.20. That is, a ten percent larger reduction in weighted average house prices in counties where the same retail chain operates leads, on average, to a 1.2-2.0 percent reduction in the local prices of that chain's establishments relative to prices of stores belonging to other chains.[8]

After showing how the geographic distribution of retail chains shapes the propagation of local demand shocks to consumer prices, I explore whether it also affects other economic outcomes. I find no similar effects on local wages or employment, which implies that those are unaffected by house price shocks in other counties that are linked by retail chains networks. This, in turn, suggests that retail chains and their geographic distribution of stores affects not only consumers' prices in distant regions, but also consumers' purchasing power.

In the final part of the paper, I propose a model of retail chains' pricing decisions to quantitatively interpret my findings and evaluate the role of retail chains in distributing economic shocks across the economy. Retailers compete under monopolistic competition and charge markups that can vary as a function of local demand conditions. In particular, I allow demand elasticity (and markups) to vary with changes in local house prices. In the

[7]Note that, for example, spillovers from one county to another through proximity (i.e: through a trade channel) are county specific and will be accounted by these fixed effects.

[8]This result also relates to recent work by Handbury and Moshary (2020) on the effects of the national school lunch program on retail prices. See discussion of related literature below.

model, retail chains' headquarters can either set a uniform price or price-discriminate across their locations. If a retail chain sets uniform prices, its optimal price depends on a weighted average of the demand conditions in the different markets where the chain operates. Hence, when faced with a negative demand shock in a given region, the retail chain decreases its prices not only in that region, but also in other regions in which the retail chain operates. The extent to which the retailer contributes to the propagation of demand shocks depends on the geographic distribution of its sales.

The model presented here provides a novel, yet intuitive test for uniform pricing responses to shocks. If retail chains charge uniform prices, then in response to a local demand shock, the effect from shocks elsewhere should be equal to the local effect, once both are weighted properly.[9] According to the results of this test, I cannot reject the hypothesis of uniform pricing strategies. The model also highlights that the effect of local shocks on local retail price indices is heterogeneous: under uniform pricing, the pass-through of local shocks to local prices becomes a function of how important the local consumer market is in the national sales of the retailers that enter the local consumption basket. I find that this degree of local pass-through varies greatly across U.S. counties.

The theoretical framework naturally lends itself to quantifying the aggregate and distributive consequences of uniform pricing during the Great Recession. I conduct two counterfactual exercises that explore 1) different pricing strategies, and 2) different spatial networks of retail chains due to mergers or acquisitions. In the first counterfactual, I consider flexible pricing strategies. Compared to uniform pricing, under flexible pricing the counterfactual cross-county dispersion of inflation is 40% larger. This implies that uniform pricing smoothed-out the effect of the shocks across regions during the Great Recession. Then, I explore the distributive consequences of uniform pricing and I find that consumers in low-income counties benefited. Intuitively, these counties were not as affected by the house price slump directly, but still experienced a drop in their local consumer prices because their retail chains were affected by the shocks in other counties.

In the second counterfactual, I assume uniform pricing and explore changes in the spatial networks of retail chains due to mergers and acquisitions. I simulate a scenario in which there is a merger between the largest retail chain in each of the four census regions of the United States. This merger would have reduced the cross-county dispersion of inflation rates during the Great Recession by 12%. This result emphasizes a new aspect of mergers: they can intensify the linkages between regions and lead to more synchronized changes in consumer prices.

This paper contributes to several strands of the literature. First, it contributes to the international and intra-national trade literature that studies how shocks propagate across regions. Most of this literature emphasizes input-output linkages between firms and sectors as the main driver of the propagation of shocks (e.g. Acemoglu et al. (2012), Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016), and Caliendo et al. (2017), Stumpner (2019)). There has

[9] The proper theoretical weight for the local shock is related to the importance of the local consumer market for the dominant retail chains operating in the county.

been less study of how shocks propagate within firms' internal networks of establishments. In the international context, a number of papers explore whether characteristics of parent companies and affiliates of multinationals generate co-movements between regions, including channels such as internal capital markets (Desai, Foley, and Hines (2009)), intermediate input linkages (Boehm, Flaaen, and Pandalai-Nayar (2019)), and transmission of technology across establishments (Cravino and Levchenko (2017), Alviarez, Cravino, and Ramondo (2020), and Bilir and Morales (2020)). My paper focuses on the propagation of shocks across firms' establishments in a given country and sheds light on a new channel: inter-dependencies in pricing strategies between the establishments of a firm. An advantage of studying propagation of shocks within the U.S. is that Nielsen scanner data allows me to observe establishment-level prices. As a consequence, unlike previous papers, I am able to directly study how shocks propagate to consumer prices.

Less has been done to understand the role of firms' internal networks in propagating shocks in the domestic context, with two notable exceptions: Hyun and Kim (2019) and Giroud and Mueller (2019). Hyun and Kim (2019) study U.S. manufacturers that are located in a given region who sell (*export*) multiple products to multiple regions (*multi-destination firms*). They find that a negative demand shock in a region can induce producers to substitute production of high-quality products for low-quality products, creating co-movement in sales across markets. In contrast, I study firms in the non-tradable sector that have establishments in multiple regions and sell locally in each one (*multi-establishment firms*).[10] My findings are compatible with multi-market producers changing their product mix, but I focus on a different mechanism. Holding constant the set of products (and quality) sold by the retailer, local demand shocks affect prices of continuing products in distant markets that are connected by the retail chains' network of stores.[11]

In a study more closely related to my paper, Giroud and Mueller (2019) analyze the role of firms' cashflow constraints in propagating local demand shocks. They find that financially constrained firms spread local demand shocks, affecting employment in distant regions where the parent firm operates. The channel I study is different: regardless of retail chains' financial constraints, their pricing strategies create inter-dependencies between their establishments. Note also that while the results of Giroud and Mueller (2019) have implications for the firms' workers, the results in my paper have implications for their consumers.

Second, this paper relates to the literature that studies the collapse in house prices during the Great Recession (Mian and Sufi (2011), Mian, Rao, and Sufi (2013), Giroud and Mueller (2019), and Stroebel and Vavra (2019)). In particular, this paper is closely related to Stroebel and Vavra (2019), which analyzes how markups and prices respond to local demand shocks during the Great Recession. They find a large positive effect of local house price movements on local retail prices. However, if retail chains set prices nationally, markups not only depend

[10] The international trade literature also makes a sharp distinction between firms exporting to many markets (multi-destination exporters) and firms that have establishments in many markets (multi-nationals). In my context, retail chains occupy the second category.

[11] Results in Hyun and Kim (2019) are entirely driven by extensive margin adjustments. In contrast, my results are entirely driven by changes in prices of continuing products.

on local demand, but also on demand shocks in other regions. I complement their results by showing that house price-induced local demand shocks not only affect local prices, but also prices in distant regions that are linked by the retail chains' networks. This finding advances our understanding of the mechanisms through which the Great Recession propagated across the U.S economy.

Third, this paper helps reconcile the conflicting findings in DellaVigna and Gentzkow (2019) and in Stroebel and Vavra (2019). While DellaVigna and Gentzkow (2019) show that retail chains charge similar prices in all their stores, Stroebel and Vavra (2019) find large effects of local demand shocks on retail prices. I show that once I control for shocks from regions linked by the same retail chains, the elasticity of local retail prices with respect to house price changes decreases by 35%. In addition, the predictions from my theoretical model indicate that uniform pricing can be consistent with large local responses to demand shocks, as long as the regions experiencing the shocks are an important market for their retail chains. On this ground, this paper highlights that to understand how local markups respond to changes in local economic conditions, one should consider the decisions of national retail chains and their spatial network of stores.

Fourth, my paper relates to a literature that studies supply-side effects of demand side policies. In a related paper, Handbury and Moshary (2020) study the effects of the National School Lunch Program (NSLP) on retail prices. Consistent with zone pricing, they find that retail chains highly exposed to the NSLP reduced prices on all their outlets. While their study focuses on the policy implications of the NSLP, this paper studies the geography of multi-establishment firms to quantify a new mechanism through which local economic shocks propagate across regions of the U.S. I derive measures of bilateral market exposure directly from a theory of firm pricing decisions, and find quantitatively that the reduced-form empirical findings can be accounted for by uniform pricing. This also allows me to quantify the distributive consequences of alternative pricing strategies.

Finally, this paper also contributes to the literature in industrial organization and macroeconomics that studies firms' pricing dynamics, and, in particular, a recent literature that has documented the existence of uniform pricing in different sectors. Nakamura (2008) shows that retail chains' effects explain a substantial share of price variation in the U.S. In the same context, DellaVigna and Gentzkow (2019) show that a given retail chain charges similar prices across different locations. Daruich and Kozlowski (2020) document uniform pricing in supermarket chains in Argentina and analyze its implications for inferring aggregate elasticities from local estimates. Cavallo (2017) finds that retailers charge similar prices online and offline. Adams and Williams (2019) find similar patterns in the retail home improvement industry. I take the insights of these papers to empirically assess the role the geographic distribution of retail chains in shaping the propagation of local demand shocks across regions in the United States.

The remainder of the paper proceeds as follows. Section 3.2 describes the data. Section 1.3 documents stylized patterns regarding the geographic distribution of retail chains. Section 1.4 presents the empirical analysis. Section 1.5 presents the model. Section 1.6 presents the quantitative analysis and explores counterfactual scenarios. Section 1.7 concludes.

1.2 Data

I combine county-level data on changes in house prices during the Great Recession (2007-2011) with Nielsen Retail Scanner data.

Retailer Scanner Data:

I use the Retail Scanner Database collected by AC Nielsen and made available through the Kilts Center at The University of Chicago Booth School of Business. The retail scanner data consist of information on weekly price and quantity sold generated by point-of-sale systems for more than 100 participating retail chains across all its markets between 2006 and 2016. When a retail chain agrees to share their data, all of their stores enter the database. As a result, the database includes more than 35,000 participating grocery, drug and mass merchandiser stores located in more than 2000 counties. These stores cover more than half the total sales volume of US grocery and drug stores and more than 30 percent of all US mass merchandiser sales volume.

I define a retail chain to be a unique combination of two identifiers in the Nielsen data: code of parent and code of retailer. "Parent code" indicates the company that owns a chain and "retailer code" indicates the chain itself (e.g: Albertson's LLC which owns Safeway). I introduce sample restrictions at the chain level. First, I require that the chains are present in the sample in every year from 2007 to 2011. Second, I require that chains are present in two or more counties. This leaves me with 91 retail chains. Finally, I require chains to be present in the counties for which there is information for all the variables in the analysis, leaving us with 84 retail chains. I also impose restriction on the sample of products. In particular, I focus on products that are frequently sold and available across markets. For each retail chain, I focus on products that are available in 80% or more of its markets in a given half-year.[12]

While the raw data are sampled weekly, I aggregate to construct half-year prices, since this reduces high-frequency noise. I construct the half-year price of an item by dividing its total value of sales by the total quantity of units sold in the half-year. As the main focus of the paper is on a) prices of existing products that are similar within chain across stores, and b) variation of price indices across time, we include an item only if it has positive sales in 2007 and 2011. We track the price of identical items (UPC-store combinations) across time, so that changes in quality or issues with comparing nonidentical products are less relevant for our results. I next describe the construction of the county-level price indices from these individual price observations.

County-level Price Index

The construction of the county-level price index necessarily entails various measurement choices. In the body of the paper I concentrate on a single benchmark price index, but in

[12] I also consider different sets of products for additional robustness. Results are robust to not-restricting the sample of products, restrict it to 50% or more markets and only considering products in the top 40 main product modules.

Appendix A.4, I show that the main results hold for price indices constructed under various alternative assumptions, including, for example, adjusting the price index for entry and exit of barcodes and stores (Appendix A.4).

I assume that consumer behavior features multi-stage budgeting in two stages. In the first stage, consumers in a county decide which of 1000 product modules to buy from based on the product module price index. In the second stage, conditional on the product module, consumers decide which variety to purchase; where a variety is defined as a store-barcode combination (eg. 12 oz. Coke in 7-eleven). Specifically, I first construct a product-module level price index as in Sato (1976) and Vartia (1976):

$$P_{mct} = \Pi_{u \in I_{mc}} \left(\frac{p_{umct}}{p_{umct-1}} \right)^{w_{umct}},$$

where p_{umct} is the price of variety u, in product module m, sold in county c at year t, and

$$w_{ucmt} = \frac{(s_{umct} - s_{umct-1})/(ln(s_{umct}) - ln(s_{umct-1}))}{\sum_{v \in I_{mc}} (s_{vmct} - s_{vmct-1})/(ln(s_{vmct}) - ln(s_{vmct-1}))} \quad ; \quad s_{umct} = \frac{p_{umct} q_{umct}}{\sum_{v \in I_{mc}} p_{vmct} q_{vmct}},$$

where q denotes quantity. I_{mc} is the set of varieties u in product module m in county c that are consumed in t and $t-1$ (continuing varieties). The weights w are ideal log-change weights and they are county specific to allow for spatial variation in the relative weight of an item.[13]

I then construct the overall county-specific price index by weighting the product module price indices by the revenue share of a particular product module in the initial year (α_{mct-1}) ,[14]

$$P_{ct} = \Pi_m \left(\frac{P_{mct}}{P_{mct-1}} \right)^{\alpha_{mct-1}},$$

where

$$\alpha_{mct-1} = \frac{\sum_{u \in m} Sales_{umct-1}}{\sum_u Sales_{uct-1}}$$

In Figure A.2 of the Appendix, I plot the histogram of county-level inflation rate between 2007 and 2011. The population-weighted average inflation is 11.09%, which contrasts well with the inflation in the food at home official CPI from BLS. Figure A.2 also shows substantial cross-county dispersion in inflation rates.

[13]Note that they are always bounded between the shares of spending in period t and period t-1.

[14]This price index is consistent with the following utility function:

$$U_c = \prod_{m \in I_c} \left[\sum_{u \in I_{mc}} q_{umc}^{\frac{\sigma_m - 1}{\sigma_m}} \right]^{\alpha_{mc} \frac{\sigma_m}{\sigma_m - 1}}$$

where σ_{mc} is the elasticity of substitution between varieties within product module, and α_{mc} is the fraction of expenditures spent on product module m in county c.

House price data

House price data is obtained from from the Federal Housing Finance agency (FHFA). The agency construct a House Price Index (HPI), which is a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties.[15] The HPI serves as a timely, accurate indicator of house price trends at various geographic levels, including county, zip code, state and Metropolitan Statiscal Areas (MSAs) levels.[16] For the main analysis, I focus on long differences between the first semester of 2007 and the first semester of 2011.[17]

The other major data set related to house prices used in the paper is obtained from the 2005 Wharton Regulation Survey. Gyourko, Saiz, and Summers (2008b) use the survey to produce a number of indexes that provides information on various aspects of local land use control environments, including the general characteristics of the regulatory process, statutory limits on development, density restrictions, open space requirements, infrastructure cost sharing and approval delay. It is supplemented by information on local ballot initiatives and state involvement in land use controls. Lower values in the Wharton Land Regulation Index (WLRI, henceforth) indicates the adoption of less restrictive policies toward real estate development. In contrast, high values of the WLRI are associated with municipalities that have zoning regulations or project approval practices that constrain new residential real estate development. I process the original municipal-based data to create average regulation indexes at the county level. A limitation of the WLRI is that it is only available for 910 counties, out of the 2300 counties for which I have retail price information from Nielsen Data. These 910 counties represent more than 70% of total sales in the Nielsen Data and cover more than 70% of the U.S. population (See Table A.1 in the appendix).

County-level macroeconomic variables

I complement the main datasets with county-level data from different sources. I use county-level data on wages, employment and number of establishments from the BLS. Data on education levels, age, and population density come from the American Community Survey (ACS).

[15] This information is obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

[16] These data is highly correlated with data from Zillow. The correlation in house prices changes from 2007 to 2011 between these two alternative datasets is 96%.

[17] This timing convention follows Stroebel and Vavra (2019) to facilitate comparisons with their results. Additionally, the house-price collapse started at the end of 2006/beginning of 2007 and from the second half of 2011, house prices stopped declining (See Figure A.1 in the appendix). All results are robust to the alternative timing 2007-2009; following, for example, Mian et al. (2013) and Giroud and Mueller (2019).

1.3 Facts on the geographic distribution of retail chains

I motivate my analysis by documenting two stylized facts about the geographic distribution of retail chains in the United States.

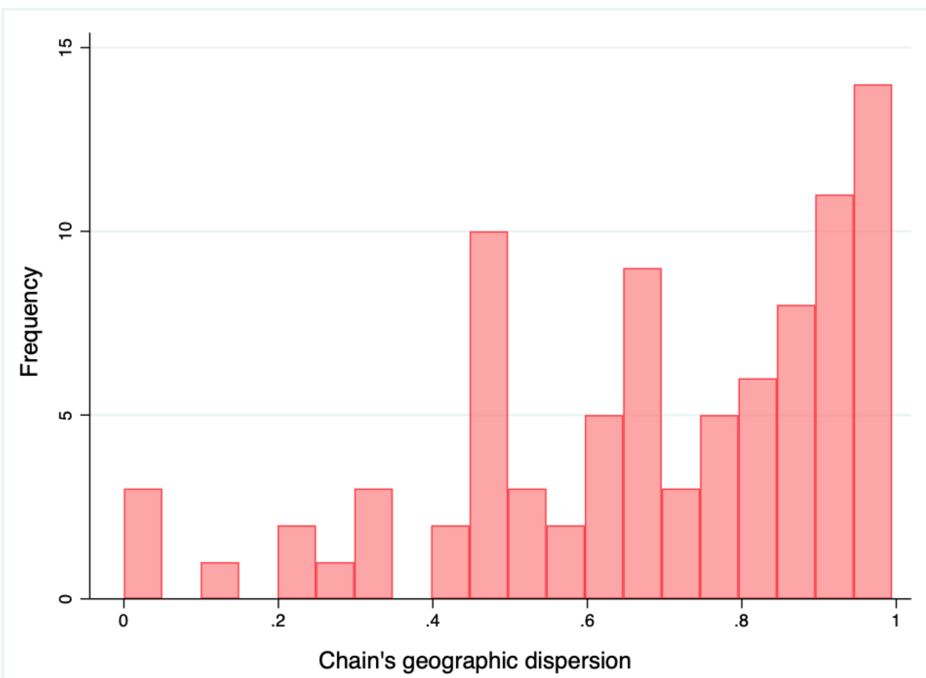
Fact 1. There is substantial geographic dispersion in retail chains' sales

Define the Geographic Dispersion Index (GDI) for each retail chain r:

$$GDI_r = 1 - \sum_c S_{rc}^2,$$

where $S_{rc} \equiv \frac{Sales_{rc}}{\sum_c Sales_{rc}}$ represents the share of retail chain r's national sales that take place in county c. Low values of the GDI indicate that sales are concentrated in a few locations. Figure 1.1 plots the distribution of the GDI. We observe substantial geographic dispersion. For example, fewer than 10% of the retail chains in the sample have a GDI below 0.5.

Figure 1.1: Geographic Dispersion of retail chains



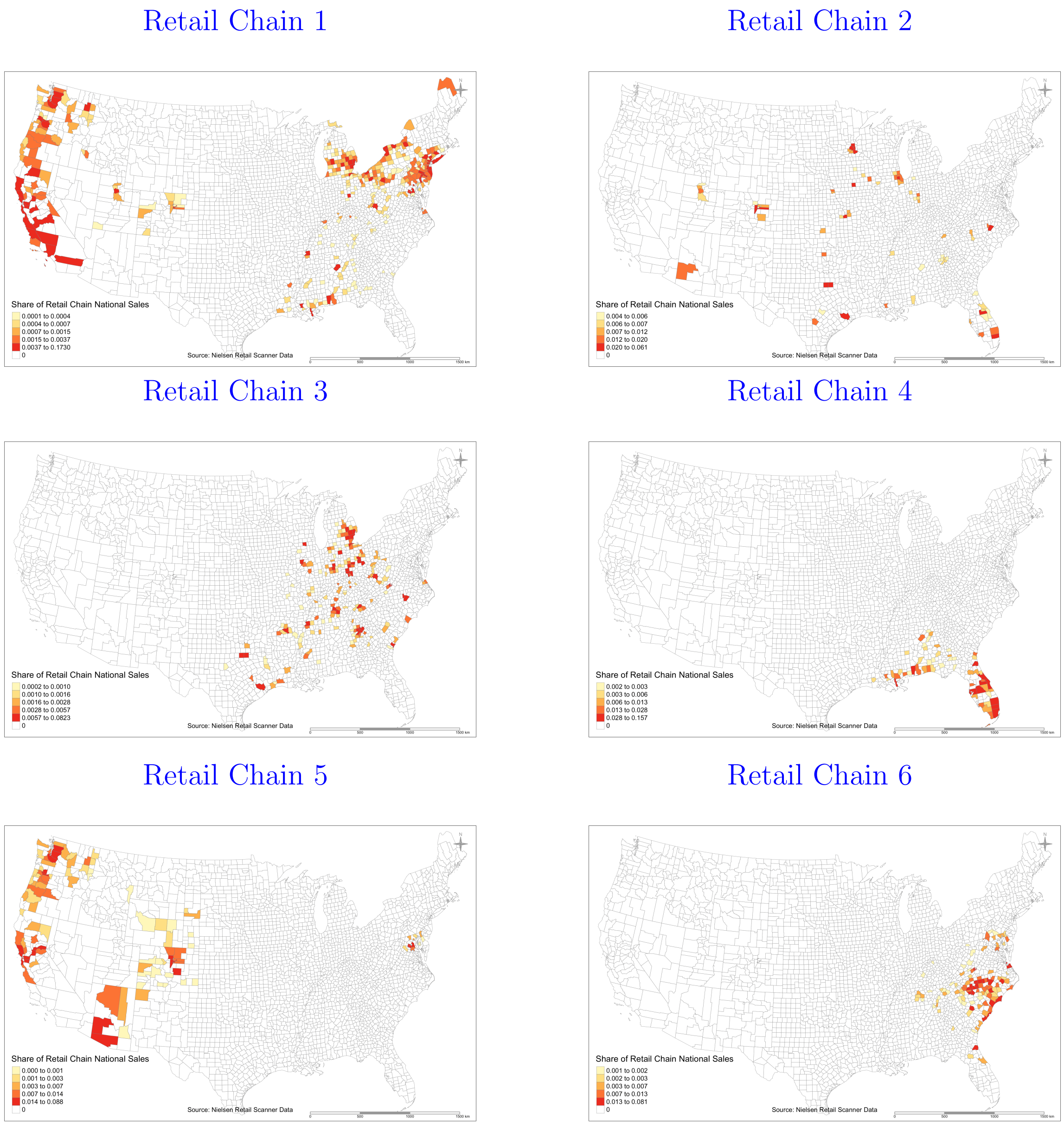
Fact 2. There is substantial heterogeneity in the spatial network of retail chains

Retail chains are distributed differently across the U.S. In Figure 1.2, I show the spatial network of six anonymous chains in my data.[18] The maps use a red-to-yellow color scale to display the sales of the retail chain in each county, where red counties are those in which the retail chain has the highest sales volume, and yellow are those in which the retail chain has the lowest sales volume. Figure A.3 shows that retail chains' networks have very different geographic layouts. For example, there are big and small retail chains, such as Chain 1 and Chain 2, which are spread across several regions in the U.S. and are active in more than 15 states. There are also other chains, such as Chain 3 and Chain 5, that cover an extensive area but are spread across counties and states in those areas. Finally, there are other retail chains that are concentrated in a specific geographic area, such as Chain 4 and Chain 6.

Notice that even though proximity seems to play a role in determining the location of retail chain stores, the spatial networks of retail chains go beyond neighboring counties. That is, firms are not only located in groups of nearby counties. Furthermore, they are widely spread throughout different states. For example, some chains have only one or two stores per state.

[18] Nielsen does not disclose the names of the chains in the data. So, in order to provide a broader view of the geographic distribution of retail chains, in Figure A.3 of Appendix A.3, I present a graph from AggData to illustrate the geographic distribution of some popular retail chains.

Figure 1.2: Examples of Retail Chains in the Data



Note: Each panel plots the distribution of sales of a retail chain in the data. The maps use a yellow-to-red color scale to display the sales of the retail chain in each county, where red represent counties where the chain has the highest amount of sales, and yellow counties where the chain has the lowest amount of sales.

The main takeaway from these empirical patterns is that retail chains are multi-regional firms that are unevenly distributed in space. This heterogeneity in the spatial networks of retail chains will creates differences in how each pair of counties is connected to each other. For instance, two counties will be very exposed to each other if they are served by the exact same retail chains. In the next section, I characterize these linkages and study their role in propagating local shocks across the geography.

1.4 Empirical analysis

I begin the analysis by constructing bilateral weights that characterize how connected each pair of counties is, given the geographic distribution of retail chains' stores. Given these weights, I construct the average exposure of each county to house price shocks in other counties and study the sensitivity of county-level retail prices to house price-induced shocks in other counties. I then discuss the identification assumptions and address potential threats to the validity of those assumptions.

Bilateral linkages and exposure variables

I use Nielsen Scanner data to characterize the bilateral linkages between each pair of counties and the exposure of stores and counties to shocks in other counties.

Define the retail chain's network weights S_{rc} as the share of retail chain r's national sales that takes place in county c in 2007:

$$S_{rc} \equiv \frac{Sales_{rc}}{\sum_c Sales_{rc}} = \frac{\text{Sales of retail chain r in county c}}{\text{National sales of retail chain r}}.$$

These weights measure how important market c is for retail chain r. Intuitively, a store located in county c belonging to a retail chain r will be more exposed to shocks in county k if county k is an important market for the retail chain r. Given these weights, I define the exposure of retail chain r in county c to house price shocks in other counties k as a weighted average of house price changes across counties in the U.S:

$$\text{Store}\Delta \log HP(others)_{rc} \equiv \sum_{k \neq c} S_{rk} \Delta \log(HP_k)^{07-11}, \tag{1.1}$$

where $\Delta \log(HP_k)^{07-11}$ is the percentage change in house prices between 2007 and 2011 in county k.

The network of retail chains create linkages between each pair of counties. These linkages will depend on which retail chains are important in each county. Define l_{rc} as the share of total retail sales in county c that correspond to retail chain r in 2007,

$$l_{rc} \equiv \frac{Sales_{rc}}{\sum_r Sales_{rc}} = \frac{\text{Sales of retail chain r in county c}}{\text{Total sales in county c}}.$$

l_{rc} measures how important the retail r is in county c. With this, I can define a county's exposure to house price changes in other counties as the weighted average exposure of retail chains that operate in the county:

$$\text{County } \Delta \log HP(others)_c \equiv \sum_r l_{rc} \text{Store} \Delta \log HP(others)_{rc}. \tag{1.2}$$

Exchanging the order of summation across r and k, I can re-write the county-level exposure (Equation 1.2) as,

$$\text{County} \Delta \log HP(others)_c \equiv \sum_{k \neq c} \underbrace{\sum_r l_{rc} S_{rk}}_{\omega_{ck}} \Delta \log (HP_k)^{07-11}, \tag{1.3}$$

where

$$\omega_{ck} = \sum_r l_{rc} S_{rk}. \tag{1.4}$$

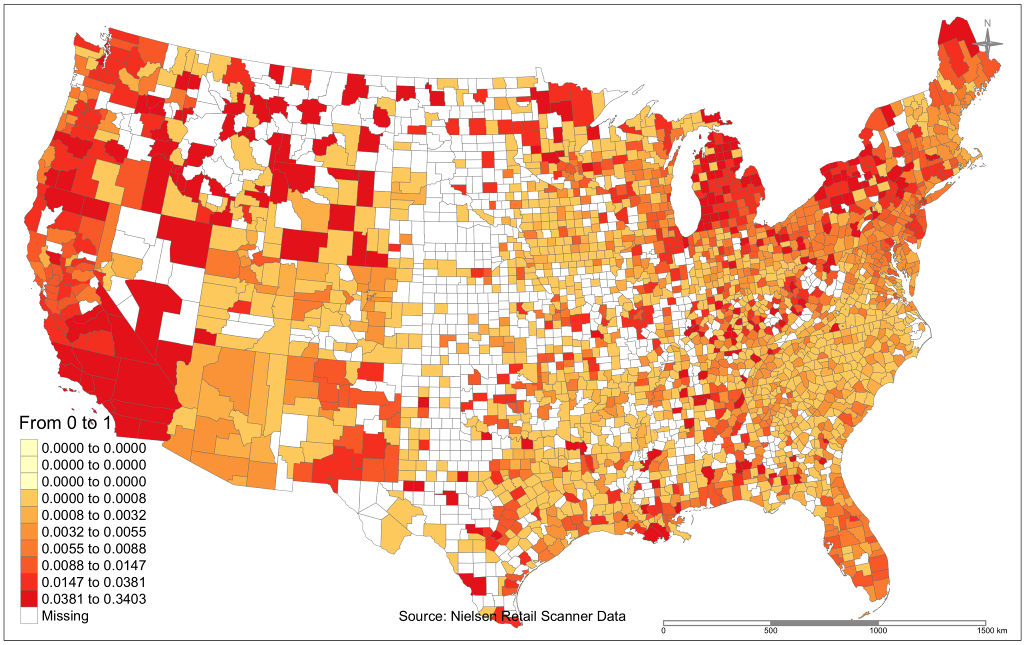
defines the bilateral exposure of county c to county k. Equation 1.3 presents the main variable in my analysis. The exposure of a county to shocks in other counties is the network-weighted average change in house prices in other counties, where the weights are given by the bilateral exposure of county c to each county k (ω_{ck}).

The weights ω_{ck} are at the center of my analysis. Intuitively, a county c will be more exposed to shocks in county k if market k is an important market (S_{rk}) for the dominant chains that operate in c (l_{rc}). The matrix that contains $\omega_{ck} \quad \forall \quad c, k$ characterizes all the bilateral linkages between each pair of counties in the retail chains' dimension.[19] Note that, unlike bilateral distance, the bilateral linkages created by the network of retail chains are intrinsically asymmetric. As an illustrative example, in Figure 1.3 I show how counties in the sample are exposed to shocks in Los Angeles County (L.A., from now on). The map plots $\omega_{c,LA}$ for every county c in the sample. I assign colors ranging from light yellow to red, with red counties c being those that are more exposed to shocks in Los Angeles (high $\omega_{c,LA}$). We can observe three patterns. First, not surprisingly, counties located near L.A. tend to be connected to L.A. Second, we also observe strong linkages with counties that are far away. For example, Santa Barbara (located 100 miles away from L.A.) is less exposed to shocks in L.A than some counties located in the states of Michigan or Maine.[20] Third, there is substantial heterogeneity in the exposure to shocks in L.A, even for counties that are next to each other.

[19] A complementary contribution of this paper is constructing the matrix that summarizes these linkages and making it publicly available for other researchers. The matrix can be useful to i) study other topics related to propagation through retail chains' networks, and ii) control for retail chain networks if the aim of the study is analyzing the effect of local shocks on retail prices. Researchers interested in using the matrix can contact the author at eglembergman@berkeley.edu.

[20] In section 1.4, I discuss in detail the role of proximity in explaining my results.

Figure 1.3: $\omega_{c,LA}$: Exposure of counties c to shocks in Los Angeles



Note: The yellow-to-red color scale represents the degree to which counties are exposed to shocks in L.A., based on $\omega_{c,LA}$ (See Equation 1.4). Red indicates higher $\omega_{c,LA}$. Source: Nielsen Retail Scanner Data.

Main analysis: OLS and Instrumental Variables

After constructing the exposure variables, I empirically show to what extent house price-induced local demand shocks propagate to distant regions through the network of retail chains.

I start by examining the sensitivity of county-level prices to changes in house prices in other counties that are linked through the network of retail chains.

I estimate the following equation in differences from 2007 to 2011:

$$\Delta \log(P_c)^{07-11} = \beta_0 + \beta_1 \Delta \log(HP_c)^{07-11} + \beta_2 \sum_{k \neq c} \omega_{c,k} \Delta \log(HP_k)^{07-11} + X_c + \Delta\epsilon_c, \tag{1.5}$$

$\Delta \log(P_c)^{07-11}$ denotes the percentage change in county-level retail price index for continuing varieties in county c.[21] $\Delta \log(HP_c)^{07-11}$ denotes the local change in house prices

[21] The price index considers only varieties that existed both in 2007 and 2011. Varieties are defined as a combination of store-barcodes. I describe in detail the construction of the price index in Appendix A.2. In Appendix A.4, I explore the effects on the extensive margin (e.g. retail chains closing stores or discontinuing products). I do not find any effect of the network of retail chains on the extensive margin.

in county c. This variable allows me to control for the direct effect of house price changes on retail prices.[22] My main variable of interest is the county-level exposure to shocks in other counties that are linked by the networks of retail chains: $\sum_{k \neq c} \omega_{c,k} \Delta \log(HP_k)^{07-11}$, as defined in Equation 1.3. X_c is a vector of time-varying controls at the county-level. It includes changes in local wages, changes in employment, and changes in number of retail establishments.[23] Standard errors are clustered at the state level.[24]

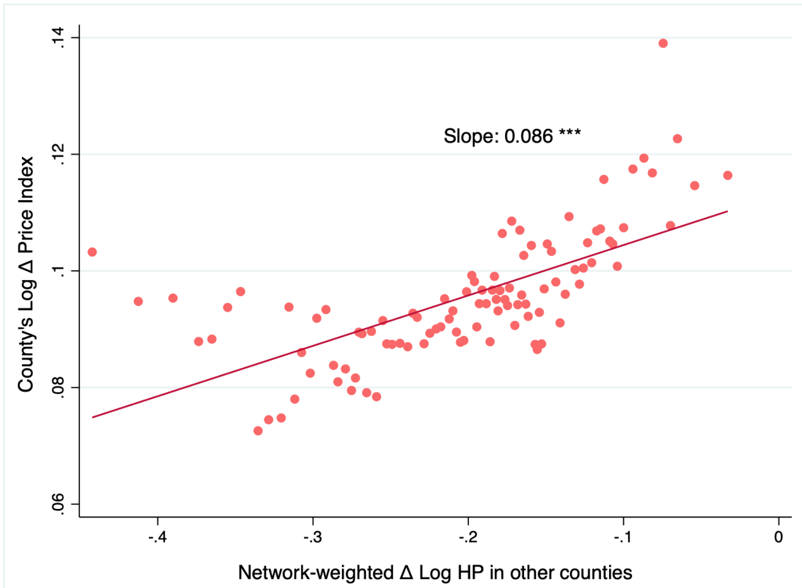
Figure 1.4 provides a visual impression of the OLS relationship between changes in the county-level retail price index and changes in house prices in other counties, linked through the spatial networks of the retail chains. The pattern is clear. Controlling for the local change in house prices, the elasticity of county-level prices with respect to changes in house prices in other counties is around 9%. In Columns (1) to (3) of table 1.1, I report the OLS estimates in table format. The first row reports the elasticity of county-level retail prices with respect to local house prices. The second row reports the elasticity of county-level prices with respect to house price changes in other counties that are linked by the network of retail chains. In Column (1), I report the direct effect of house price changes on county-level prices. Similar to previous papers, I find that there is a positive relationship between house price changes and local retail prices. In Column (2), I add network-weighted house price changes in other counties. Conditional on the local changes in house prices, a drop of 10% in network-weighted house prices in other counties is associated with a 0.88% reduction in county-level prices. This result remains almost unchanged in Column (3), after including county-level controls such as changes in employment, wages and number of establishments.

[22] The coefficient β_1 is also useful to compare with previous papers' estimates of the effect house price-induced local shocks on local prices (e.g. Stroebel and Vavra (2019)).

[23] Results are robust to other combinations of controls at the county-level. See A.3 of Appendix A.4.

[24] As a robustness check, in Table A.11 of Appendix A.4, I compute standard errors allowing for arbitrary cross-regional correlation in the regression residuals as suggested by Adao et al. (2019).

Figure 1.4: Relationship between network-weighted changes in house prices and county-level change in prices



Note: The binscatter plots the OLS relationship between the network weighted house price changes in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$) and county-level retail prices ($\Delta \log(P_c)$). Counties are sorted into percentile bins based on their value on $\Delta \log(P_c)$. The sample includes 910 counties, so each percentile bin therefore represents 9 counties. To filter out any confounding effects, I control for the local change in house prices ($\Delta \log(HP_c)$). Hence, the dot indicates the average value of (residual) $\Delta \log(P_c)$.

Although the OLS estimates constitute suggestive evidence of the propagation of shocks across the network of retail chains, both the local change in house prices and the exposure to house price changes in other counties can suffer from endogeneity. For instance, contemporaneous negative productivity shocks could lead to an increase in retail prices and, at the same time, a decrease in house prices. This would imply a downward bias in our estimate for the direct effect. More importantly, it is hard to argue that the location of retail chains' stores is random. For instance, to reduce transportation costs, retail chains' might be clustered geographically. If this were the case, regional productivity shocks that affect regional house prices could generate co-movement in prices between counties that are connected by the retail chains.

My first strategy to deal with potential endogeneity issues is to use instruments for the two main variables. Regarding local house prices changes, I follow an extensive literature that exploits across county variation in housing supply elasticity (e.g. Mian and Sufi (2011), Adelino et al. (2015), Stroebel and Vavra (2019), among others). The idea is that in response to a national level negative housing demand shock, areas with lower housing supply elasticity (e.g. tighter land regulations, WLRI) will experience a larger drop in house prices. In particular, in my baseline specification, I use the county-level Wharton Land Regulation Index (WLRI) from Gyourko, Saiz, and Summers (2008a) and its interaction with the spatial network of retail chains: [25]

$$WLRI_c \rightarrow \Delta \log(HP)_c$$

More importantly, I combine the WLRI with data on the location and sales of the retail chain stores to construct an instrument for retail chains' exposure to house price shocks in other counties. I instrument network-weighted changes in house prices with network-weighted change in WLRI.

$$\sum_{k \neq c} \omega_{ck} WLRI_k \rightarrow \sum_{k \neq c} \omega_{ck} \Delta \log(HP)_k$$

Intuitively, a county will be more exposed to house prices drops in other counties if the dominant chains in the county have stores concentrated in counties with tighter land regulations. While house price changes in counties linked by the retail chains might correlate with regional productivity changes that generate co-movement in prices, the WLRI isolates variability in house prices that is not correlated with those productivity changes.[26] Hence, my main identifying assumption is that in the absence of linkages between counties through the retail chains' network of stores, changes in county-level retail prices would be uncorrelated with WLRI in regions that are linked by the network of retail chains.[27] It is important to note that in my shift-share design, identification relies on exogeneous variability in the shocks (WLRI, in this case). As shown by Borusyak, Hull, and Jaravel (2018), if the shocks are as good as random, then it is possible to identify the causal effect of interest even when, as in most applications, the exposure shares are not random.[28]

[25] Gyourko et al. (2008a) conduct a nationwide survey to construct a measure of local regulatory environments pertaining to land use or housing. The idea is that in areas with a tighter regulatory environment, is harder to expand (contract) the housing supply in response to demand shocks. In a complementary analysis, I repeat the estimations using the Saiz (2010) Housing supply elasticity (Saiz HSE). The Saiz HSE uses geographic information of the metropolitan area to measure how easy is constructing new houses (e.g: areas with a flat topology are assigned with a higher elasticity). The coefficient across different IV strategies is remarkably similar and I cannot reject the hypothesis that they are equal (See Table A.4 of Appendix A.4).

[26] Note that these assumptions are milder than those in studies that use local housing supply elasticity to instrument house price changes. Those studies rely on the assumption that housing supply elasticity only affects the outcomes through its impact on house prices. That assumption is a sufficient condition (though not necessary) for exogeneity of the network-weighted WLRI.

[27] Note that this assumption is milder than the OLS assumptions; namely that in the absence of linkages between counties through the retail chains' network of stores, changes in county-level retail prices are uncorrelated with changes in house prices in regions that are linked by the network of retail chains.

[28] In a recent paper, Goldsmith-Pinkham, Sorkin, and Swift (2020) provides conditions under which the shift-share instrument is exogeneous when the shares are exogeneous. However, in most of the interesting economic settings (including the one studies here), the shares are not necessarily random. Borusyak et al. (2018) shows that as long as the shocks are as good as random, then identification is granted, even when the exposure shares are endogeneous. In section 1.4 I perform a series of robustness exercises and discuss extensively the plausibility of my identification assumptions.

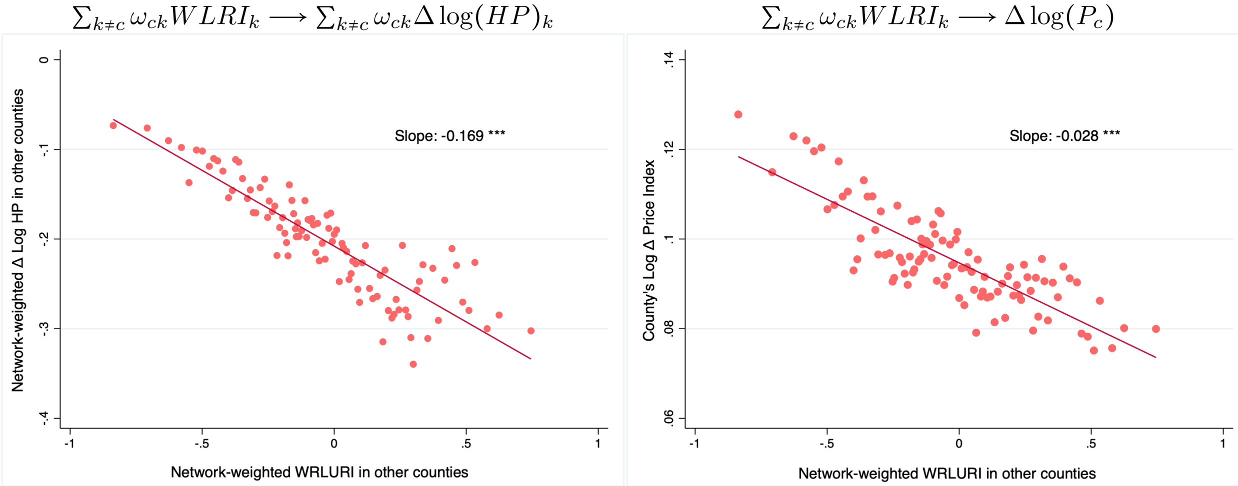
There are important remaining challenges to my identification assumptions. In particular, even when this instrument has been widely used in the literature as an exogeneous shock to house prices, it might not be as good as random. If it is not and, for example, retail chains locate their stores in neighboring counties, then unobserved regional shocks that correlate with housing supply elasticity could generate co-movement in prices, even in the absence of the linkages created by the retail chains' networks. In this section, I present the main results of the paper and I address this and other concerns in Section 1.4.

I begin by providing a visual impression of the first stage and the reduced-form coefficient of the indirect effect. In Panel a of Figure 1.5, I plot the relationship between the network-weighted WLRI and the network-weighted change in house prices (first-stage). As expected, the network-weighted WLRI is negatively correlated with the network-weighted change in house prices. That is, counties exposed to counties with tighter land regulations are counties exposed to counties that experienced higher drops in house prices. In Panel b of Figure 1.5, I plot the relationship between network-weighted WLRI and local retail prices (reduced-form). The pattern is clear: counties more exposed to a higher network-weighted WLRI in other counties experienced a higher drop in local retail prices.

Figure 1.5: Propagation of house price-induced local shocks: first stage and reduced-form

Panel a: First Stage $\sum_{k\neq c}\omega_{ck}WLRI_k \longrightarrow \sum_{k\neq c}\omega_{ck}\Delta\log(HP)_k$

Panel b: Reduced Form $\sum_{k\neq c}\omega_{ck}WLRI_k \longrightarrow \Delta\log(P_c)$



Note: The binscatter plots the first stage and reduced-form relationship. Panel A plots the first stage: the relationship between the network-weighted WLRI (x-axis) and the network weighted house price changes (y-axis). Panel B reports the reduced-form coefficient: the relationship between network-weighted WLRI (x-axis) and county-level change in consumer prices (y-axis). Counties are sorted into percentile bins based on their value on network-weighted change in house prices (Panel A) and county-level changes in consumer prices (Panel B), respectively. My sample includes 910 counties, so each percentile bin therefore represents 9 counties. To filter out any confounding effects, I control in both cases for the local change in house prices (so the dot indicates the average value of the (residual) outcome variable.

After inspecting the data visually, I report the main findings of the paper in Table 1.1. Columns (4) to (6) present the IV estimates. In Column (4), I report the local elasticity of county-level retail prices with respect to house prices. The elasticity is 0.125. This estimate is in line with findings by Stroebel and Vavra (2019) that range between 0.15 and 0.25. In Column (5), I add the network-weighted change in house prices in other counties. First, note that once I control for the propagation from other counties, the direct effect declines 40%. This suggests that previous papers that did not account for the network of retail chains overestimated the elasticity of retail prices with respect to house prices. More importantly, in the second row, I report the elasticity of local retail prices with respect to shocks in other counties that are linked by the retail chain networks. Conditional on the local changes in house prices, a 10% drop in house prices in other counties linked by the network of retail chains leads, on average, to a decrease of 1.35% in county-level consumer price index. Reassuringly, the coefficient remains stable and almost unchanged after including county level controls in Column (6). To provide a benchmark of the quantitative relevance of these results, a county exposed to an average drop in house prices in other counties of 26% (25th percentile) has a predicted inflation of around 9.5%. In contrast, a county exposed to a 14% (75th percentile) drop in house prices in other counties has a predicted inflation of 11.5%.[29]

[29] These predictions are calculated including the constant and assigning the median change in local house prices in both cases.

Table 1.1: Propagation of house price-induced local shocks through the network of retailer chains

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.056***	0.031**	0.029*	0.125***	0.074**	0.076**
	(0.014)	(0.013)	(0.015)	(0.027)	(0.034)	(0.037)
Chain-linked Δ Log HP (other counties)		0.088***	0.086***		0.129***	0.135***
		(0.026)	(0.026)		(0.039)	(0.040)
Panel B: First Stage						
F-stat				21.358	18.642	14.756
County controls	no	no	yes	no	no	yes
Observations	910	910	910	910	910	910
R-squared	0.154	0.257	0.264	0.084	0.071	0.060

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's $\Delta \log HP$ is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) denotes the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$), as defined in Equation 1.3. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$) with network-weighted WLRI ($\sum_{k \neq c} \omega_{ck} WLRI_k$). County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments and changes in log employment. Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Retail Scanner Data. Housing price data is obtained from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

In Appendix A.4, I explore the sensitivity of my results to alternative specifications. First, I show that the main coefficient remains stable after adding different county-level controls (Table A.3). Second, I repeat the main analysis, but now instrumenting the endogeneous variables with the Saiz (2010) geography-based housing supply elasticity (Table A.4). The main coefficients remains almost unchanged under the alternative instruments. Third, I show that my results are not sensitive to: a) constructing price indices under different assumptions (Table A.6), b) replicating the analysis for the period 2007-2009 (Table A.7), c) including different combinations of regional fixed effects (Table A.8), d) considering three digits zip code as the relevant market, and e) excluding California (Table A.10). Fourth, in Table A.11, I follow Adao et al. (2019) methodology to conduct valid inference for shift-share designs under arbitrary cross-regional correlation in the regression residuals. Although the standard errors increase slightly, the coefficients remain statistically significant at the usual levels.[30]

[30] Even though in the main analysis, I cluster standard errors at the state-level, there could be errors correlated across regions independent of geographic location.

In the next section, I discuss the main challenges to my identification assumptions and address each of these challenges.

Validity of identification assumptions

The key identification assumption is that, in the absence of the retail chains' network of stores, changes in county-level prices are uncorrelated with housing supply elasticity in the regions that are linked by the retail chains networks. In regards to this assumption, the biggest challenge is to separate propagation of shocks through retail chains' networks from common shocks in the regions in which the retail chains operate. For example, to minimize transportation costs, retail chains might locate their stores in neighboring counties where wages and prices co-move because of other reasons, such as integrated labor markets or trade linkages. In this section, I address these concerns.

First, I document that my results hold after controlling for trade relationships due to proximity between counties. In fact, once the retail chain's channel of propagation of shocks is taken into account, the effect of proximity disappears. Second, I show that the network of retail chains does not affect other economic outcomes in distant locations, which suggests the absence of other factors creating co-movements. Third, I filter out any remaining concerns about common regional shocks by turning to more granular data at the retail chain-by-county level, which allows me to include county by time fixed effects. These fixed effects absorb any common variation within a county that is due to a regional shock, regardless of whether the shock is region-specific or correlated with shocks in other regions.

Retail chains' network of stores or proximity channel?

Thus far, I have abstracted from the role of geographic proximity in the propagation of shocks. However, it is important to disentangle whether my results are explained specifically by the network of retail chains or by trade relationships due to proximity that correlate with the network of retail chains.

I begin by showing that even shocks in out-of-state counties are propagated through the network of retail chains. I construct the network-weighted change in house prices, excluding changes in house prices in counties that are in the same state. I then estimate the leave-state-out version of my main specification (Equation 1.5):

$$\Delta \log(P_c)^{07-11} = \beta_1 \Delta \log(HP_c)^{07-11} + \beta_2 \sum_{k \neq State_c} \omega_{c,k} \Delta \log(HP_k)^{07-11} + \epsilon_c, \tag{1.6}$$

where $State_c$ denotes the state in which county c is located. Similar to my main analysis, I construct a leave-state-out instrument: $\sum\limits_{k \neq State_c} \omega_{c,k} WLRI_k$.

Results are reported in Table 1.2. Across a variety of specifications, I find that local prices are sensitive to shocks in distant counties (out-of-state) that are linked by the network of retail chains. In addition, I cannot reject the hypothesis that the coefficient for out-of-state shocks is equal to the coefficient of my main specification. This is suggestive evidence that shocks emanating from out of state are as important as shocks from nearby regions.

Table 1.2: Propagation of house price-induced local shocks to out-of-state counties

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.056***	0.057***	0.056***	0.125***	0.126***	0.121***
	(0.014)	(0.013)	(0.016)	(0.027)	(0.024)	(0.028)
Chain-linked Δ Log HP (other counties)		0.078***	0.078***		0.121***	0.129***
(excl state)		(0.023)	(0.023)		(0.032)	(0.032)
Panel B: First Stage						
F-statistic				21.358	11.032	9.712
County controls	no	no	yes	no	no	yes
Observations	910	910	910	910	910	910

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (out-of-state counties) is the network-weighted percentage change in house prices in other counties, excluding the state in which the county is located ($\sum_{k \neq State} \omega_{ck} \Delta \log(HP_k)$) as defined in Equation 1.6. Columns (1) to (3) report results for OLS estimations. County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments and changes in log employment. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq State} \omega_{ck} \Delta \log(HP_k)$) in out-of-state counties with network-weighted WLRI in out-of-state counties ($\sum_{k \neq State} \omega_{ck} WLRI_k$). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

After showing that the shocks propagate to distant regions through the network of retail chains, I now directly study the question of to what extent propagation of local shocks is explained by the retail chains that serve the county and to what extent it is explained by trade relationships due to proximity. Comparing these two channels has two purposes. First, it allows me to check that my results are not explained by other networks that happen to be correlated with the network of retail chains. This is specially important, given that the correlation between county-level linkages by the network of retail chains and county-level linkages due to proximity is 17%. Second, exploring the role of proximity in shaping the propagation of shocks is interesting in its own right, since it allows me to compare my new channel of propagation of shocks with the more traditional channel of propagation of shocks through trade relationships between nearby regions.

Define,

$$\text{prox-weighted}\Delta\log(HP)_c^{others} = \sum_{k\neq c}\delta_{ck}^{prox}\Delta\log(HP)_k^{07-11},$$

where

$$\delta_{ck}^{prox} = \frac{d_{ck}^{-\theta}Population_{k,2007}}{\sum_k d_{ck}^{-\theta}Population_{k,2007}}$$

where d_{ck} is the distance in miles between county c and k.[31] I assume $\theta = 1$ as it is standard in the trade literature. Intuitively, the closer county c and county k are to each other and the bigger county k is, the more a shock in county k will affect county c. [32]

Then, I add this variable to my main Equation 1.5 and estimate the following equation:

$$\Delta\log(P_c)^{07-11} = \beta_1\Delta\log(HP_c)^{07-11}+\beta_2\sum_{k\neq c}\omega_{c,k}\Delta\log(HP_k)^{07-11}+\beta_3\sum_{k\neq c}\delta_{ck}^{prox}\Delta\log(HP)_k^{07-11}+\epsilon_c, \tag{1.7}$$

In addition to the instruments discussed in previous sections, I instrument Prox-weighted $\Delta\log(HP)_c^{other}$ with prox-weighted $WLRI$. Formally,

$$\text{Prox-weighted } WLRI_c = \sum_{k\neq c}\delta_{ck}^{prox}WLRI,$$

Table 1.3 reports results for different versions of equation 1.7. Columns (1) to (3) present OLS estimates. Columns (4) to (6) report IV estimates. In all cases, the instruments have predictive power. The first row reports the coefficient associated with the proximity-weighted shocks. The second row reports the coefficient associated with the local effect of the shock. The third row reports the coefficient associated with the retail chains networks. In Column (1), I show the role of propagation through trade relationships due to geographic proximity. A 10% drop in house prices in nearby regions is associated with a 1.25% lower retail price index in the county. More importantly, in Column (3), I add the retail chains' channel of propagation of shocks. The results are striking. Once I take into account the propagation of shocks through the network of retail chains, the coefficient related to geographic proximity is no longer significant. In contrast, propagation of shocks through retail chains' network of stores remains positive and significant. Columns (4) to (6) repeat the analysis, but

[31] The matrix of distances between each pair of counties is obtained from the County Distance Database, provided by the National Bureau of Economic Research and compiled by Jean Roth (2014)

[32] Note that a first order approximation to market access of a county in standard trade models (e.g. Donaldson and Hornbeck (2016)) is given by:

$$MA_c = \sum_k \tau_{ck}^{-\theta}Population_k.$$

Hence, the weights serve as a proxy for the relative importance of county k in county c's market access. Alternatively, in Appendix A.4, I construct the weights based on trade flows between county c and county k at the state-level.

instrumenting each of the variables. I arrive at the same conclusions. Specifically, I conclude that, controlling for proximity-weighted changes in house prices and local changes in house prices, the elasticity of local retail prices with respect to shocks in distant counties -linked by the same retail chains- is 0.16.

These results indicate that county-level retail prices depend more on shocks to the retail chains that happen to serve the county than on shocks to neighboring counties.

Table 1.3: Channels of propagation of shocks: retail chains versus geographic proximity

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instruments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
Prox-weighted Δ Log HP (other counties)	0.125***	0.085***	0.020	0.212***	0.072	-0.139
	(0.009)	(0.015)	(0.016)	(0.050)	(0.097)	(0.092)
County's Δ Log HP		0.024***	0.025***		0.153***	0.099*
		(0.007)	(0.007)		(0.053)	(0.054)
Chain-linked Δ Log HP (other counties)			0.083***			0.166***
			(0.009)			(0.035)
Panel B: First Stage						
F-statistic				12.122	26.215	12.726
County controls	yes	yes	yes	yes	yes	yes
Observations	910	910	910	910	910	910
R-squared	0.172	0.182	0.250	0.088	0.123	0.074

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$) as defined in Equation 1.3. Trade-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, where the weights are given by proximity between counties: $\sum_{k \neq c} \delta_{c,k}^{prox} \Delta \log(HP_k)^{07-11}$. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the three main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument Chain-Linked Δ Log HP (other counties) with Chain-Linked WLRI in other counties ($\sum_{k \neq c} \omega_{ck} WLRI_k$). I instrument Trade-Linked Δ Log HP (other counties) with Trade-Linked WLRI in other counties ($\sum_{k \neq c} \delta_{ck}^{prox} WLRI_k$). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Retail Scanner Data. Housing price data is obtained from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b).

The effect of retail chains' network of stores on other economic outcomes

If my results were explained by common shocks to regions in which the retail chains operate, then we would expect co-movement not only in retail prices, but also in other economic outcomes. For example, if results were explained by trade relationships between counties in which retail chains operate, we would expect house price movements to affect wages in distant counties that are linked through these networks. In contrast, it is less clear why the network of retail chains would affect wages in distant counties. I test this by estimating the following version of Equation 1.5:

$$\Delta \log(Y_c)^{07-11} = \beta_1 \Delta \log(HP_c)^{07-11} + \beta_2 \sum_{k \neq c} \omega_{c,k} \Delta \log(HP_k)^{07-11} + X_c + \Delta\epsilon_c, \tag{1.8}$$

where Y_c are the three alternative outcomes: county-level employment, number of retail establishments and wages, respectively. Results are reported in Table 1.4. Column (2) reports the effect on employment. Although house price-induced local shocks affect local economic outcomes, these shocks do not affect labor market outcomes in distant counties. This is consistent with the network of retail chains being the driver of propagation of shocks.

Note that this results has another interesting implication. As retail chains affect the propagation of shocks to prices in distant regions, but not to wages, the chains' spatial networks of stores have consequences for real income.

Table 1.4: Propagation of house price-induced local shocks to other economic outcomes

	Δ Log Price Index	Δ Log L	Δ Log # of Establishments	Δ Log Wages
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.074**	0.155	0.126*	0.309*
	(0.034)	(0.103)	(0.076)	(0.162)
Chain-linked Δ Log HP (others)	0.129***	-0.029	0.070	-0.114
	(0.039)	(0.111)	(0.058)	(0.170)
Panel B: First Stage				
F-statistics	18.642	18.642	18.642	18.642
Observations	910	910	910	910
R-squared	0.071	0.077	0.109	0.094

A unit of observation is a county. Each column has a different dependent variable: Column (1) shows $\Delta \log(P_c)$. Column (2) shows the percentage change in the county's employment rate between 2007 and 2011 ($\Delta \log(L_c)$). Column (3) shows the percentage change in the county's number of retail establishments. Column (4) shows the percentage change in wages. County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$), as defined in Equation 1.3. All columns report IV estimates. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq c} \omega_{ck} \Delta log(HP_k)$) with network-weighted WLRI ($\sum_{k \neq c} \omega_{ck} WLRI_k$). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b). County-level macroeconomic variables are obtained from the BLS.

Retail by county level analysis

In order to address remaining concerns about separating the effect of the network of retail chains from common regional shocks, I turn to more granular data at the county-by-chain level. This allows me to include county-level fixed effects to absorb any common variation within a county that is due to a regional shock, regardless of whether the shock is region-specific or correlated with shocks in other regions. Note that, for example, spillovers from one county to another because of trade relationships due to proximity are county specific and will be accounted for by these fixed effects.

Formally, I estimate the following equation:

$$\Delta\log(P_{rc})^{07-11} = \beta_2 \sum_{k \neq c} S_{r,k} \Delta\log(HP_k)^{07-11} + \gamma_c + X_r^{2007} + \epsilon_{rc}, \tag{1.9}$$

where, as defined in equation 1.1, the weights S_{rk} are the share of the retail chain r's national sales that take place in county k. The dependent variable is the percentage change in the price index for continuing varieties of retail chain r in county c.[33] I aggregate stores of a retail chain in a given county to the retail chain by county level. Therefore, $\Delta\log(P_{rc})^{07-11}$ denotes the percentage change in price index for retail chain r in county c from 2007 to 2011.[34] Analogously to the county-level analysis, I also instrument the local changes in house prices and the store-level network-weighted changes in house prices with WLRI and store-level network-weighted WLRI, respectively. I cluster standard errors at both the retail chain and the state level.

Table 1.5 report results for the OLS (Columns 1 to 3) and the IV estimations (Columns 4 to 6). Focus first in the OLS estimates. In Column (1) I report results without including county fixed effects. In Column (2), I include county fixed effects. Hence, I compare stores operating in the same county that are exposed to the same regional shocks, but that are exposed differently to shocks in other locations because they belong to different retail chains. We can observe that elasticity of retail chain prices with respect to house prices in other regions is similar to the corresponding elasticity without county fixed effects. In Column (3), I add controls at the retail chain level to account for differential trends for different retail chains. Reassuringly, the elasticity of store-level prices with respect to house prices in other locations remains stable. We observe a similar pattern when analyzing the IV estimates. In my preferred specification (Column 6), I include county fixed effects, as well as the initial amount of national sales of the retail chain as a control. I conclude that the elasticity of store-level prices with respect to house price changes in other counties where the same retail chain operates is 0.18. Note that this result is also consistent with Handbury and Moshary (2020)'s finding that retail chains highly exposed to a national school lunch program reduced prices across all outlets.

[33] In appendix A.2, I explain in detail the assumptions to construct the price index.

[34] Results are similar if I take each store of the retail chain in a county separately. I present the retail chain-by-county level estimates to avoid repeating similar observations and be conservative with the standard errors.

Table 1.5: Propagation of local shocks: within county analysis

	Dep Variable: Chain's Δ Log Price in county c					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.029***			0.070***		
	(0.009)			(0.023)		
Store $\Delta \log HP(others)_{rc}$	0.082***	0.080***	0.094***	0.136***	0.185***	0.183***
	(0.026)	(0.027)	(0.032)	(0.046)	(0.043)	(0.037)
Panel B: First Stage						
F-statistic				11.184	19.351	19.932
County controls	yes	-	-	yes	-	-
Retail chain controls	no	no	yes	no	no	yes
County FE	no	yes	yes	no	yes	yes
Observations	3,747	3,747	3,747	3,747	3,747	3,747
R-squared	0.165	0.601	0.612	0.047	0.495	0.497
# retailers	84	84	84	84	84	84
# counties	910	910	910	910	910	910

A unit of observation is a retail chain by county. The dependent variable is the percentage change in the retail chain by county price index between 2007 and 2011 ($\Delta \log(P_{rc})$). County's Δ Log HP is the county-level percentage change in house prices between 2007 and 2011. Store $\Delta \log HP(others)_{rc}$ is the store-level network-weighted percentage change in house prices in other counties ($\sum_{k\neq c} S_{rk} \Delta \log(HP_k)$), as defined in Equation 1.1. County-level controls include log change in wages, employment and number of retail establishment. Retail chain-level controls include log national sales at 2007. In Columns (4) to (6), I instrument the local percentage change in house prices with the local WLRI and I instrument store-level network-weighted percentage change in house prices in other counties ($\sum_{k\neq c} S_{rk} \Delta \log(HP_k)$) with store-level network-weighted WLRI in other counties ($\sum_{k\neq c} S_{rk} WLRI_k$). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at both the retail-chain level and state-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

In appendix A.4, I explore the sensitivity of my results to alternative specifications, and test for alternative stories. In appendix A.4 I control for similarity-weighted house price changes in other counties, based on income, population, household debt, and education. The main coefficient remains stable (between 0.129 and 0.137). In Appendix A.4, I explore whether my results could be explained by common regional shocks that affect differently retail chains that cater to different income groups. I show that my main conclusions remain unchanged after comparing price changes of stores in a given county that cater to individuals of similar income group.

Until here, I have shown that retail chains play a key role in shaping the propagation of shocks through space. The network of retail chains connect counties economically, beyond the linkages that arise from, for example, proximity in space. I now turn to a model of retail chains' pricing decisions to rationalize this findings and investigate the quantitative implications of this new channel of propagation of shocks.

1.5 A model of retail chains' pricing decisions

I build and estimate a simple model of retail chains' pricing decisions to quantitatively interpret my findings, test for uniform pricing strategies and evaluate the role of retail chains in distributing economic shocks across the economy. In this section, I introduce the main ingredients of the model and in the next section I make further assumptions to take the model to the data and conduct quantitative analysis.

Demand

Consider a country that has a finite number of markets, $c = 1, .., C$. The market definition I use for my benchmark case is the county, so retail chains only compete for consumers within a county.[35]

Define Ω_c as the set of active retail chains in county c, p_{rc} as the price of retail r in county c, and P_c as the price index in county c. Assuming direct separability, the demand for retail chain r in county c when prices are $\mathbf{p} \equiv \{p_{rc}\}_{r \in \Omega_c}$ is given by:

$$q_{rc} = D(p_{rc}/P_c),$$

where $D(x) \in C^2(x)$ is twice differentiable with $D'(x) < 0$ and partial price elasticity given by $\sigma_c = \frac{\partial q_{rc}}{\partial p_{rc}} \frac{p_{rc}}{q_{rc}}$. I allow for variable markups by letting σ_c vary with demand conditions in county c.

I now turn to the price setting of retail chains. I consider two possible pricing strategies: uniform pricing and flexible pricing. First, I briefly discuss the standard case of flexible pricing in order to contrast the conclusions under uniform pricing. Then, I solve the model for uniform pricing: a case in which firms are constrained to set the same price in all their markets.

Retail chains pricing decisions

I assume that retail chains engage in monopolistic competition. In what follows, it is useful to define Ω_r as the set of counties in which chain r is active and Ω_c as the subset of retail chains active in county c. Since in the empirical analysis I do not observe adjustments on the extensive margin, I assume that there is no entry and exit of stores (for a discussion on the extensive margin, see Appendix A.4). I assume that retail chains' costs are national and do not depend on local conditions: $c_{rc} = c_r$. This is consistent with the fact that more than 80% of retail chains' marginal costs are related to wholesale costs of tradable goods, which are generally not produced locally (Stroebel and Vavra (2019)). In addition, it allows me to

[35] My results will be robust to using a more aggregate measure of market (the MSA) or the truncated zip code (3-digit zip code) as the relevant market definitions instead of the county.

focus on the demand channel of the shocks; which has been emphasized by previous papers that study the collapse in house prices during the Great Recession.[36]

Flexible pricing

In the flexible pricing case, firms discriminate prices across markets, so each store operates as an independent business unit. In particular, the maximization problem is given by,

$$\underset{p_{rc}}{max} \quad \sum_{c \in \Omega_r} \pi_{rc} = \sum_{c \in \Omega_r} (p_{rc} - c_r) q_{rc}.$$

This implies,

$$p_{rc}^{flex} = \frac{\sigma_c}{\sigma_{c-1}} c_r \quad \forall \quad c \in \Omega_r.$$

Note that under flexible pricing, the price in county c is independent from demand shocks in other markets $k \neq c$. For simplicity, I aggregate prices at the county-level with a Laspeyers Geometric weighted average price index, where the weights are given by l_{rc}. Then, the county-level price index for flexible prices is given by:

$$P_{ct}^{Flex} = \prod_{rct \in \Omega_c} \left(\frac{\sigma_c}{\sigma_c - 1} c_r \right)^{l_{rc}}$$

There are two main takeaways from flexible pricing: a) demand shocks in county k, do not affect price index of county c; and b) the spatial network of the dominant chains in the county $(S_r = \{S_{rc} \ for \ c = 1, ..., c, ..., C\})$ does not affect the price index of the county.

Uniform Pricing

Now consider the case of uniform pricing. For simplicity, I take uniform pricing as a constraint that retail chains have. This could be rationalized in a menu-cost model in which retail chains need to pay a fixed cost of adjustment to set different prices across regions. In this case, retail chains set a uniform price across their markets. In particular, the retail chain solves:

$$\underset{\bar{p}_r}{max} \quad \sum_{c \in \Omega_r} \pi_{rc} = \sum_{c \in \Omega_r} (\bar{p}_r - c_r) q_{rc}$$

Solving the maximization problem, we get that the optimal price of retail chain r is,

$$p_{rc}^{u} = \bar{p}_r = c_r \frac{\sum_{k \in \Omega_r} \sigma_k S_{rk}}{\sum_{k \in \Omega_r} S_{rk}(\sigma_k - 1)} \quad \forall c \in \Omega_r, \tag{1.10}$$

[36] Using PromoData from Nielsen, Stroebel and Vavra (2019) show that most of marginal cost of retail chains are wholesale costs that do not vary significantly across markets. In addition, they show that these costs do not react to local house price changes.

In appendix A.5, I solve the model allowing for local costs.

where, as in the empirical section, I define S_{rc} as the share of sales of retail chain r that take place in county c.

$$S_{rc} = \frac{\bar{p}_r q_{rc}}{\sum\limits_{k \in \Omega_r} \bar{p}_r q_{rc}} = \frac{\text{Sales of chain r in county c}}{\text{National sales of chain r}}.$$

Note that under uniform pricing:

1. p^u_{rc} depends on demand conditions in every market $k \neq c$.
2. A retail chain weights more demand conditions in markets where S_{rk} is larger.

Equation 1.10 anticipates the main mechanism through which uniform pricing operates. The price of a retail chain in a county is a weighted average of demand conditions in each of the markets where the retail chain operates, where the weights are increasing in the share of the retail chain's sales that take place in the market. Hence, retail chains' prices react more in response to shocks in its larger markets.[37]

After characterizing the retail chain's optimal prices under uniform pricing, I explore the theoretical implications at the county-level. To do so, I aggregate optimal prices in order to construct a county-level price index. For simplicity, I construct a Geometric Laspeyers Price Index:

$$P^U_{ct} = \prod_{rct \in \Omega_c} \left(\frac{P_{rct}}{P_{rc0}} \right)^{l_{rc}},$$

where, as in the empirical section, the weights l_{rc} represent the share of retail chain r in county c annual revenues. Replacing the optimal uniform prices, I obtain the theoretical county level price index under uniform pricing:

$$P^U_{ct} = \prod_{rct \in \Omega_c} \left(\frac{\sum\limits_{k \in \Omega_r} \sigma_k S_{rk}}{\sum\limits_{k \in \Omega_r} S_{rk}(\sigma_k - 1)} c_r \right)^{l_{rc}}$$

By total differentiating the county-level price index under uniform pricing, I can explore theoretically the sources of variation of this price index:

$$d \log P^U_{ct} = - \left[\sum_{r \in \Omega_c} l_{rc} \theta_{rc} \right] d \log \sigma_c - \sum_{k \neq c \in \Omega_r} \sum_{r \in \Omega_c} l_{rc} \theta_{rk} d \log \sigma_k + \sum_{r \in \Omega_c} l_{rc} d \log c_r \tag{1.11}$$

where

[37] Note that if I define the markup in market c as $\mu_c = \frac{\sigma_c}{\sigma_c - 1}$, I can re-write equation 1.10 as a weighted average of markups in the different markets; where the weights are given by $S_{rk}(\sigma_k - 1)$:

$$p^u_{rc} = \bar{P}_r = c_r \frac{\sum_{k \in \Omega_r} \mu_k S_{rk}(\sigma_k - 1)}{\sum_{k \in \Omega_r} S_{rk}(\sigma_k - 1)} \quad \forall c \in \Omega_r.$$

$$\theta_{rk} = \frac{S_{rk}\sigma_k}{\left[\sum_{k\in\Omega_r} S_{rk}\sigma_k\right]\left[\sum_{k\in\Omega_r} S_{rk}(\sigma_k - 1)\right]}.$$

The weights θ_{rk} determine the importance of county k for retail chain r. Note that θ_{rk} is increasing in S_{rk}, but it is not necessarily equal. The weights θ_{rk} would be proportional to S_{rk} only if the initial demand elasticity is equal for every county. In particular, if $\tilde{\sigma} = \sigma_c$ for all markets c, then $\theta_{rk} = \frac{1}{\tilde{\sigma}-1} S_{rk}$. Where $\tilde{\sigma}$ denotes the average demand elasticity across counties. In the next section, we explore the implications that cross-county heterogeneity in initial demand elasticity has for my empirical analysis.

Define the theoretical exposure of county c to county k as,

$$\kappa_{ck} = \sum_{r\in\Omega_c} l_{rc}\theta_{rk} \tag{1.12}$$

Equation 1.11 summarizes the three sources of variation for the county-level price index. First, local demand shocks will affect the local consumer price index, as long as the county is important for its dominant chains (high κ_{cc}). Second, demand shocks in other locations will also affect the local price index. The extent to which demand shocks in a county k affect county c price index depend on how important is market k (θ_{rk}) for dominant chains (l_{rc}) in county c (l_{rc}). Finally, changes in the national costs of retail chains that operate in the county (c_r) will also affect the county-level price index.

In the next section, I use Equation 1.11 to take the model to the data in order to 1) quantitatively test for uniform pricing, 2) rationalize the reduced-form estimates and 3) conduct counterfactual analysis.

1.6 Quantitative analysis

In the empirical section, I evaluated the propagation of shocks throughout the different counties, by analyzing the effect of a house prices shock in counties $k \neq c$ on the retail price index in county c. In this section, I conduct a model-based analysis to interpret the results through the lens of the model, quantitatively test for uniform pricing, and conduct counterfactual analysis.

Taking the model to the data

In this section, I introduce assumptions about the relationship between house price changes and the parameters in the model in order to rationalize the main findings in the empirical section.

In order to emphasize the demand channel of the Great Recession, I assume that the elasticity of demand varies with house prices. Let,

$$\beta^H = -\frac{\partial \log \sigma_c}{\partial \log HP_c} \tag{1.13}$$

In principle, β^H could have any sign. However, I expect $\beta^H > 0$, reflecting that when a county is exposed to a house price-induced negative demand shock, it becomes relatively poorer and the price elasticity increases (as, for example, in Simonovska (2015)). Note that I relax the CES assumptions by letting the demand elasticity vary with house prices, but I assume that it varies in the same proportion in every county (β^H is constant across counties).

I assume that national costs of the retail chain are uncorrelated with local house price shocks to retail chains. Several pieces of evidence suggest that this may be a reasonable assumption. For example, Stroebel and Vavra (2019) use data on wholesale costs and show that geographic variation in the costs is minimal. In addition, they show that marginal costs are not affected by local house price shocks. They present further evidence suggesting that neither variation in labor costs nor variation in retail rents play a significant role.[38]

Plugg ing Equation 1.13 in Equation 1.11 to make explicit that the demand elasticity is a function of house prices,

$$d\log P_{ct} = \frac{\beta^H}{\tilde{\sigma}-1}\kappa_{cc} d\log HP_c + \frac{\beta^H}{\tilde{\sigma}-1}\sum_{k\neq c\in\Omega_r}\kappa_{ck} d\log HP_k + \sum_{r\in\Omega_c} l_{rc} d\log c_r, \tag{1.14}$$

Equation 1.14 resembles my main empirical Equation 1.5 (which I re-write below), with two important differences that I account for.

$$d\log P_c = \beta_1 d\log HP_c + \beta_2 \sum_{k\neq c\in\Omega_r}\omega_{ck} d\log HP_k + \epsilon_c \tag{1.15}$$

The first difference is related to the direct effect of a house price shock (see blue terms). The model highlights the fact that the effect of local shocks on local retail prices is heterogeneous. It is a function of how important the local consumer market is in the national sales of the retailers who enter the local consumption basket (κ_{cc}).[39] This has two important implications. First, it implies that uniform pricing strategies can be consistent with large local elasticity of prices with respect to demand shocks; as long as the shocks are in regions with high κ_{cc}. Given that counties with higher κ_{cc} were more affected by the house price slump, this helps reconcile uniform pricing (DellaVigna and Gentzkow (2019)) with large local elasticity of retail prices with respect to house prices (Stroebel and Vavra (2019)).[40]

[38] In Appendix A.2, I formally discuss the relevance and implications of this assumption.

[39] κ_{cc} varies greatly across US counties. The mean is 0.03 and ranges from 0.0001 in the 5th percentile to 0.12 in the 95th percentile, with a standard deviation of 0.06.

[40] A remaining problem in Stroebel and Vavra (2019) is that shocks in other counties are correlated with shocks in the own county. Hence, the direct effect in their paper captures part of the propagation from counties connected by the network of retail cahins.

Second, it implies that researchers interested in the structural parameter β^H (or the elasticity of σ to other economic conditions) should weight the local shocks by the importance of the county for the dominant chains in the county.

The second difference is related to the construction of the weights (see terms in red). Although the theoretical weights θ_{rk} are increasing in the empirical weights S_{rk}, they are not exactly equal. This implies that $\kappa_{ck} \neq \omega_{ck}$. In particular, the weights θ_{rk} adjust S_{rk} by initial heterogeneity in demand elasticity across counties. In order to check the sensitivity of my results, I adjust for heterogeneity in initial elasticity of demand and construct the empirical counter-part of the weights θ_{rk}. To do so, I use county-level estimates of σ_c by quartile of population from a paper by Hottman (2014): 3.9 for the 1st and 2nd quartiles, 4.5 for the 3rd quartile and 4.8 for the 4th quartile of population (average: 4.1). Results from running my main specification, adjusting ω_{ck} for heterogeneity in initial demand elasticity are reported in Table A.15 of the appendix. Reassuringly, the coefficient is similar to the coefficient in my empirical specification.

I now proceed to construct the empirical counterpart of Equation 1.14 in order to test for uniform pricing and recover the structural parameter β^H.

A test for uniform pricing

The theoretical Equation 1.14 provides i) a quantitative test for uniform pricing; and, at the same time, ii) a methodology to recover the structural parameter β^H. If retail chains prices respond uniformly across markets, then the direct effect -weighted by the own county exposure (κ_{cc})- should be equal to the indirect effect from counties connected by the network of retail chains: $\beta_1 = \beta_2 = \frac{\beta_H}{\tilde{\sigma}-1}$.

I use county-level demand elasticities from Hottman (2014) and adjust the local change in house prices with κ_{cc} in order to construct the empirical counterpart of theoretical equation 1.14. I then run my main empirical specification, but using the empirical counterpart of Equation 1.14. Results are reported in Table 1.6. First, note that I cannot reject the hypothesis that the coefficient for the direct effect and for effect from propagation are statistically equal (I report the t-test in the last row of Panel A). That is, I cannot reject the hypothesis that the uniform pricing model accounts for the observed co-movements in county-level prices. Second, by scaling the estimate in column (6) by the average demand elasticity ($\tilde{\sigma}$-1=3.1), I obtain an estimate for β^H: $\hat{\beta}_H = 0.48$. I use this estimate for counterfactual analysis in the next section.

Table 1.6: A test for uniform pricing: $\beta_1 = \beta_2$?

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP (adjusted)	0.314***	0.108*	0.106*	0.609***	0.168	0.179
	(0.095)	(0.059)	(0.058)	(0.116)	(0.112)	(0.114)
Chain-linked Log Δ HP (other counties)		0.109***	0.108***		0.155***	0.155***
		(0.027)	(0.028)		(0.047)	(0.049)
Observations	910	910	910	910	910	910
R-squared	0.035	0.235	0.249	0.006	0.118	0.132
County controls	no	no	yes	no	no	yes
p-value $\beta_1 = \beta_2$	-	0.989	0.979	-	0.830	0.922
Panel B: First Stage						
First Stage F-stat				13.340	11.348	11.127

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). The table reports results of estimating the empirical counterpart of Equation 1.14. County's $\Delta LogHP$ is adjusted by κ_{cc}. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument $(\sum_{k\neq c} \theta_{ck} \Delta \log(HP_k))$ with network-weighted WLRI in other counties $(\sum_{k\neq c} \theta_{ck} WLRI_k)$. Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

Counterfactuals

We now have the theoretical structure, the estimates of the key parameter $\beta^H = 0.48$, demand elasticities estimated in previous papers and the data to carry out a quantitative assessment of the influence of retail chains on the spread of demand shocks during the Great Recession.

In particular, I hold constant changes in retail chains' costs ($d \log c_r = 0$) and use Equation 1.14 from the calibrated model to evaluate how the demand shocks during the Great Recession would have affected prices in different counties under different scenarios.

I propose two set of counterfactuals to evaluate the implications of uniform pricing and the geographic distribution of retail chains for the cross-county dispersion of inflation and for the distribution of the effect of the shocks. First, I compare different pricing strategies. Second, I compare different spatial networks of retail chains, generated by mergers and de-mergers of the largest retail chains.

Counterfactual 1: Pricing strategy

In this counterfactual, I map the shares S_{rk} and l_{rc} to retail chains in the data and analyze two polar opposite pricing strategies: uniform pricing (benchmark) and flexible pricing.

I use these counterfactuals to quantitatively answer two questions: What would have been the the cross-county dispersion of inflation rates during the Great Recession if pricing strategies were different? Which consumers would have benefited from the different pricing strategies?

The effect on cross-county dispersion of inflation rates

I study the quantitative implications of uniform pricing for the cross-county dispersion of inflation rates. Table 1.7 reports the average change in retail prices during the Great Recession by quintiles of changes in local house prices under the two alternative pricing strategies. The first quintile represents counties more directly exposed to the house price slump.[41] The first column reports the change in consumer retail prices for the uniform pricing case, while the second column reports the change in consumer retail prices for the flexible pricing case.

Note that the average inflation rate of the U.S. under the two alternative pricing strategies is similar. However, there are important differences in the dispersion of the inflation rate induced by the demand shocks during the Great Recession. Comparing the coefficient of variation (CV), we observe that the dispersion in cross-county inflation under uniform pricing is 40% lower than under flexible pricing. The lower cross-county dispersion of inflation rates indicates that uniform pricing smoothed-out the effect of the shocks that took place during the Great Recession. In particular, counties more affected by local drops in house prices "exported" price reductions to counties less affected by the house price slump. Hence, in the context of a negative demand shock, uniform pricing makes worse off those counties affected by the shock, which experience a deterioration of their purchasing power. Intuitively, under flexible pricing, drops in consumer prices act as buffers for counties during a recession. In contrast, under uniform pricing, the local reduction in retail prices is attenuated.[42]

Specifically, compared to flexible pricing, the reduction in consumer prices under uniform pricing was 1.25 percent points lower for the top county quintile most affected by the house price slump, while it was 2.23 percent points higher for the county quintile least affected by the house price slump. Examples of counties that would have been better off with flexible pricing include Riverside (CA), Clark County (Nevada), Maricopa (Arizona) and Miami-Dade (Florida). In contrast, St. Louis (Minessota), Aroostook (Maine), Graham (Arizona), Houston (Texas), Philadelphia (Pennsylvania) are examples of counties that benefited from uniform pricing (See Figure A.6 of Appendix A.6).

[41] In Figure A.4 of Appendix A.6 I plot the distribution of changes in prices for each of the alternative scenarios.

[42] This may not be the case for workers in the retail sector. While consumers of retail chains exposed to negative shocks in other counties benefit from lower prices, their workers might lose their jobs (See Giroud and Mueller (2019)).

Table 1.7: Inflation rates

Quintile of Δ House Price	Uniform ΔP_c^u	Flexible ΔP_c^{flex}
1	-4.19%	-5.44%
2	-2.67%	-2.07%
3	-2.61%	-1.55%
4	-2.56%	-1.13%
5	-2.59%	-0.36%
Mean	-3.42%	-3.22%
SD	1.52%	2.75%
CV	44.44%	85.47%

The quintiles are defined in terms of the house price changes. The largest drop in house prices corresponds to the first quintile. Observations are weighted by population in 2007.

The effect of uniform pricing on real income inequality

In the cross-section, uniform pricing tends to exacerbate inequality, as long as the demand elasticity is higher for poorer consumers.[43] However, it is less clear how uniform pricing affects real income inequality in response to a shock. It will depend on the magnitude, sign and location of the shocks, as well on the geographic distribution of retail chains. In this section, I explore whether uniform pricing strategies during the Great Recession benefited consumers from low-income or from high-income counties.

Define the losses from uniform pricing relative to flexible prices as,

$$\Delta_c^{Losses} = \Delta \log(P_c^u) - \Delta \log(P_c^{flex}),$$

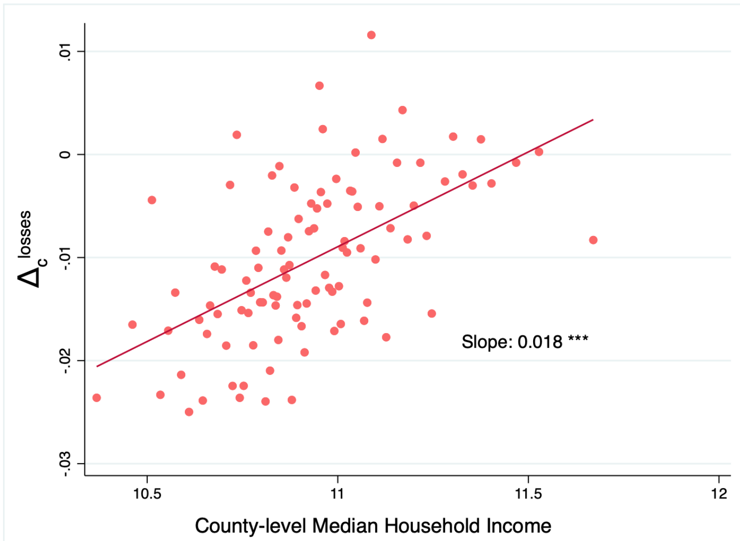
where higher values imply that county-level inflation under uniform pricing is higher than under flexible pricing. In Figure 1.6, I plot the binscatter of the relationship between Δ^{Losses} and the log county-level median household income. The pattern is clear. Compared to a scenario in which prices are flexible, low-income counties benefited most from uniform pricing. Intuitively, low-income counties were less exposed to local drops in house prices, but still benefited from drops in local consumer prices because their retail chains also operate in counties that were more exposed to the house price slump.

It is worth mentioning that the re-distributive consequences of uniform pricing discussed above are specific to the local shocks that took place during the Great Recession. For instance, one can imagine that, in the years prior to the crisis, when house prices were increasing, uniform pricing actually benefited high-income counties. More generally, uniform pricing leads to a more synchronized inflation rate across counties. Hence, understanding the bilateral linkages between counties helps a policy maker to design better-informed policies

[43] In calibrated example, DellaVigna and Gentzkow (2019) shows that uniform pricing increases the prices faced by consumers in the poorest decile of zip-codes.

to alleviate the local effects of shocks, and also the indirect effects through the network of retail chains.

Figure 1.6: Uniform pricing benefited low-income counties during the Great Recession



Note: Binscatter of the relationship between the logarithm of county-level median household income (x-axis) and $\Delta_c^{losses} = (\Delta \log(P_c^U) - \Delta \log(P_c^{flex})$ (y-axis). The elasticity is 0.018 and is statistically significant at 1% level.

Counterfactual 2: Mergers or acquisitions

Mergers have been one of the most important public policy concerns in the design of antitrust laws. A salient feature of the retail sector is that oftentimes firms expand their network of stores by merging with (or acquiring) firms that operate in different regions. For example, in 1998, Kroger merged with the then fifth-largest grocery company Fred Meyer, along with its subsidiaries, Ralphs, QFC, and Smith's. This type of merger changes the spatial networks of retail chains, affecting the linkages between counties and, thus, the propagation of shocks.

In this counterfactual, I study what would have been the cross-county dispersion of inflation rates during the Great Recession if the ownership structure of the major retail chains had been different. Note that in the extreme scenario in which there is only one retail chain, then the cross-county dispersion of inflation after a shock would be zero. Alternatively, if all retail chains split up into local stores, the cross-county dispersion of inflation will tend to the dispersion under flexible pricing. I explore two other scenarios:

(a) *De-merger:* the largest retail chain splits up into four different retail chains, each corresponding to one of the four Census regions: West, Midwest, Northeast, South.

(b) *Merger:* merger between the largest retail chain in each of the four Census regions of the U.S. (West, Midwest, Northeast, South).

Results are presented in Table 1.8. First, notice that the average inflation rate is very similar in the three scenarios. However, the cross-county dispersion of inflation would have been considerably different under the alternative scenarios. As expected, when the largest firm split up into regions, the cross-county dispersion of inflation increases 5%. The reason for this is that the largest chain now only propagates shocks within regions, but not across them. In contrast, when the four largest chains in each region merge, the cross-county dispersion of inflation rates declines 12%. Intuitively, this merger expands the retail chains' spatial networks, which increases the connections between counties. This, in turn, indicates that, under uniform pricing, mergers between retail chains in different regions would have smoothed out the impact of local shocks during the Great Recession across regions even further.

Table 1.8: Changes in the distribution of firms: Mergers and Partitions

$\Delta \log(P_c)$	Empirical	De-merger	Merger
Mean	-3.42 %	-3.42%	-3.45%
SD	1.52%	1.59%	1.36%
CV	0.44	0.46	0.39

Note: Counties are weighted by population.

As mergers smooth out the effects of local shocks across regions, they might also have redistributive consequences in the event of a shock. For example, during the Great Recession, I find that low-income counties would have been made better off had there been a merger between the largest retail chains in each region. Specifically, in the scenario of a merger, the poorest quintile would have experienced a 0.18 p.p lower inflation (6%) than under the benchmark case. In contrast, the richest quintile, would have experienced a 0.13 p.p. higher inflation rate (4%). The reason for this pattern is that high-income counties were more affected by shocks during that period than were low-income counties. Therefore, as mergers between retail chains in different regions intensify the linkages between those regions, the effect of the shock in high-income counties spreads to low-income counties which benefit from reduction in their retail prices.

Again, it is worth mentioning that conclusions related to the redistributive effects are specific to this period, and to the shocks I am analyzing. The more general conclusion that we obtain from this findings is that, under uniform pricing, mergers between retail chains that are located in different regions intensify the linkages between these regions, increasing the contribution of retail chains to the observed co-movement in county-level consumer prices.

1.7 Conclusion

I study the role of retail chains' spatial networks of stores in shaping the propagation of shocks across regions in the United States. My empirical results show that the county-level consumer price index is sensitive to shocks in distant counties in which the same retail chains operate. My results hold after controlling for trade relationships due to proximity. In fact, I show that once the network of retail chains is taken into account, the most traditional channel of propagation of shocks to nearby counties plays no additional role.

I find that the key mechanism behind the propagation of shocks is the inter-dependencies in pricing strategies between stores of a given retail chain. As retail chains set prices uniformly, they take into account demand conditions in all their markets to determine optimal prices. Hence, in response to a negative demand shock in one market, they react by changing prices in many markets.

The pricing strategies of retail chains have important consequences for the re-distribution of shocks in the economy. Uniform pricing strategies smooth-out the effect of local shocks on prices. This has two direct implications. First, uniform pricing attenuates the pro-cyclical behavior of local prices. Second, uniform pricing increases the synchronization of consumer prices across counties. In the context of a negative demand shock, uniform pricing deteriorates the situation of consumers in counties more directly affected by the shock. On this ground, I show that during the Great Recession, uniform pricing reduced the cross-county dispersion of inflation by 40% (compared to flexible pricing). Since low-income counties were relatively less directly exposed to the house price slump, they benefited from uniform pricing.

These findings have important implications for the design of policies. My paper emphasizes that retail chains' networks create linkages between regions. These linkages determine the patterns of propagation of shocks to consumer prices. Therefore, when weighting the costs and benefits of a policy, policy makers should consider not only the impact on local prices, but also the indirect impact on prices in distant regions. More broadly, when prices are rising in a region (for example, due to gentrification), the design of optimal policies should also take into account what is happening in the regions that are connected by the network of retail chains.

Chapter 2

Multi-destination Exporters, Market Power and the Elasticity of Markups Across Destinations[1]

2.1 Introduction

Recent literature has documented that heterogeneous firms charge variable markups.[2] Most of these papers have focused on understanding how the elasticity of markup vary with firm-level characteristics.[3] It is also well-known that trade is highly concentrated in a few firms that export to many markets.[4] The fact that multi-destination exporters are predominant in trade suggests that understanding their behavior is important in many contexts. Yet, surprisingly, there is no evidence on how multi-destination exporters adjust their markups in their different markets and which are the firm-destination characteristics that determine these adjustments. In this paper, we aim to fill this gap. How do multi-destination exporters respond in different markets to a cost shock? Does the elasticity of markup for a given firm differ across its destinations? Does the elasticity of markup of a given firm depend on its relative size in the destination?

Analyzing the responses of a given firm, across its many destinations requires rich micro-level data and substantial exogenous variability on the exposure of firms to shocks. Most of the papers that study the elasticity of markup exploit variability from bilateral exchange rate shocks. However, the nature of this variability has prevented the authors to compare responses of a given firm, across its destinations (e.g: Amiti et al. (2014)). In order to address this problem and be able to answer these questions, we develop a methodology

[1]This Chapter comes from a joint work with Federico Bernini. He gave his permission to use this material as a chapter of this dissertation.

[2]Atkeson and Burstein (2008); Berman, Martin, and Mayer (2012); Goldberg, Khandelwal, Pavcnik, and Topalova (2010); Amiti, Itskhoki, and Konings (2016)

[3]For instance, Berman et al. (2012) shows that higher performance firms have a higher elasticity of markup. Similarly, Amiti, Itskhoki, and Konings (2014) shows that within a destination, comparing across firms, the elasticity of markup is increasing in the firm's market share in the market.

[4]In our sample, 99.50% of total manufacturing exports are explained by multi-destination exporters.

that combines the structure of an international trade model with an empirical strategy that exploits exogenous shocks to firms' costs of production.

Our empirical strategy is based on analyzing how a firm responds in its different destinations after being hit by a shock to its costs. We use a comprehensive database of Argentinian firms for the period of 2002-2011 and exploit exogenous variability coming from the timing in which barriers to imports of certain products where imposed between 2005 to 2011, combined with the firm's previous share of imports of the affected product previous to the policy this period. The idea is that barriers to imports of intermediate inputs increase firms' costs to produce. We assume that a firm is more exposed to these cost shocks when it was already using the imported input in its production function and that the shock is firm-year specific.

Our first empirical result is at the firm level in order to show that barriers to importing were, in fact, a cost shock. We show that more exposed firms reduce their amount of exports considerably.[5] Once we have established that import barriers affect costs, we use the shock to uncover our main fact. Conditional on destination-sector-year fixed effects, we test whether firms' responses to the shock vary across its destinations depending on their relative size in the market. We find that a given firm reduces more its export revenues (increase more its prices) in markets where the firm's market share is relatively higher.

Explaining the nature of the observed behavior is at the core of this paper. Therefore, in order to guide the empirical analysis, we develop a model of export and import choices that allows for variable markups for a given firm in different markets.[6] On the demand side, the framework incorporates variable markups to a standard model of heterogeneous firms, closely following the analysis in Atkeson and Burstein (2008).[7]. On the supply side, we propose a model of import behavior that shares the main ingredients of standard models of importing (Antras, Fort, and Tintelnot (2014); Blaum, Lelarge, and Peters (2013); Blaum (2017); Halpern, Koren, and Szeidl (2009)). We assume that firms draw core productivity and that firms combine inputs in a CES production. We further assume that inputs markets are perfectly competitive as it is standard in the importing literature.

By closely following the model structure, we show that our empirical findings are consistent with a mechanism in which multi-destination exporters decide to adjust more their markups in response to cost shocks in those markets where they are relatively bigger. That is, the elasticity of the elasticity of markup with respect to a firm's market share in a destination (markup super-elasticity) is positive. Intuitively, when hit by a negative shock,

[5] We also revisit the elasticity of exports with respect to imports. We find that this elasticity is around 50%. We also show a remarkable decline in the probability of exporting and the number of destinations that the firm reaches after access to imports of intermediate goods becomes more costly.

[6] So far the model does not explicitly incorporates quality standards when serving different markets, but in a future version we aim to have this. However, we do present some empirical results that may be consistent with the quality hypothesis being part of the explanation

[7] The main conclusions regarding variable markups hold in a wider class of models of trade that have been used in recent papers. However, the direction of the elasticity of markups with respect to the firm's market share is model specific. We test the hypothesis that this term is positive. See for instance Arkolakis and Morlacco (2017) for a review of different ways of incorporating variable markups

multi-destination exporters are able to absorb a part of this shock by reducing its markups in markets where they have higher market power.

Our paper contributes to different strands of the literature. We document a previously unexplored dimension of firm heterogeneity. We highlight the importance of the elasticity of markups for a given firm, across its export destinations. Previous papers have documented in the cross-section of firms that a given firm, charges different prices across destinations (e.g: Manova and Zhang (2012)). However, these papers have not analyzed how these prices respond to shocks specific to the firm. We show that firms adjust not only product scope and total export volumes, but also their markups across destinations. In making decisions, multi-destination firms optimally decide to adjust more their markups to cost shocks in markets where they have higher market shares. As most of the trade flows are concentrated in a few firms that export to many markets, this margin of adjustment could potentially be important to estimate welfare gains from trade. In addition, this may have consequences on the distribution of gains from unilateral trade liberalization in foreign countries.

We also contribute to a growing literature that studies heterogeneous responses of firms in the context of exchange rate movements and incomplete exchange rate pass-through. For instance, Berman et al. (2012) find that higher performance firms tend to absorb exchange rate movements in their markups so that their average prices in the foreign market are less sensitive. Amiti et al. (2016) also show the existence of variable markups in the domestic market and analyze the role of strategic complementarity. However, these papers do not analyze differential responses in foreign markets and don't take a stand on whether a firm adjustment depends on characteristics specific to the firm-destination. Perhaps, more similar to ours is Amiti et al. (2014), which decomposes the exchange rate pass-through into the role of firms marginal costs, import intensity, and market power of a firm in a given market and do analyze adjustments of firms depending on their market share. However, their focus on bilateral exchange rates (demand shock) is not the most convenient setting to specifically test whether firms adjust differently their markups in different markets because a) a bilateral exchange rate shock may not hold demand constant, and b) the shock provides less variability for a firm across destinations. Hence, their analysis focuses on comparing firm-responses within a given destination. We innovate by exploiting an import costs shock (supply shock) that let us identify the markup elasticity and how it depends on market share of the firm in different markets while holding constant demand shocks. By comparing the same firm across destinations, our estimate can be interpreted as a more accurate estimate of the super-elasticity of markup, or as an estimate of a new super-elasticity. In any case, the estimate is important to develop and calibrate models that analyze the exchange rate pass-through. Therefore, we see our contribution as complementary to the literature that aims to understand price-to-market and incomplete exchange rate pass-through.

When it comes specifically to import costs shocks, De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) find that after India trade liberalization the price declines are small relative to the declines in marginal costs since firms offset their reductions in marginal costs by raising markups. They also demonstrate heterogeneity across firms. However, their focus is on variable markups in domestic markets. Our paper complements these findings by analyzing the responses of firms across export destinations.

We also provide new insights on the causal elasticity of firm-level exports with respect to imports, contributing to recent literature that studies the specific interplay between importing and exporting activities. Surprisingly, only a few papers have investigated how imports of intermediate goods causally affect exports. Bas (2012) uses survey data for 1000 Argentinian firms and exploits variability coming from changes in industry tariffs after Argentina trade liberalization in 1990 to study the effect of input tariffs on exports. However, as data on imports was not available, the author is not able to relate imports to exports. More closely to ours is the work of Feng, Li, and Swenson (2017) that uses tariff liberalization episodes in China between 2006-2010 to establish the connection between imports of intermediate inputs and exports. Their analysis relies on industry level weights of exposure. Finally, Kasahara and Lapham (2013) develop a theoretical model that allows for complementarity between exporting and importing and shows that this complementarity is important to understand the welfare implications of openness to trade.[8]

Finally, the last contribution of the paper is studying the causal effect of a non-tariff barrier to trade. These barriers have been increasingly important on the world trade and are expected to become more predominant in the future, given the restrictions on tariffs by the WTO.[9] Literature on the effects of these barriers on firms' export decisions is scarce. In this paper, we provide new insights about their effect on firms' performance.

The remainder of the paper is structured as follows. We begin Section 1 by describing the data and documenting patterns in the data that guide our theoretical and empirical approach. Section 2 develops the theoretical framework. In Section 3 we describe the empirical strategy, the policy that we exploit, and discuss our identification assumptions. In section 4, we present the main results. We conclude in section 5.

2.2 Data

Description

Our main data source is administrative data from Argentinian Customs, which provides a comprehensive panel of the universe of Argentinian trade flows by firm, product at most detailed aggregation level (12 digit level, which includes HS 6-digit level and 6 digits specific to Argentina), exports by destination, and imports by source country. The panel has a monthly frequency and spans from 2002 to 2011. We merge these data, using a unique firm identifier, with firms' employment and main sector of activity (CLAE-6digits) from Argentinian Tax Authority, comprising the universe of formal sector. We restrict the sample

[8] Under a different mechanism, Albornoz and Garcia-Lembergman (2018) studies how exporting activity affect importing.

[9] For instance, Nicita and Gourdon (2013) shows that non-automatic licenses are the most used measure to control import quantities (since quotas were made illegal by WTO) and they are specially implemented in developing countries.

to manufacturing firms to avoid trading companies whose imports are not intermediate inputs to their own production and whose exports are not produced by other firms. We also restrict the sample to firms that exported at least once in the period 2002-2007. Hence, we focus on the 12,165 manufacturing firms that exported in the period 2002-2007.[10]

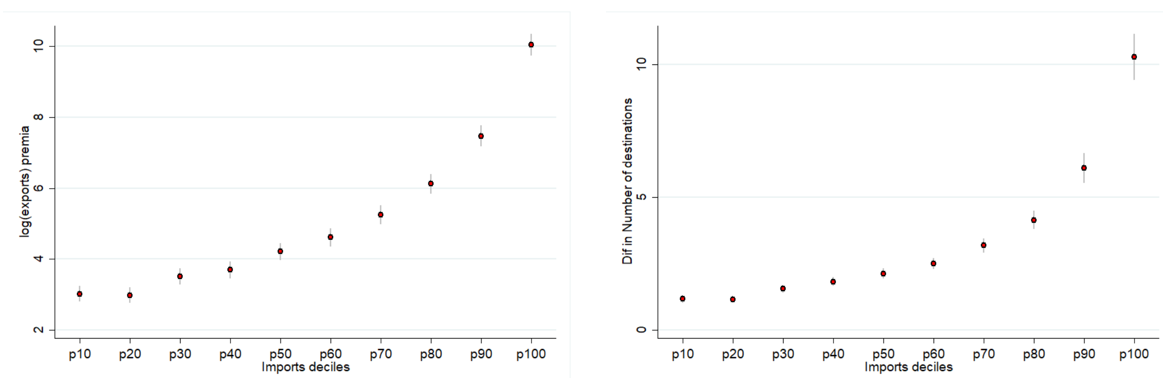
Finally, we constructed a unique database containing monthly data on (non) tariff barriers to different products imposed in Argentina during 2002-2011 period. We tracked and digitized executive decrees during the period in order to construct a database listing the month-year in which an administrative barrier was imposed to each of the products at (HS-8-Digit). The policy is described more in detail in the empirical strategy section.

Stylized Facts

In this section we document patterns in the data that guide our theoretical model assumptions and empirical strategy, as well as motivates our research questions.

Fact 1. Relation between importing and exporting: An empirical regularity is that larger importers are more successful as exporters. This salient pattern is also present in many other datasets. Even after controlling for firm's characteristics such as size, the correlation between importing and exporting is still important. This suggests that, even conditional on firm's characteristics, access to foreign inputs is a key factor to be able to reach export markets. For instance, imports of intermediate inputs help firms to reduce their unit costs (or improve the quality of their products). In the following figures we document this pattern. We separate firms in import deciles and show that larger importers export more and reach more destinations. In addition, the effect intensifies for the largest importers.

Figure 2.1: Firm total exports, number of destinations and size as importer



Fact 2. Price (unit values) dispersion across firms and also within a firm across destinations A salient feature in our data is that there is substantial price dispersion.[11].

[10] Results remain qualitatively unchanged if we don't impose this last restriction.

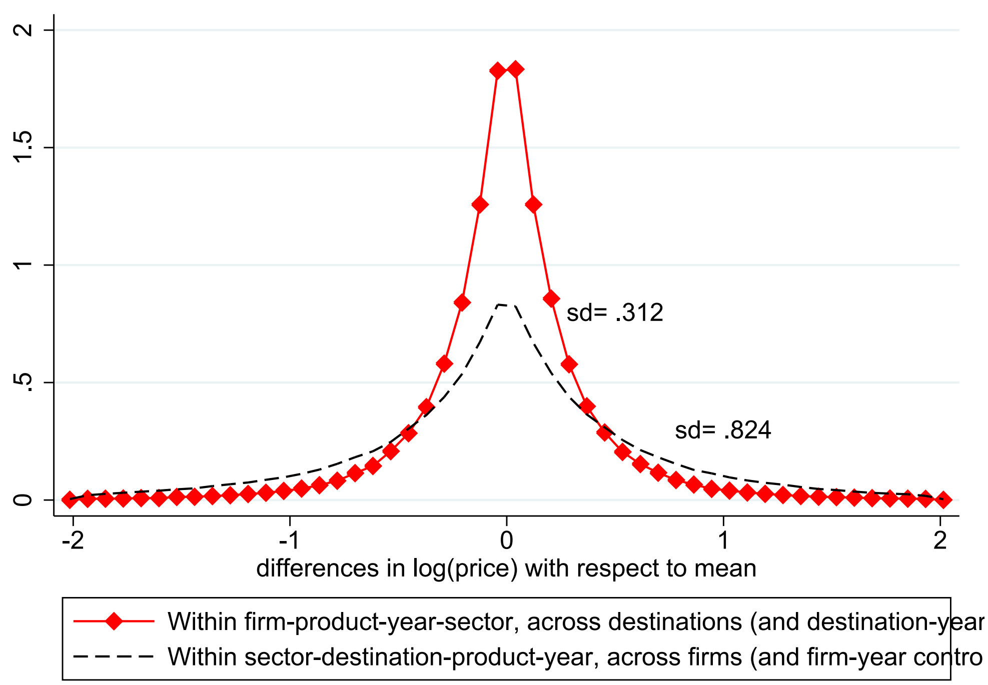
[11] From hereafter, we proxy prices with unit values and compare products that are in the same unit of measure (e.g: units, kg)

First, in a given destination, for a given product (at 12-digits level), controlling for total exports and employment, we can observe that the standard deviation of log (prices) is around 1.04. Put it differently, in a given destination, different firms in a given sector sell similar products at very different prices.

Notably, a fact that has been less explored by the literature is that price dispersion is still remarkably important when we compare prices for a given product in a given year for a given firm, across its destinations markets.[12] This is true even controlling for sector-by-destination-by-year fixed effects in order to compare similar destination markets (i.e: control for size of the market, as well as growth of a particular sector). The standard deviation of prices of the same firm for the same product across similar destinations is around 0.61. This suggests that there are characteristics specific to a firm-destination that affect considerably the price that a firm set for a given product in each market.[13]

The graph below summarizes the price dispersion described above by plotting the density functions of the difference in log prices with respect to the mean across firms (dashed black line) and within firms across destinations (connected red line).

Figure 2.2: Price dispersion across and within firms



[12] Manova and Zhang (2012) provides similar evidence of this pattern for Chinese firms.

[13] We acknowledge that unit prices are measured with error. Hence, our methodology derive conclusions by focusing on changes in export revenues (similar to Berman et al. (2012)). However, we believe that using unit values is informative in the descriptive analysis.

Fact 3. Firm's relative size in the market is relevant to explain the price differences

In order to present this fact, it is convenient to construct a variable that will be key in our analysis. Lets denote S_{iskt} the share of firm i exports to market k relative to all firms belonging to sector s, supplying in the destination market k, including Argentinian exporters and exporters from other countries. We define sectors at the HS-4digits level.[14]

$$S_{iskt} = \frac{Exports_{iskt}}{WorldImports_{skt}} * 100,$$

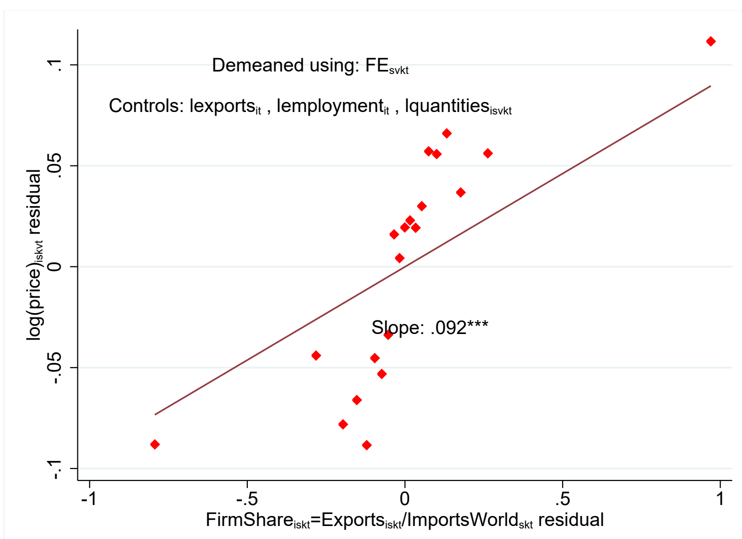
where $WorldImports_{skt}$ is total imports of country k of products belonging to sector s. We summarize the distribution of this variable in Table B.1 of the appendix.

First, in order to estimate the correlation for a given product-by-destination-by-sector across similar firms, we run the following regression:

$$\log(price)_{isbkt} = \beta S_{iskt} + FE_{sbkt} + controls_{it} + \epsilon_{ispkt}$$

where b is the product at 12 digits.[15] To be as transparent as possible with the variability that we are capturing, we plot the bin scatter of the demeaned variables, as well as the fitted line; which slope is the main coefficient of the regression (β). The figure shows that the same product, sold in the same market in a given year is increasing in the firm's market share in the destination. This is true, even controlling for the size of the firm.

Figure 2.3: Market power and price dispersion across firms, within a destination



[14] Alternatively, this fact and main results of the paper remains qualitatively unchanged if we define the sector at the HS6 level. Results are availabe upon request.

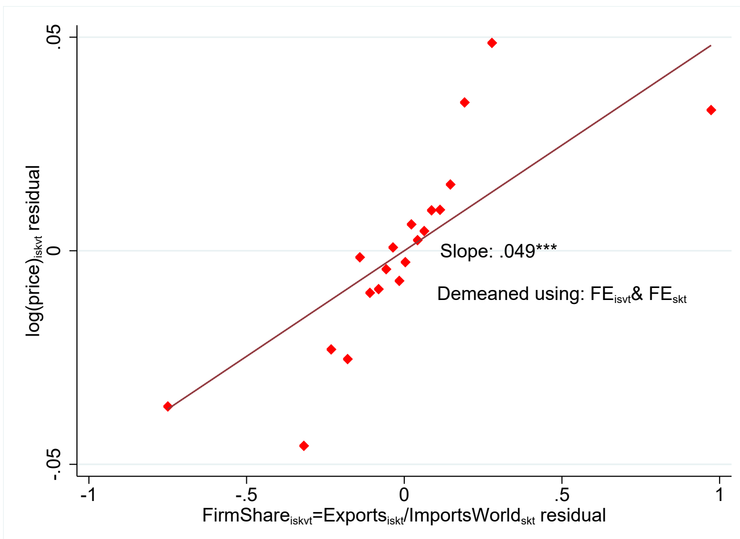
[15] In addition, we compare products which quantity is measure in the same unit.

More importantly, we document a new stylized fact: Conditional on destination-by-sector-by-year characteristics, the same firm, exporting the same product, charges higher prices in markets where it represents a larger share of the country imports in the sector. To do so, we run the following regression:

$$\log(price)_{ispkt} = \beta S_{iskt} + FE_{isbt} + FE_{kt} + \epsilon_{isbkt}$$

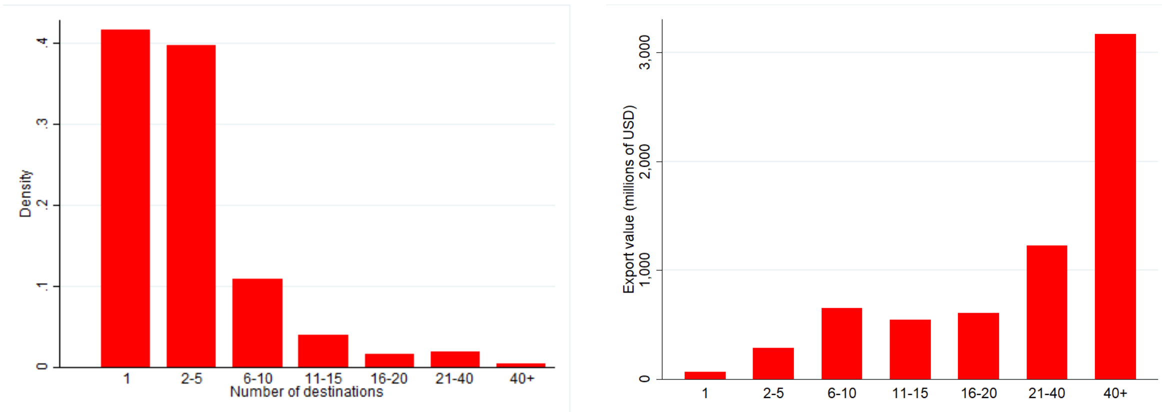
In Figure 2.4 we document that a given firm charges higher prices in markets where its market share is relatively higher. This is true even controlling for destination-by-sector-by-year FE.

Figure 2.4: Market power and price dispersion within firm, across markets



Fact 4. Most of trade flows are explained by multi-destination exporters
It is well-known that trade is concentrated among a few big firms. In our sample, roughly 60% of the exporters, export to more than one destination in a given year. In addition, these firms represent more than 99% of Argentine manufacturing exports. Figure 4 summarizes the importance of multi-destination exporters.

Figure 2.5: Most of trade is concentrated among multi-destination exporters.



2.3 Model

We consider a static small open economy where local firms can import their intermediate inputs and export their output. As it is standard in the literature, importing inputs from abroad reduces the unit cost of production of firms, but it is subject to fixed costs (Antras et al. (2014); Blaum et al. (2013); Blaum (2017); Halpern et al. (2009)). For now, we will focus on the intensive margin of exports and imports in the theoretical section.[16]

We allow firms to sell their products to k foreign markets which differ in their demand. Importantly, guided with the patterns in the data described below, we allow for variable markups of a firm in each market. In particular, we want the model to generate higher markups for firms with higher shares in a market. Our model follows closely Atkeson and Burstein (2008) variable markups model.[17]
As a side-note, the model offers an alternative way to measure the average elasticity of markups with respect to prices when information on unit costs or prices is not easily available.[18] In particular, it suggest that it is possible to estimate it using only information on firm's total imports and exports.

Demand

Consider a firm producing in sector s, at year t, a differentiated good i supplying it to destination market k in period t.[19] Consumers in each market have a nested CES demand over

[16] Although 1) We will show results on the extensive margin in the empirical section; and 2) soon we will add propositions for the extensive margin
[17] other papers using this
[18] Even when available, unit cost and prices information is typically measured with error.
[19] For brevity, we drop the subscripts s and t for sector and time. To facilitate to relate this paper to other papers with variable markups, we will try to follow closely the notation in Atkeson and Burstein (2008),

the varieties of goods.

In particular, provided exporting to market k, a firm i faces the following demand:

$$Q_{ik} = \gamma_{ik} P_{ik}^{-\rho} P_k^{\rho-\eta} D_k,$$

where γ_{ik} is a taste shock for the final good of firm i in market k, P_{ik} is the price of the firm in market k, P_k is the price index in the sector in which the firm operates, D_k is the size of market k. ρ denotes the elasticity of substitution across the varieties within sectors, while η stands for the elasticity of substitution across sectoral aggregates. We assume that $\rho > \eta > 1$. This demand endogenously generates variable markups that crucially depend on a firm's market share in market k. Define this market share as,

$$S_{i,k} = \frac{P_{i,k} Q_{i,k}}{\sum_{i'} P_{i',k} Q_{i',k}} = \mu_{i',k} \left(\frac{P_{i',k}}{P_k} \right)^{(1-\rho)}.$$

Note that the effective demand elasticity for firm i in market k is given by,

$$\sigma_{i,k} = \rho(1 - S_{i,k}) + \eta S_{i,k}.$$

As $\rho > \eta$, this elasticity is decreasing in the market share of the firm. Intuitively, when a large firm changes its price, it also affects considerably the sectorial price index. Hence, market demand for those firms is less responsive to changes in their own price.

Then, the markup, $\mathcal{M}$, is given by

$$\mathcal{M}_{ik} = \frac{\sigma_{i,k}}{\sigma_{i,k} - 1} = \frac{\rho + (\eta - \rho) S_{i,k}}{\rho + (\eta - \rho) S_{i,k} - 1}$$

It will be informative for the rest of the analysis to understand how mark-ups react to changes in the price of a firm in market k. Holding constant sector price index, markup elasticity with respect to firm's price is given by,

$$\Gamma_{ik} = -\frac{\partial \log \mathcal{M}_{ik}}{\partial \log P_{ik}} = \frac{S_{ik}}{\left(\frac{\rho}{\rho-\eta} - S_{ik} \right) \left(1 - \frac{\rho-\eta}{\rho-1} S_{ik} \right)} > 0$$

Three key features arise from inspection of the equations above that worth mentioning. First, firms that have a higher share in market k also have higher markups in that market. This feature is consistent with Fact 3. Second, the elasticity of markup with respect to prices is negative. Third, the absolute value of the elasticity of markups with respect to price is increasing in the firm's share in market k. Put it differently, the super-elasticity ($\S = \partial \log \Gamma_{ik} / \partial \log S_{ik} > 0$) is positive. Intuitively, firms with larger market share have larger markups and choose to adjust markups in response to shocks, while keeping quantities and

Amiti et al. (2014) and is standard in the literature.

prices more stable.

Definition 1
Super-elasticity of markup (§): **The derivative of the absolute value of the elasticity of markup with respect to market share in destination k. Formally, ($\S = \partial \log \Gamma_{ik} / \partial \log S_{ik}$).**

1. Markup of firm i ($\mathcal{M}_{ik}$) is increasing in a firm's market share in the market.
2. The elasticity of markup with respect to price ($-\Gamma_{ik}$) is negative.
3. Increasing superelasticity (§): The absolute value of the elasticity of markup with respect to price is increasing in market share of the firm.

Proof. See appendix. □

Import Decision and unit costs

We now turn to the import behavior of the firm. This together with its productivity draw determines the firm's unit costs. We consider a standard framework of import behavior where firms' import decisions are the solution to a maximization problem. Since foreign suppliers can be more efficient at producing some of the intermediate varieties, firms may be willing to demand imported inputs as a vehicle to reduce unit cost of production. A measure N of final-good producers each produces a single differentiated product. Firms are characterized by an heterogeneous attribute φ that, for concreteness, is interpreted as core productivity. Just like in Melitz (2003), this parameter is exogenously drawn from a probability distribution $g(\varphi)$ and revealed to the firms once they start to produce. The production function takes the following CES form:

$$Q = q(z) = \varphi \left[\sum_{v} (z_v)^{\frac{\theta-1}{\theta}} \right]^{(\theta/\theta-1)}$$

z_v denotes the amount of imports of product variety v (item p sourced from market j) and $\theta > 1$ is the elasticity of substitution of inputs. As for the moment we will not focus on the source market, lets assume that there is only one market from where the firm can source inputs. Hence, $v = product$ from that market. [20] Importing variety v involves a fixed cost (κ^m), which (for now) we assume common across firms and sources. We further assume that firms take input prices (adjusted by quality) as given and determined by characteristics specific to the origin-product, A_v(i.e: quality, technology and wages in country j for producing product p), and bilateral trade costs specific to the firm-variety (τ_{iv}):

[20] This leads the same prediction as Antras et al. (2014) where the gains from variety comes from productivity draws of foreigners from a Frechet distribution function of foreigners akin to Eaton Kortum

$$P_v = \frac{\tau_{iv}}{A_v}$$

Firm Import Behavior

We briefly analyze the firm's behavior in equilibrium. It is convenient to define a sourcing strategy Ω as the set of input varieties v, such that the firm imports positive amounts of these varieties. We focus first in firms' decision, conditional on the sourcing strategy Ω.

Optimal amount of imports conditional on sourcing strategy

To obtain the amount of imports of variety v, the firm minimizes its cost function subject to its production function.

The optimal quantities of variety v are given by,

$$z_v^*(\varphi, \Omega, Q) \equiv arg \min_{z_v} \sum_{v \in \Omega} p_v z_v \text{ s.t } Q = \varphi \left[\sum_{v \in \Omega} (z_v)^{\frac{\theta-1}{\theta}} \right]^{(\theta/\theta-1)}. \tag{2.1}$$

Solving,

$$z_v(\varphi, \Omega, Q) = \frac{Q}{\varphi} \frac{\left(\frac{1}{p_v}\right)^{\theta}}{\left[\sum_{(v) \in \Omega} \left(\frac{1}{p_v}\right)^{\theta-1}\right]^{\theta/\theta-1}} \qquad \forall v \in \Omega, \tag{2.2}$$

Or in terms of value,

$$p_v z_v(\varphi, \Omega, Q) = \frac{Q}{\varphi} \frac{\left(\frac{1}{p_v}\right)^{\theta-1}}{\left[\sum_{v \in \Omega} \left(\frac{1}{p_v}\right)^{\theta-1}\right]^{\theta/\theta-1}} \qquad \forall v \in \Omega, \tag{2.3}$$

Once we have the intensive margin of imports for any variety that belongs to the firm sourcing strategy (Equation 2.3), it is straightforward to obtain the minimum unit cost function for a given sourcing strategy.

$$c_i = \frac{h(\Omega)}{\varphi} = \frac{1}{\varphi} \left[\sum_{v \in \Omega} \left(\frac{1}{p_v} \right)^{\theta-1} \right]^{-\frac{1}{\theta-1}} = \frac{1}{\varphi} \left[\sum_{v \in \Omega} \left(\frac{A_v}{\tau_{iv}} \right)^{\theta-1} \right]^{-\frac{1}{\theta-1}} = \frac{1}{\varphi} \left[\Phi \right]^{-\frac{1}{\theta-1}}, \tag{2.4}$$

where h() is the part of the unit cost given by inputs and in the last identity we defined the sourcing capability of a firm as,

$$\Phi_i = \left[\sum_{v \in \Omega} \left(\frac{A_v}{\tau_{iv}} \right)^{\theta-1} \right].$$

Also note that total amount of imports of intermediate goods of firm i is given by,

$$M_i(\Omega) = \frac{Q_i}{\varphi}\left[\sum_{v\in\Omega}\left(\frac{A_v}{\tau_{iv}}\right)^{\theta-1}\right]^{-\frac{1}{\theta-1}}, \tag{2.5}$$

Expenditure share of firm i on imported variety v is given by,:

$$m_{iv}(\Omega) = \frac{\left(\frac{A_v}{\tau_{iv}}\right)^{\theta-1}}{\left[\sum_{v\in\Omega}\left(\frac{A_v}{\tau_{iv}}\right)^{\theta-1}\right]} \qquad \forall v \in \Omega;$$

$$m_{iv}(\Omega) = 0 \qquad \forall v \notin \Omega$$

and, by Shepard's Lemma:

$$\frac{\partial log c_i}{\partial log \tau_{iv}} = m_{iv} \tag{2.6}$$

Note that the model predicts that the barrier to import has a higher impact on costs, the larger the share of the firm's expenditure on the input affected by the barrier. In our empirical section, we use this to construct our firm level shock.

As we will not derive conclusions on the extensive margin of imports, in what follows we omit the argument Ω.

Price setting

Given a sourcing strategy, with its corresponding unit cost $c_i(\Omega, \varphi)$, solving for optimal price in market k is standard:

$$P_{ik} = \frac{\sigma_{ik}}{\sigma_{ik}-1}c_i(\Omega,\varphi)$$

Holding constant the sectoral price P_k, the elasticity of price with respect to a tariff to input v of firm i is given by,

$$\frac{d\log P_{ik}}{d\log \tau_{iv}} = \frac{1}{1+\Gamma}m_{iv}$$

Proof.

$$P_{ik} = \mathcal{M}\left(\frac{P_{ik}}{P_k}\right)c(\Omega,\varphi)$$

$$d\log P_{ik} = -\Gamma(d\log P_{ik} - d\log P_k) + \frac{\partial \log c(\tau,\varphi)}{\partial \log \tau_{iv}}d\log\tau_{iv}$$

$$\frac{d\log P_{ik}}{d\log\tau_{iv}} = \frac{1}{1+\Gamma}\frac{\partial\log c(\Omega,\varphi)}{\partial\log\tau_{iv}}$$

Applying Shepard's Lemma and rearranging we have the result:

$$\frac{d\log P_{ik}}{d\log \tau_{iv}} = \frac{1}{1+\Gamma} m_{iv}$$

□

We hold constant P_k, as we do so throughout the empirical section by including sector-year FE in every specification. If markup is constant, then the effect of a tariff to a intermediate input on price is equivalent to the initial share of the input that the firm was using m_{iv}. In contrast, if markups are variable, we expect that the impact is lower for larger firms which have a higher Γ. This will be a key feature to explain differential effects of (lack) of access to intermediate inputs on exports depending on the relative position of the firm in the market.

Revenues in equilibrium

Revenues for firm i in market k are given by:

$$R_{ik} = \frac{1}{\mathcal{M}_{ik}^{\rho-1}} \frac{\varphi^{\rho-1}}{h_i^{\rho-1}} P_k^{\rho-\eta} D_k,$$

and, total revenues of a firm are given by,

$$R_i = \frac{\varphi^{\rho-1}}{h_i^{\rho-1}} \sum_k \frac{1}{\mathcal{M}_{ik}^{\rho-1}} P_k^{\rho-\eta} D_k,$$

[21]

Predictions

The model generate two set of predictions that will guide our empirical section. The first set of results are firm-destination specific. We establish the direct effect of an increase on trade barriers for a given input on the firm's exports in each market k. Importantly, this proposition predicts the expected responses of a multi-destinations firm in its different markets, depending on variable markups and characteristics of the firm-destination. The second set of results are at the firm level. These predictions show how trade barriers affect total export revenues and total imports and guide the estimation of the elasticity of exports with respect to imports at the firm level.

We begin by establishing the effect of import cost shocks on export revenues in a given market k.

[Firm-destination responses]

[21] Note that when we extend the model to allow for entry and exit into import and export, lower costs through higher inputs may let us

A. Provided $\rho > 1$, revenues in market k are weakly decreasing in the costs of importing variety v (τ_{iv}). In addition, the effect is larger (more negative), the higher is m_{iv}:

$$\frac{\partial \log R_{ik}}{\partial \log \tau_{iv}} = (1-\rho)\left[\frac{1}{1+\Gamma_{ik}} m_{iv}\right] \leq 0 \tag{2.7}$$

$$\frac{\partial \log R_{ik}}{\partial \log \tau_{iv} \partial m_{iv}} = (1-\rho)\left[\frac{1}{1+\Gamma_{ik}}\right] \leq 0 \tag{2.8}$$

B. The effect of increasing import costs on exports to market k is weakly decreasing in the elasticity of markup Γ_{ik} (it is strictly decreasing if markups are not constant):

$$\frac{\partial \log R_{ik}}{\partial(\log \tau_{iv} \partial m_{iv}) \partial \Gamma_{ik}} \geq 0 \tag{2.9}$$

C. if $\S = \frac{\partial \log \Gamma_{ik}}{\partial \log S_{ik}} > 0$, then the absolute value of the elasticity of exports to market k with respect to import costs is weakly decreasing on the size of the firm S_{ik}. It is decreasing if markups are not constant:

$$\frac{\partial \log R_{ik}}{\partial(\log \tau_{iv} \partial m_{iv}) \partial S_{ik}} \geq 0 \tag{2.10}$$

Proof. Proofs are straigh-forward from the inspection of equations above. See appendix. □

We now turn to analyze the effects at the firm level.
[Firm level predictions]

A. **(Effect on total exports)** The effect on total exports is negative and decreasing in the size of the firm.

$$\frac{\partial \log R_{i}}{\partial \log \tau_{iv}} = (1-\rho)\sum_{k} \frac{R_{ik}}{R_i}\left[\frac{1}{1+\Gamma_{ik}} m_{iv}\right] < 0 \tag{2.11}$$

B. **(Effect on total imports)** Provided $\rho > 1$, imports are weakly decreasing in the trade costs of importing variety v (τ_{iv}). In addition, the negative effect is stronger, the higher the share of firm's imports corresponding to v:

$$\frac{\partial \log M_{i}}{\partial \log \tau_{iv}} = -m_{iv}\left[\rho \sum_{k} \frac{Q_{ik}}{Q_k} \frac{1}{1+\Gamma_{ik}} - 1\right] \leq 0 \tag{2.12}$$

$$\frac{\partial \log M_{i}}{\partial(\log \tau_{iv} \partial m_{iv})} = -\left[\rho \sum_{k} \frac{Q_{ik}}{Q_k} \frac{1}{1+\Gamma_{ik}} - 1\right] \leq 0 \tag{2.13}$$

C. **(Elasticity of exports with respect to imports)** The total amount of exports of a firm are increasing on the amount of imports of the firm. That is,

$$\mathcal{E}_{XM} = \frac{\frac{\partial \log R_i}{\partial \log \tau_{iv}}}{\frac{\partial \log M_i}{\log \tau_{iv}}} = \frac{\partial \log R_i}{\partial \log M_i} = \frac{(1-\rho)\sum_k \frac{R_{ik}}{R_i}\left[\frac{1}{1+\Gamma_{ik}}\right]}{1-\rho\left[\sum_k \frac{Q_{ik}}{Q_k}\frac{1}{1+\Gamma_{ik}}\right]} > 0 \tag{2.14}$$

Proof to proposition 4. A.

B. First, we prove that the elasticity of imports with respect to τ_{iv} is as described above.

Imports are given by:

$$M_i = Qc_i$$

By Shepard Lemma's, we know that the derivative of the log unit cost with respect to $log(\tau_{iv})$ is equal to m_{iv}. Then,

$$\frac{\partial \log M_i}{\partial \log \tau_{iv}} = \frac{\partial \log Q_i}{\partial \log \tau_{iv}} + m_{iv}$$

The adjustment in quantities is given by,

$$\frac{\partial \log Q_i}{\partial \log \tau_{iv}} = -\rho m_{iv} \sum_k \frac{Q_{ik}}{Q_k}\frac{1}{1+\Gamma_{ik}},$$

so

$$\frac{\partial \log M_i}{\partial \log \tau_{iv}} = -m_{iv}\left[\rho \sum_k \frac{Q_{ik}}{Q_k}\frac{1}{1+\Gamma_{ik}} - 1\right]$$

C. Note that the elasticity of total exports with respect to total imports is the ratio between the effect of barriers on total exports over the effect of barriers on total imports.

□

2.4 Empirical Strategy

The model described above suggests that in order to answer the questions of this paper, we need a supply shock to import costs of specific products (i.e: τ_{iv}), combined with information of the share of imports of the product of a firm m_{iv}. On this ground, we exploit exogenous variability in import costs to specific products coming from the timing in which Argentinian government imposed (non-tariff) barriers to imports of specific products from between 2002 and 2011. We combine the timing of the restrictive policy to a product with data on the share of that product on firm's total imports before the policy took place.

In this section we describe the context, the policy, the identification assumptions and how we implement the empirical strategy.

Context: description of the policy

Governments have different tools to discourage imports allowed by WTO: tariff measures (a tax that is applied to import products, whether ad-valorem or fixed amount), measures against unfair trade (anti-dumping, safeguards and countervailing measures), technical barriers to trade (Which imposes minimum requirements of quality in the products) and import licensing (permit that allows an importer to bring in a specified quantity of certain goods during a specified period), among others.[22]

In Argentina, Import Licensing Procedures take two forms: Automatic Import Licencing and Non-Automatic Import Licencing (NAILs, from now on). Automatic import licensing procedures are generally use to collect information about imports and they are not administered in such a manner as to have restricting effects on imports.[23] In contrast, Non-automatic import licensing procedures (NAILs) are used, among other policy objectives, to administer quantitative restriction and tariff quotas justified within the WTO legal framework. Non-automatic import licensing procedures are much more complex and may imply important transaction costs for importers of those items affected. In particular, it can take up to 2 months to process an application and approval is not granted. In practice, the NAILs works as a non-tariff barrier to trade.

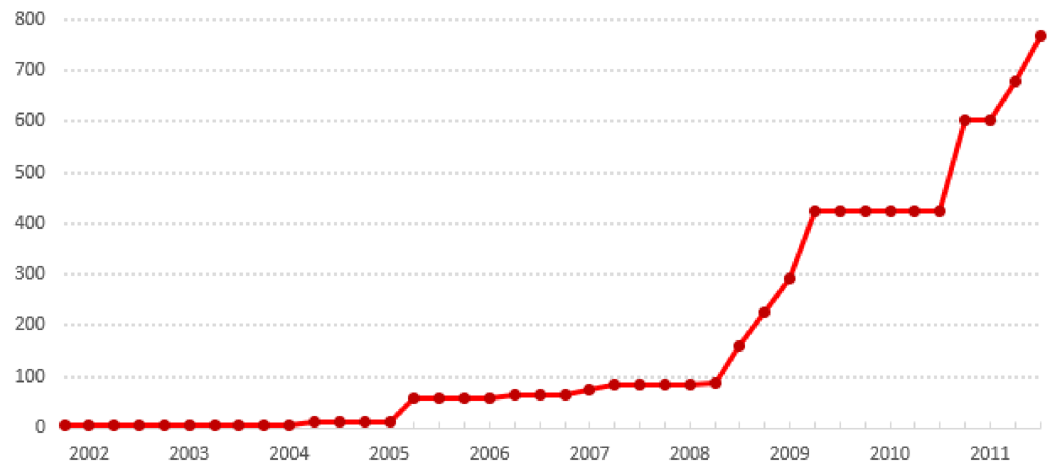
From 2005 to 2011, Argentine government systematically increased the number of products in the NAILs, usually with the objective of reducing trade imbalances. The products were added in different months by executive decrees. Figure 2.6 summarizes the timing in which products were added to the NAILs system. As the government had limited capacity to quickly impose other measures to discourage imports, the NAILs represented the main increase in trade restrictions during that period. In the paper, we exploit variability in the timing in which a intermediate input entered to the NAILs system as exogeneous variation to the costs of the firms.[24]

[22] Each of these measures requires different periods of time to be applied. For example, Argentina's tariff measures are determined under Mercosur's common external tariff, with limited scope for individual deviation. Measures against unfair trade require an investigation to demonstrate that there is genuine injury to the competing domestic industry.

[23] In fact, approval of the import application through Automatic Licenses is granted in all cases. According to their definition (i) any person fulfilling the legal requirements should be equally eligible to apply for and obtain import licences (non-discrimination); and, (ii) the application shall be approved immediately on receipt when feasible or within a maximum of 10 working days

[24] We restrict the period of analysis to 2011 since during 2012 the Argentine government implemented a new licensing system that affected all imported products.

Figure 2.6: Evolution of NAILs over time.



A remarkable feature of the NAILs imposed in Argentina is that there were not concentrated in a few sector of the economy. The barriers ended up affecting firms in most of the sectors, as shown in Figure B.1 of the appendix. This let us compare firms within a given sector.

Methodology

We will use the policy described above to construct a cost shock for a firm. In particular, in order to construct a time-varying firm-level variable that proxy a firm's exposure to import barriers, we proceed as follows. We use the import basket in the period 2002-2006 (before the large increase in the products included in this policy) and calculate the share of the firm's expenditure on imported inputs that corresponds to each product v ($m_i v$). Then, holding this share constant over time, we multiply it by an indicator that takes value 1 in those years when the product is affected by the NAILs. Then, we sum across products for a given firm. Formally, we define a firm's exposure to NAILs in time t as,

$$NAILexposure_{it} = \sum_v m_{iv} NAIL_{vt}, \tag{2.15}$$

Where m_{iv} represents the share of expenditure on imported input v in the period 2002-2005 and $NAIL_{vt}$ is an indicator that takes value 1 if the product v is affected by NAILs in period t.

Intuitively, guided by Proposition 2.3.B, we assume that a firm is more exposed to the import shock, the higher the initial share of expenditure that corresponded to the affected product in the period before the policy took place.

Relevance of the policy and identifying assumption

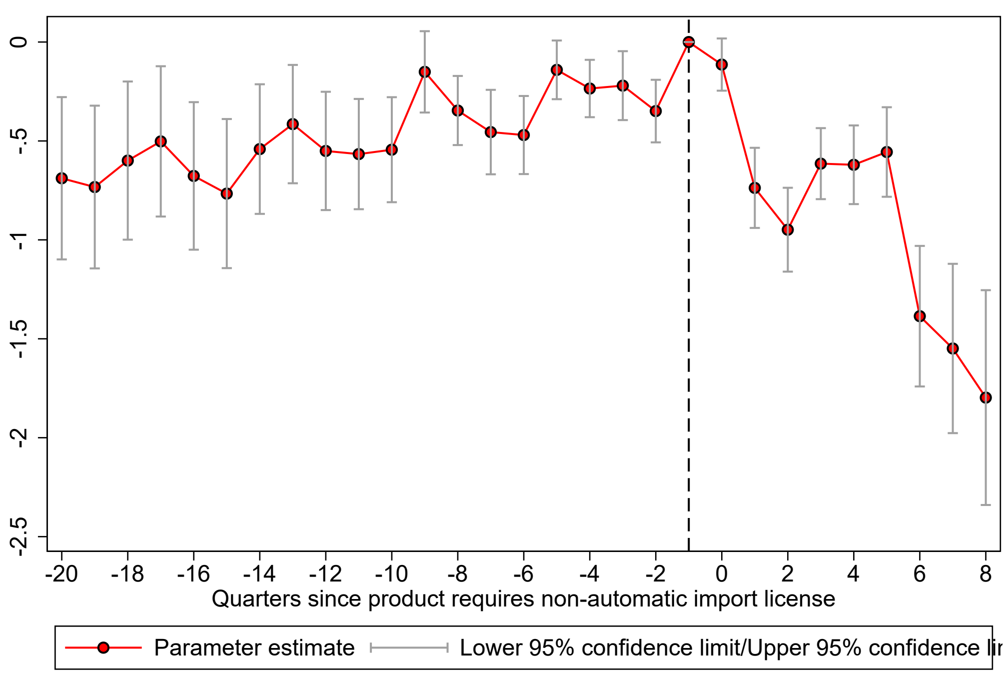
Effectiveness of the NAILs in reducing imports

Before moving to the results of the paper, we first explore whether the NAILs were actually effective in reducing imports of those items that were added to the list. We can perform an event study at the product level to analyze if being added to NAILs, reduce imports of a item at HS-8-digits level. Formally,

$$\log(Imports_{vt}) = \sum_{j=-27}^{12} \beta_j 1[QuartersSinceNAILs_{it} = j] + \alpha_i + \gamma_t + u_{it},$$

where the negative values correspond to years before the product entered to the NAILs list. We focus on parameter β that represent the impact of the incorporation of NAIL on products' imports. Figure 2 plots the coefficients β. [25] Reassuring, we do not observe systematic differences in the years before the product was added to the NAIL system. As expected, the NAILs seem to work as an important barrier to trade, specially since the second quarter after the product was included.[26]. Imports of a product that is added to the NAILs list decline by 50% the first year with respect to its counterfactual.

Figure 2.7: Event study. The impact of Non Automatic Import License on $\log(imports)$.



[25] We restrict the sample to those products that entered at some point to the NAILs system.

[26] In the first months, importers used previous approved authomatic lisencing to import, so NAILs might require some months to effectively affect the firm.

Identification assumption

Once we have proven that including a product in NAIL system reduces the amount of imports of that product, we want to test our identification assumption. Our main identification assumption is that the timing in which a product enters to the NAILs system is not correlated with changes in firm's export decisions and/or characteristics of the destination market. Put it differently, the evolution of exports in firms that were more exposed to NAILs would have been similar to the evolution of exports of firms less exposed in the absence of the policy. One of the main threats to our identification assumption is reverse causality. It could be the case that the government targeted products used by firms that were predicted to experience a decline in its exports. Before turning to the results, a graph provides a useful way of both seeing the relevant variation in the data, and of gauging the plausibility of the parallel trends assumption.[27] We construct a graph as follows. Again, we define as $t = 0$ the year for which at least one product of the firm was affected. Then, we divide firms into high and low exposure to NAILs, being the later those that are in the lowest 25th percentile of exposure.[28] We then graph the event study for the differences in log(exports) between these groups. Formally, we run the following regression,

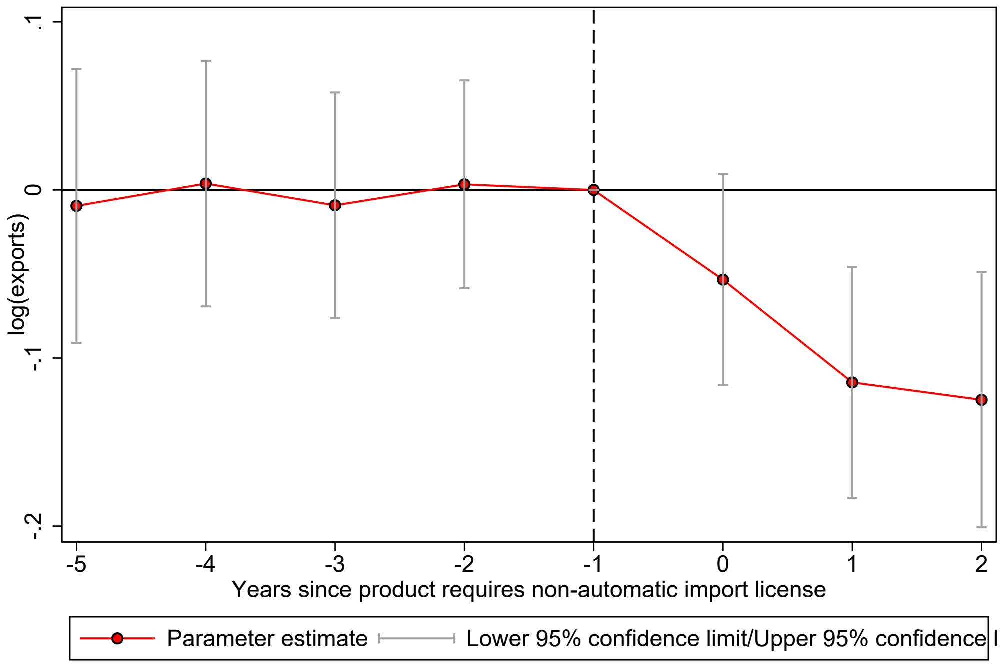
$$\log(exports_{it}) = \sum_{j=-6}^{3} \beta_j 1[YearsSinceExposureToNAILs_{it} = j] + \alpha_i + \gamma_t + u_{it}.$$

Figure 2.8 plots the coefficients β of this regression. Reassuring, we do not observe any systematic differences in the firms' exports in the years before the firm became affected by NAILs. This suggests that the parallel trend assumption may hold in our context. In addition, the Figure provides a first glance of the results that we will show in the next section: the value of exports are significantly reduced after the firm is exposed to NAILs.

[27] In fact, our main identification assumption is milder. The assumption is that the government did not target inputs that were specifically used for firms to export to markets in where they have less market share.

[28] We are aware that the test is not clean since we don't actually have two groups, but it is reassuring to observe that under this arbitrary grouping, we don't observe much going on before the event takes place. In our main empirical strategy, we use the continuous measure of exposure. In addition, for our main results, the assumptions are even milder than this paralell trends since we exploit variability across destinations.

Figure 2.8: Event study. The impact of Non automatic Import License on firms' log(exports).



In this section we documented that the NAILs were actually effective on reducing imports and that the government do not seem to target the NAILs based on the behavior of the exporters that use more intensively those imported inputs.
We now turn to the empirical results of the paper.

2.5 Results

In this section we present the main results of the paper. First, we document the effect of the policy at the firm level in order to have a sense on the magnitude of the effect of the import barriers on firms' exports. First, we identify the direct effect of NAILs on exports and the elasticity of total exports with respect to total imports. Then, we use the predictions of the model to identify the elasticity of markup of a firm across its destinations and estimate whether it is increasing on a firm's relative size in the market.

Firm-level elasticity of exports with respect to imports of intermediate inputs

As discussed in the introduction, there is still scarce evidence about the elasticity of exports with respect to imports of intermediate goods at the firm level. In this subsection we use the exogenous variation on the timing of the policy to document this elasticity at the firm level.

As Proposition 2.3.C indicates, this elasticity is given by $_{XM} = \frac{\frac{\partial \log R_i}{\partial(\log \tau_{iv} m_{iv})}}{\frac{\partial \log M_i}{(\log \tau_{iv} m_{iv})}}$.
Put it differently, the elasticity of exports with respect to imports is the coefficient of an IV estimation where the reduced form coefficient and the first stage coefficient are obtained by estimating:

$$\log(Imports)_{it} = \beta NAILexposure_{it} + \gamma_i + \gamma_t + \mu_{it},$$

and

$$\log(Exports)_{ist} = \beta NAILexposure_{ist} + \gamma_i + \gamma_t + \gamma_{st} + \mu_{it}, \tag{2.16}$$

where $imports_{it}$, $exports_{it}$ are the amount of imports and exports for firm i in year t respectively, $NAILexposure_{it}$ is defined as in equation 2.15, γ_i, γ_t and γ_{st} are fixed effects at the firm, year and sector-year level.
We begin by estimating the reduced form (equation 2.16). According to our model, introducing import barriers to intermediate inputs v increases the marginal cost for those firms that used to import the input and reduces their competitiveness in foreign markets. Therefore, we expect to observe that those firms that use more intensively products affected by the NAILs, export a lower amount, are less likely to enter an export market and are more likely to reduce the number of markets that they served. Results from the estimation of equation 2.16 are reported in Table 2.1.

Table 2.1: Reduced form: The effect of NAILs exposure on firm's total exports

	$\log(exports)_{it}$	$Exportstatus_{it}$	$\#Destinations$
$NAILexposure_{it}$	-0.3882**	-0.0333**	-0.1911***
	(0.1563)	(0.0137)	(0.0591)
Observations	126,150	126,150	126,150
R-squared	0.6268	0.4982	0.8818
Firm FE	yes	yes	yes
Year FE	yes	yes	yes
Sector-Year FE	yes	yes	yes
Mean dep variable	6.562	0.539	2.342

Note: Clustered standard error at firm level in parenthesis. Column (1) outcome use the inverse hyperbolic sine transformation. *** p<0.01, ** p<0.05, * p<0.1

As expected, being exposed to NAILs reduced considerably the intensive and extensive margin of exports. For instance, firms whose import basket is entirely affected by NAIL system, reduce 39% their export amount with respect to a non-affected firm. In addition, the restriction also has considerable effects on the extensive margin of exports. The probability of being an exporter and the number of destination that the firm reaches is affected negatively by the raise in import costs.

Once we have shown the reduced form effects, we turn to the instrumental variable estimation of the elasticity of substitution of exports with respect to imports at the firm level. Results are reported in Table 2.2. The first thing to notice is that the coefficient for the first stage is −0.95. Namely, a firm for which the 10% of their inputs is affected by the NAILs, reduce their total imports by 8.3%. Additionally, the F statistic of the first stage is over the conventional threshold. Second, we find that an increase in 10% of imports of intermediate inputs increases export values in 4%.[29] In addition, imports also have considerably effects on extensive margin of exports. An increase in 10% of imports increase 3.5 percent points the probability of being active in export markets (6.5% with respect to the unconditional probability). We also observe significant effects of imports on the number of products and destinations that the firm is able to serve.

Table 2.2: Elasticity of exports with respect to imports at the firm level

	(1) $\log(exports)_{it}$	(2) $Exportstatus_{it}$	(3) # Products	(4) $\#Destinations$
$\log(imports)_{it}$	0.4083**	0.0351**	0.4781*	0.2010***
	(0.1613)	(0.0142)	(0.2570)	(0.0654)
Observations	126,150	126,150	126,150	126,150
R-squared	0.6452	0.5149	0.8298	0.8828
Firm FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes
First Stage				
$NAILexposure_{it}$	-0.9508	-0.9508	-0.9508	-0.9508
F	38.99	38.99	38.99	38.99
Mean dep variable	6.562	0.539	4.251	2.342

Note: Clustered standard error at firm level in parenthesis. Column (1) outcome use the inverse hyperbolic sine transformation. *** p<0.01, ** p<0.05, * p<0.1

[29] Remarkably, this is far below the elasticity of 100% that standard models with constant markup would predict

Within firm, across destinations markup super-elasticity

We now turn to the empirical estimation of the super-elasticity of markup. That is, we aim to test whether a given multi-destinations firm adjusts less its prices (export revenues) in response to a cost shock in those destinations where it has higher market share. In order to compute firms' market share in destination k, S_{iskt} we combine Argentinian customs data with import values at country-product (HS 4-digit) level from BACI dataset:

$$S_{iskt} = \frac{Exports_{iskt}}{WorldImports_{skt}} * 100,$$

where $WorldImports_{skt}$ is total imports of country k of products in sector s.[30]
Proposition 2.3 C. of our model guides the methodology to estimate the theoretical relationship between the elasticity of markup and market share in the destination (super-elasticity of markup). Adding the time subscript to equation 2.7 and recalling that we include sector-year-destination FE throughout the empirical analysis, the effect of barriers on exports to market k is given by,

$$\frac{\partial \log R_{iskt}}{\partial \log \tau_{ivt} m_{iv}} = (1-\rho)\left[\frac{1}{1+\Gamma_{ik}}\right] \leq 0$$

We can rewrite the above derivative as,

$$\frac{\partial \log R_{ikt}}{\partial \log \tau_{ivt} m_{iv}} = (1-\rho)\left[\frac{1}{1+\bar{\Gamma}_i}\right] + (1-\rho)\left[\left(\frac{1}{1+\Gamma_{ik}(S_{ik})}\right) - \left(\frac{1}{1+\bar{\Gamma}_i}\right)\right],$$

where $\bar{\Gamma}_i$ is the average elasticity of markup of firm i and we make explicit that the elasticity of markup in market k Γ_{ik} depends on the share of the firm in that market.
We can identify the theoretical coefficients in the relationship between markup elasticity and market share by estimating the following equation for those firms that report active exports to a market in $t-1$ and in t:

$$\Delta \log Expo_{iskt} = \beta_1 \Delta Nailexposure_{it} + \beta_2 \Delta Nailexposure_{it} * S_{ikt-1} + \gamma S_{ikt-1} + \gamma_{it} + \gamma_{skt} + \Delta e_{iskt}. \tag{2.17}$$

where

$$S_{ikt} = 100 \frac{ExportValues_{ikt}}{\sum_{i \epsilon s} ExportValues_{iskt}}$$

Equation (2.17) is our benchmark empirical specification. Given that we are focusing on markups, we restrict our attention to firm-destinations that have positive revenues in t and

[30] The distribution of this variable is summarized in Table B.1 of the appendix.

$t-1$. Note that in our preferred specification, we include firm-by-year fixed effects, firm-by-destination fixed effects, and sector-by-destination-by-year fixed effects. Hence, the strategy relies on comparing changes in the response of the firm to a change in its costs, in the same year, in similar destination-year-sectors, across destinations in which the firm has different market shares. If the elasticity of markup does not depend on a firm's size in the market, then we expect β_2 to be zero. In contrast, if the elasticity of markup is increasing in the market share, then we expect $\beta_2 > 0$. In Figure **??** we provide a graphical representation our methodology to identify the markup super-elasticity.

Table 2.3 reports the results for different versions of equation (2.17). In the first row we report the coefficient for the average effect, while in the second one the interaction between exposure and market share. We begin with a simple specification and build up to our preferred specification. In column (1), we include sector by destination by year fixed effects and firm fixed effects. The sector-by-destination-by-year fixed effects control for trends in the destination country where the firm exports; such as the country growing in the sector of the firm. As expected, the average effect of the cost shock on exports in negative. An increase of 10% on exposure, cause a decline of 2.3% in average exports. However, consistent with the theory, the negative effect on exports is attenuated in markets where firms have higher market share. This suggest that the super-elasticity of markup is positive. In column (2) to (4), we add firm-year fixed effects and report the main results of the paper. Adding firm-year fixed effects allows us to compare responses of a given firm across its markets. Our preferred specification is Column (4) where we saturate the model with the full vector of fixed effects. We find that a given firm in a given year, comparing across similar sector-destinations-years, adjust less their export revenues (and thus prices) in those destinations where it is relatively large. Interpreting our results quantitatively, we find that a firm that was affected 100% by the cost shock reduced its export values by 23% in a destination in which the firm has nearly zero market share, while it only reduced 11% its export revenues in a market in which the firm has 5% of the market share.

Table 2.3: Elasticity of markup and relation with market share

	(1)	(2)	(3)	(4)
	$\Delta log(Exports_{iskt})$			
$\Delta Nailexposure_{it}$	-0.2306***			
	(0.0544)			
$\Delta Nailexposure_{it}$*	0.0197***	0.0238***	0.0245***	0.0190***
$*S_{iskt-1}$	(0.0034)	(0.0058)	(0.0058)	(0.0063)
Observations	104,532	76,707	76,707	76,707
R-squared	0.1412	0.3375	0.3401	0.4725
Firm FE	yes	yes	yes	yes
Sector-Year FE	yes	yes	yes	yes
Sector-Destination FE	yes	yes	yes	yes
Firm-Year FE	no	yes	yes	yes
Sector-destination-year FE	yes	no	no	yes
$log(gdppc)_{kt-1}$ control	no	no	yes	no
S_{ikt-1} control	yes	yes	yes	yes

Standard errors clustered at the firm-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Conditional on firm-markets with positive values of exports.

Robustness Checks

In Table 2.4 we show that results are not explained by other factors. In Column (1) we present the results for our benchmark regression. A concern is that the market share might be correlated with income of the destination country. Hence, we are capturing changes in exports due to the interaction between the cost shock and characteristics of the destination country. In Column (2), we control for the interaction between exposure to NAILs and GDP per capita in the destination. The main coefficient remains almost unchanged. A second concern is that firms might import more from destinations that they export more. Hence, a shock to imports might affect deferentially destinations where the firm is large. In Column (4), we control for imports of the firm from the destination market. Similarly, in Column (5) we exclude China from the sample. Reassuringly, the coefficient remains stable throughout the different specifications.

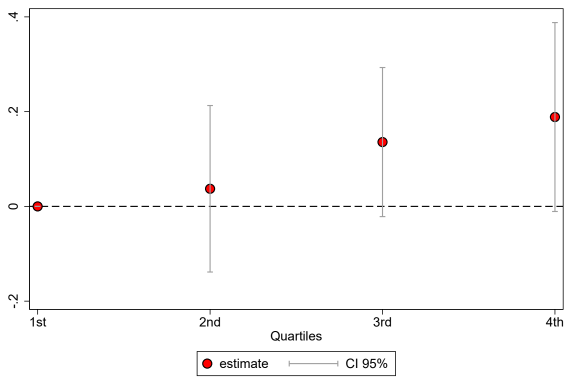
Table 2.4: Robustness Check: Elasticity of markup and relation with market share

	(1)	(2)	(3)	(4)	(5)
			$\Delta log(Exports_{iskt})$		
$\Delta Nailexposure_{it}$	0.0190***	0.0185***	0.0172***	0.0171***	0.0187***
$*S_{iskt-1}$	(0.0063)	(0.0058)	(0.0065)	(0.0062)	(0.0063)
$\Delta Nailexposure_{it}$		0.0354			
$*log(gdppc)_{kt-1}$		(0.0478)			
$\Delta Nailexposure_{it}$			0.0026**		
$*ShareWithinFirm_{iskt-1}$			(0.0012)		
Observations	76,707	76,707	76,707	76,707	76,707
R-squared	0.4725	0.3509	0.4773	0.4725	0.4751
Firm-Year FE	yes	yes	yes	yes	yes
Sector-destination-year FE	yes	yes	yes	yes	yes
imports from k	no	no	no	yes	no
Exc China	no	no	no	no	yes

Standard errors clustered at the firm-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Conditional on firm-markets with positive values of exports two consecutive years.

Our empirical findings reflect that that multi-destination exporters adjust more their markup in those destinations where they have a higher market share. This is consistent with the predictions of our model. However, we want to ensure that this results is not driven by outliers and/or are only explained by our linear specification or the continuity of the market share variable. In order to address this concern, we re-estimate equation 2.17, but splitting market share variable into quartiles. In figure 2.9 we plot the coefficient of the interaction for each quartile. The base group is the 1st quartile of market share. Although not significant at 5%, we can observe that the interaction between NAILexposure increase monotonically as we move from low to high market share.

Figure 2.9: Market share and markups, non-parametric results



2.6 Conclusion

Most of trade is concentrated in a few firms that export to many markets. In our sample, roughly 60% of the exporters serve more than one destination. These firms, represent more than 99% of total exports in the manufacturing sector. As a consequence, understanding the behavior of these firms, how they set prices and how they react to shocks, is crucial to understand aggregate trade flows, welfare gains from trade, and the distribution of these gains.

We develop a methodology that combines a theoretical model with a empirical strategy to explain how multi-destination exporters adjust markups and prices in response to cost shocks. When a firm is hit by a firm-year specific cost shock, it reduces its export revenues (increase prices) in every destination. However, in those destinations where the firm is relatively larger, it adjusts less it export revenues, while absorbing part of the shock by reducing its markup in the destination.

Our main contribution is providing empirical evidence of this margin of adjustment of multi-destination exporters. We exploit exogenoeus variability of firms costs coming from the timing in which import barriers were imposed by Argentinian government between 2005 and 2011 to document that the within-firm responses across different destinations is a key margin of adjustment.

This heterogeneity of responses across destinations is interesting by its own right, and it also has important implications for the impact of shocks on exports at the aggregate level. The mechanism that we document suggest that an unilateral trade liberalization that reduces local costs for every Argentinian firm, will increase relatively more (reduce prices relatively more) exports to destinations in which the firm has lower market share. In our sample, these destinations are typically countries with high GDP per capita. Therefore, the margin of adjustment analyzed in this paper will determine that the gains from Argentina liberalization will be unevenly distributed in foreign countries, being the richer countries the ones that benefit the most. In contrast, poorer countries, where multi-destination exporters have a higher market share, the reduction in costs would be partially absorbed in the markups of the firm. In further versions of the paper, we plan to explore more closely this conclusion.

Chapter 3

Importing after Exporting[1]

3.1 Introduction

It is well known that importers and exporters are more productive than firms serving only domestic markets. Firms engaged in international trade also use skilled labor and capital more intensively, pay higher wages and are associated with higher quality standards. Firms involved in both activities (global firms) rate even higher in these measurements (Bernard, Jensen, Redding, and Schott, 2012; Kasahara and Lapham, 2013; Manova and Zhang, 2012; Bernard, Jensen, Redding, and Schott, 2018). Yet, surprisingly, the research in international trade mainly focuses on either exporting or importing as if they were independent activities.[2] As a consequence, little is known about how exporting and importing interact with each other.

We begin our analysis by establishing a novel fact about the relationship between exporting and importing. Using a comprehensive database of Argentine firms for the period of 2002-2008, we find that exporting to a new destination raises the probability that the firm will begin importing from that market within a year (by 51% in our preferred estimation). This fact is intriguing. Why does a new destination for exports become a new source of imports? Why does the effect require time? As both activities are jointly determined by productivity, "importing after exporting" might be the result of a particular productivity process through which firms gain efficiency. An alternative potential explanation involves exporting reducing import costs. A priori, it is unclear whether the effect of export entry on

[1]This Chapter comes from joint work with Facundo Albornoz. He gave his permission to use this material as a chapter of this dissertation.

[2]Redding (2011); Bernard et al. (2012); Melitz and Redding (2014) summarize the literature on exporting. There is far less work available about importing. Halpern et al. (2009) and Amiti and Konings (2007) find that importing is associated with higher productivity. Goldberg et al. (2010) find that importing extends the product scope. Finally, Blaum, Lelarge, and Peters (2019) and Antras et al. (2014) propose models of firms' sourcing decisions. Early exceptions considering both import and export decisions are provided by Kasahara and Lapham (2013), finding a positive association between importing and exporting sunk costs, and Bas and Strauss-Kahn (2014) and Bas (2012), where importing increases the probability of becoming an exporter. More recent examples are Blaum (2019) and Bernard et al. (2018).

firms' sourcing decisions reflects changes in productivity or in import costs. Furthermore, if export entry reduces import costs, it is also unclear whether this is due to concurrent complementarities in export and import costs or due to the effect of export experience on import costs. In this paper, we provide answers to these questions and discuss their relevance to understand firm export and import dynamics in global markets.

We develop a model of exporting and importing. As in Bernard et al. (2018) and Blaum (2019), we put together a standard model of sourcing decisions (e.g. Antras et al., 2014; Blaum et al., 2019; Gopinath and Neiman, 2014; Halpern et al., 2009) with the canonical model of exporting. A novel feature of our framework is that we let import costs from a sourcing market vary with export experience of a firm in that market. This generates heterogeneity of import costs at firm-market level.[3] In this framework, whether export entry affects sourcing decisions as a result of productivity gains or by reducing import costs yields contrasting empirical implications. If the driver of new sourcing is productivity, export entry in a given market should affect the firm's probability of new imports from any potential sourcing market. This is one of the channels explored in Bernard et al. (2018).[4] Contrarily, if export entry reduces import costs in the new market, then it should only affect the firm's decision to source from that same market; and not from others. Also, productivity should affect the intensive margin of imports from every existent source. This is not the case if new sourcing reflects reductions in market-specific import costs. Based on these predictions, we use the observed effect of reaching a new destination to infer that exporting does reduce market-specific import costs, ruling out productivity as a driver of "importing after exporting". This conclusion opens a new set of questions.

Why does exporting reduce the cost of importing? Are import and export costs complementary? This would be the case if, for example, both activities shared the same concurrent operational fixed costs. Do import costs vary with experience as exporter in international markets? Does this type of complementary take place at the destination level? This would be the case if, for example, finding input sources in a particular market required knowledge about potential suppliers, and if acquiring this knowledge was facilitated by previous export experience in the market. Explaining the nature of import cost-savings associated with export entry is one of the contributions of our analysis. In our framework, we derive a number of predictions that contrast according to whether "importing after exporting" reflects concurrent complementarities in import and export costs, or whether experience in new export destinations reduces import costs from that market. First, as experience in a market requires time, sourcing from a new export destination should come after export entry. We find that this is the case. Second, if import and export operational costs are concurrent, the effect of exporting on import sourcing should not be restricted to new exports. This is not corroborated by the data: exporting affects the probability of importing only when the destination is new for the firm. Moreover, we observe that the effect vanishes when we

[3] Other papers analyzing global firms focus on complementarities between importing and exporting that do not depend on whether the export and import activities are in the same markets (e.g. Blaum, 2019; Bernard et al., 2018).

[4] We discuss more in detail this paper below.

consider firms that re-enter the export market, suggesting that export entry of experienced firms does not affect sourcing decisions. Third, if exporting affects the sourcing strategy by providing experience, and experience eases the process of finding potential suppliers, we should find a stronger association between export entry and importing in situations where the firm is poorly informed about the characteristics of the destination market, or when importing involves relatively rare goods. Consistent with the explanation based on experience, we find that the effect of exporting on importing is stronger (a) in long-distance destinations; (b) for varieties that are rarely imported by Argentinian firms; and (c) for differentiated or high-tech intermediate inputs. Finally, import and export cost concurrent complementarity requires both activities to be carried out simultaneously. In contrast, if the effect is driven by experience, newly established relationships with foreign suppliers in the new export market may last, regardless of whether the firm continues serving that market as exporter or not. Consistent with the experience being the driver of “importing after exporting”, we find a higher probability of importing from the new export market even if the firm stops exporting right after entry.

Our analysis bolsters the importance of firm’s experience to make sourcing decisions, which is expressed in lower import costs. Experience gained in a market after export entry provides, for example, an opportunity for the firm to gain knowledge on -or establish links with- potential suppliers. The effect of export entry on import costs in the new market is more than a qualitative insight. We use our model to derive the quantitative implications of export entry on import fixed costs. The estimated effects are large. For a median firm, import costs fall 53% in a given destination after export entry; while the estimated fixed cost to start sourcing from a market without export experience is US$ 49,600, the cost for importing after export entry falls to US$ 26,600.[5] Notably, we find that the entire distribution of estimated import fixed costs lies below for firms that enter a new export destination prior to start importing from that market. Importantly, we estimate fixed costs in a source country that vary according to firms’ recent export experience in that market. As noted by Antras et al. (2014), the literature generally assumes homogeneous import costs; which is at odds with the data and contradicted by our results. In particular, we rationalize variations in import fixed costs with differences in experience of the firm in a given market. Our findings show that this experience can be acquired by exporting.

Our work contributes to a literature on importing and exporting. Early research focused on how importing favors export performance. For example, Bas and Strauss-Kahn (2014) and Bas (2012) observe that importing intermediate goods (from any source) reduces firms marginal costs (or increases quality) and, thus, extends the extensive margin of exporting. Our findings are compatible with firms using imported intermediate goods as a way to prepare for new export activities, but we stress different aspects of the import-export interplay. More closely related to our work, Amiti and Davis (2012), Bache and Laugesen (2013), and

[5] Our estimated reduction in import costs is consistent with Halpern et al. (2009), where fixed costs of importing for local firms are compared to those for foreign firms in Hungary. According to Halpern et al. (2009), foreign firms pay 60% lower fixed costs of importing than local firms.

Kasahara and Lapham (2013) emphasize complementarities between exports and imports costs. For example, Kasahara and Lapham (2013) provide evidence that supports concurrent complementarity between importing and exporting sunk costs. More recently, Bernard et al. (2018) emphasize that exporting increases firm revenue, which makes it more likely that the firm will find it profitable to incur the fixed costs of sourcing inputs from any market. Similar to the effect of productivity gains, this interaction between exporting and importing generates interdependence between the import and export decisions across markets. Our paper emphasizes a completely different facet of the interaction between importing and exporting, which is not driven by productivity, scale or reductions in variable costs, but by interconnected activities between importing and exporting that are confined to the same foreign market. In particular, our paper highlights experience gained in the import market after export entry.

The existence of complementarities between importing and exporting that are confined to the same market bears important implications. Consider first the effect of currency devaluations on aggregate productivity. As mentioned above, the literature on importing (e.g. Halpern et al., 2009; Amiti and Konings, 2007) find that importing is associated with higher productivity. By increasing the cost of imported inputs, devaluations may have a negative effect on aggregate productivity as emphasized by Gopinath and Neiman (2014). However, the net effect of devaluations on importing, and therefore on productivity, requires considering the expansion of exporters and the associated increase in the demand for imported inputs. A recent paper by Blaum (2019) makes precisely this point. If sufficiently large, devaluations increase import intensity and aggregate productivity. Our emphasis on the complementarity between exporting and importing at the destination level could generate an additional complementary channel through which a currency devaluation may affect productivity: export entry in a market affecting firms' sourcing decisions. Second, as noted by Amiti et al. (2014), when a firm sources from an export market, the exchange rate pass-through into destination prices is lower. In our framework, it is not just that large exporters are simultaneously large importers, but also that exporters are more likely to import inputs from their new export markets. According to our calculations, one year after export entry to a market, new imports from that market account for 22% of the value generated by exports in the new destination. This market specific connection between exporting and importing is what attenuates the effect of bilateral exchange rate shocks on exporters' decisions. Third, our findings warn against interpretations of "learning by exporting" that rely exclusively on firms improving their core productivity after entering export markets (i.e: De Loecker (2013)). We highlight that, even holding constant a firm's core productivity, part of the evidence on learning by exporting could be explained by the association between exporting and importing: a new export destination triggers a re-optimization process of import sourcing through which the firm becomes more productive. At the same time, our findings give new content to "learning by exporting" as they reflect a specific way of gaining efficiency. Finally, although only positive, our analysis could have normative implications if firms do not fully internalise the effect of reaching new export destinations on subsequent sourcing decisions. We consider this analysis beyond the scope of our paper but note that if that was the case, "importing after exporting" would provide a novel rationale for export promotion.

Our paper highlights that importing is not a simple activity. In making import decisions, firms must evaluate how imports of intermediate goods affect their production costs and weigh this against the fixed costs when dealing with foreign suppliers. However, this decision requires knowledge about products and potential suppliers that is not fully available for firms *ex ante*. Therefore, experience in foreign markets is a way to overcome potential informational barriers to importing. Our results suggest that exporting is a source for such experience. On this ground, this paper is also related to recent literature on export dynamics that emphasizes the role of export experience in learning about a firm's potential in foreign markets (e.g. Albornoz, Calvo Pardo, Corcos, and Ornelas, 2012; Timoshenko, 2015). While these papers focus on uncertainty related to the demand and profitability abroad, our paper highlights that experience in new export markets affects firms' sourcing decisions. On this score, we also provide estimates that show that the cost-saving effect of experience is quantitatively relevant.[6]

The remainder of the paper is organized as follows. In Section 2, we present the data and the preliminary observations. In section 3, we establish the main fact. In section 4, we derive predictions on how productivity and import costs affect the intensive and extensive margins of importing and show how importing after exporting is only empirically consistent with falls in import costs triggered by export entry in new destinations. In section 5, we analyze the channels through which exporting reduces import costs. In Section 6, we estimate the fall in import costs associated with export entry. Section 7 discuss implications of our results. To finish, we assess the plausibility of alternative explanations (Section 8) and offer some concluding remarks (Section 9).

3.2 Facts on importing

In this section, we describe the data, report relevant descriptive statistics, and provide preliminary observations about the relationship between exporting and importing.

Data

We use Argentine customs data comprising the universe of the country's exports and imports transactions. This data set covers the 2002-2009 period and includes annually reported information about the value (in US dollars) of foreign sales and imports for each firm, distinguished by country (origin / destination) and product (HS8). We focus on manufacturing firms and restrict imports to intermediate goods (inputs and capital goods) according to BEC classification.

[6]On this ground, Startz (2016) provides further evidence related to our mechanism in a fairly different context. Consistent with our mechanism, the author shows that Nigerian final good importers spend a considerably amount of money to travel in order to reduce informational barriers and contracting frictions.

Export entry to a destination and sourcing from a new origin are rather rare events at the firm level. Hence, the analysis is more meaningful if we aggregate countries into regions, thus reducing the number of potential markets. In the main analysis, we restrict our attention to 10 regions: ASEAN+3 (ASEAN), Rest of Asia (RAsia), European Union (EU), Rest of Europe(REu), Africa, Australia, Mercosur, Rest of South America (RSA), North America (NA) and Central America (CA).[7] The results are robust to other ways of grouping countries.[8]

For most of our analysis, we collapse the database at the firm-market-year level; where we fill in with zeros every market- year combination for which the firm does not report any trade. Using unique firm identifiers, we have matched this data set to fiscal files generated by the Fiscal Administration of Public Revenue (AFIP) from which we have obtained information on formal employment and firms' main sector of activity.

The main sample consists of a balanced panel of 14,636 manufacturing firms. In an average year, total export value is US$ 19 billions and total import value is US$ 7 billions. The median only-exporter firm exports US$ 42,000 in an average year, reaches one market and employs 19 workers. The median only-importer firm imports US$ 46,000, combines inputs from two sources and employs 21 workers. The median global firm (importer and exporter) exports US$ 180,000 to two destinations, imports US$ 113,000 from two sources and employs 48 workers.

Table 3.1 reports aggregate statistics on exports and imports across different regions. Mercosur accounts for 30% of Argentine exports within the period, followed by the Rest of South America (21%), North America (11%), EU (10%) and the Asean region (10%). As to imports, Mercosur is also the main partner with roughly 35% of total imports. The rest of imports is explained by the EU (21%), ASEAN countries (17%), North America (16%) and the Rest of South America (4%). In an average year, Argentine firms import from a total of 4,940 new sources and reach a total of 3,703 new destinations. Interestingly, the main new sourcing markets and new destination markets are not the same. While most of new sources are explained by new imports from Mercosur (30%), EU(22%) and ASEAN(18%), new export destinations mostly involve The Americas (Mercosur, 23%, Rest of South America, 21%, and North America, 13%).

[7] In the Appendix, we describe the main sources and destinations within each region (tables **??** and **??**).

[8] We obtain qualitatively similar results at the country level. In Table C.4 in the Appendix, we replicate the main analysis discussed in Section 3.3 using a sample of the top 30 trading partners. This sample represents roughly 93% of total Argentinian imports and exports.

Table 3.1: Descriptive statistics: by year

Year	Imports (millions US$)	Exports (millions US$)	New sources #	New destinations #
2003	3576	11598	5164	3819
2004	4893	14754	4765	3425
2005	6007	17708	5053	4018
2006	7310	17967	5070	3441
2007	8887	23521	4706	3443
2008	11180	31426	4883	4073
Average	6976	19496	4940	3703

Exports and imports values are in millions of US$

In our analysis, we exploit two additional features about exporting. First, around 25% of firms that reach a new export destination are re-entrants. That is, firms that exported to a market in year $t-2$ or before, do not export in $t-1$ and re-enter in t (See Table C.1 in Section C.1 of the Appendix). Second, a remarkably high number of firms reaching a new destination leave within a year. Only about 50% of exporters that reach a new destination in year t remain active in that market after two years (See Figure C.1 in Section C.1 of the Appendix).

Preliminary observations

To take a preliminary look at the relationship between exporting and importing, we compute the probability of starting to import from a market conditional on having started to export to that market the previous year ($\Pr[\text{NewOrigin}_{ijt}{=}1/\text{Export Entry}_{ij,t-1}{=}1]$). Table 3.2 reports conditional and unconditional probabilities.

Table 3.2: Probability of starting to import from a new region in t conditional on having started to export to that region in $t-1$

	Pr[NewOrigin$_{ijt}$=1]	Pr[NewOrigin$_{ijt}$=1/Export Entry$_{ij,t-1}$=1]	$\triangle$%
All	2.7	4.9	81
ASEAN	6.1	12.2	100
RAsia	3.2	5.9	84
EU	7.3	12	64
REu	1.6	5.6	250
Africa	0.3	1.9	533
Australia	0.3	2.6	767
Mercosur	4.5	5.6	24
RSA	1.8	2.5	39
NA	4.8	6.6	38
CA	0.2	0.3	50

Table 3.2 reveals two relevant preliminary patterns about the relationship between importing and exporting. First, export entry in a market is positively associated with sourcing new imports from the same market within a year: the probability of start importing from a market after export entry in that market is 81% higher than the unconditional probability. Second, this association is stronger in more distant regions. For example, exporting to the European Union rises the probability of importing from there within a year by 64%, while exporting to Mercosur only rises this probability by 24%.

3.3 The main fact: importing after exporting

In this section, we study the observed association between exporting and importing in further detail. We use OLS to estimate the probability for a firm to start importing from a new source.[9] Our basic linear probability model is given by:

$$New\ Origin_{ijt} = \alpha Export\ Entry_{ij,t-s} + \beta X_{i,t} + \{FE\} + \mu_{ijt} \tag{3.1}$$

where $NewOrigin_{ijt}$ is a dummy indicating whether firm i imported from market j in year t for the first time, $Export\ Entry_{ij,t-s}$ indicates whether firm i exported to destination j in $t-s$ for the first time, where $s = \{0,1,2,3,4\}$. $X_{i,t}$ is a set of time-varying characteristics of the firms. Since there are other factors that affect a firm's decision to start to import from and start to export to a region (e.g. specific characteristics of a market, economic shocks in a given year, firm specific characteristics, etc.), we take advantage of the multi-dimensionality

[9]Results are robust to non-linear estimations such as Probit or Logit models.

of the data set and include a wide range of fixed effects, $\{FE\}$. In particular, vector $\{FE\}$ includes different combinations of firm, year, and market fixed effects, as well as interactions between them such as firm-year, firm-market and year-market fixed effects.

Since there can only be one new origin per pair firm-region $'ij'$, we drop that pair from $t+1$ onward after the first observation of positive imports at t (i.e. $imports_{ij,t} > 0$). Similarly, as we want to identify the effect of export entry to j on the probability of sourcing from j for those firms without any previous experience as exporters in that market, we drop pair firm-regions $'ij'$ from t onward whenever exports in $t-s$ to region j are positive ($exports_{ij,t-s} > 0$).[10] Finally, as errors can be correlated across markets or over time we allow standard errors to be clustered at the firm level.[11]

Table 3.3 reports the estimation results for a series of models based on equation 3.1. For reasons that become clear below, we focus on $s = 1$.[12] The results reported in Table 3.3 establish the main fact: export entry to a market increases the probability of sourcing from that market in the following year.[13] Column 1 reports the basic specification including firm, year and market fixed effects. We find that export entry to a market increases the probability of sourcing from that market in the following year by 0.9 percent points. As the firm's decision to import and export from a market might be a joint decision due to, for example, a stable specific relationship with a partner abroad, we include firm-market fixed effects in the regression displayed in column 2. In column 3, we add market-year fixed effects to capture those aggregate shocks that affect the general attractiveness of a market, such as exchange rate variations or political changes. When included, we find that export entry increases the probability of sourcing from that market in the following year by 1.5 percent points (55% with respect to the unconditional probability). However, even if firm fixed effects control for time-invariant unobserved heterogeneity, it is possible that positive idiosyncratic productivity shocks induce firms to initiate export and import activities. In order to address this concern, we adopt two different approaches. First, results reported in column 4, column 5 and column 6 add different combinations of firm's characteristics as proxies for productivity (or any change in the scale): total amount of exports, imports and level of employment.[14] Second, and more importantly, in column 7 we include firm-year fixed effects that control for all the firm's characteristics that vary over time, but are constant across markets. Arguably, productivity shocks fit under this category since they are specific to a firm and are unlikely varying across markets. We find that the main coefficient remains positive and significant in all these different specifications, suggesting that productivity is not

[10]Notice that this definition drops every firm-region pair that is always positive in our sample.

[11]Main results are robust to different clustering strategies: year-market, firm, firm-year, firm-market.

[12]This implies estimating the effect of an export incursion to a market on new imports from that market in the following year.

[13]This result is robust to alternative grouping strategies. For example, in Table C.4 of the Appendix we replicate our main estimation at the country level on a sample of the top 30 trade partners of Argentina (which represent more than 92% of the total value of imports and exports) and find qualitatively similar results.

[14]Results remain stable if we also include the growth of these variables (See C.5 of the Appendix).

driving the observed relationship between exporting and importing. As reported in column 7, once every firm-year specific characteristics are controlled for, export entry to a given market increases the probability to start sourcing from that market by 1.4 percent points. Reassuringly, the main coefficient remains stable throughout the different ways to proxy for productivity. Our finding remains even after several additional robustness checks. For example, in Table C.5 of the Appendix, we show that the effect of exporting on importing withstands the inclusion sector-market trends. This way, we control for the possibility of industry-market shocks (e.g. a new trade agreement that disproportionately affects some industries more than others). Table C.5 also shows that our findings are robust to using other proxies for productivity. Furthermore, in Table C.6 we show that the main conclusion holds if we focused on a sample of firms that were already exporters in the first year of our data. As the regression reported in column 7 includes the full battery of fixed effects, we adopt it as our preferred estimation in the following sections. In order to have a magnitude of the quantitative relevance of the uncovered fact, an increase of 1.4 percent points implies that the probability of start importing after export entry is 51% higher than the unconditional probability of start importing.

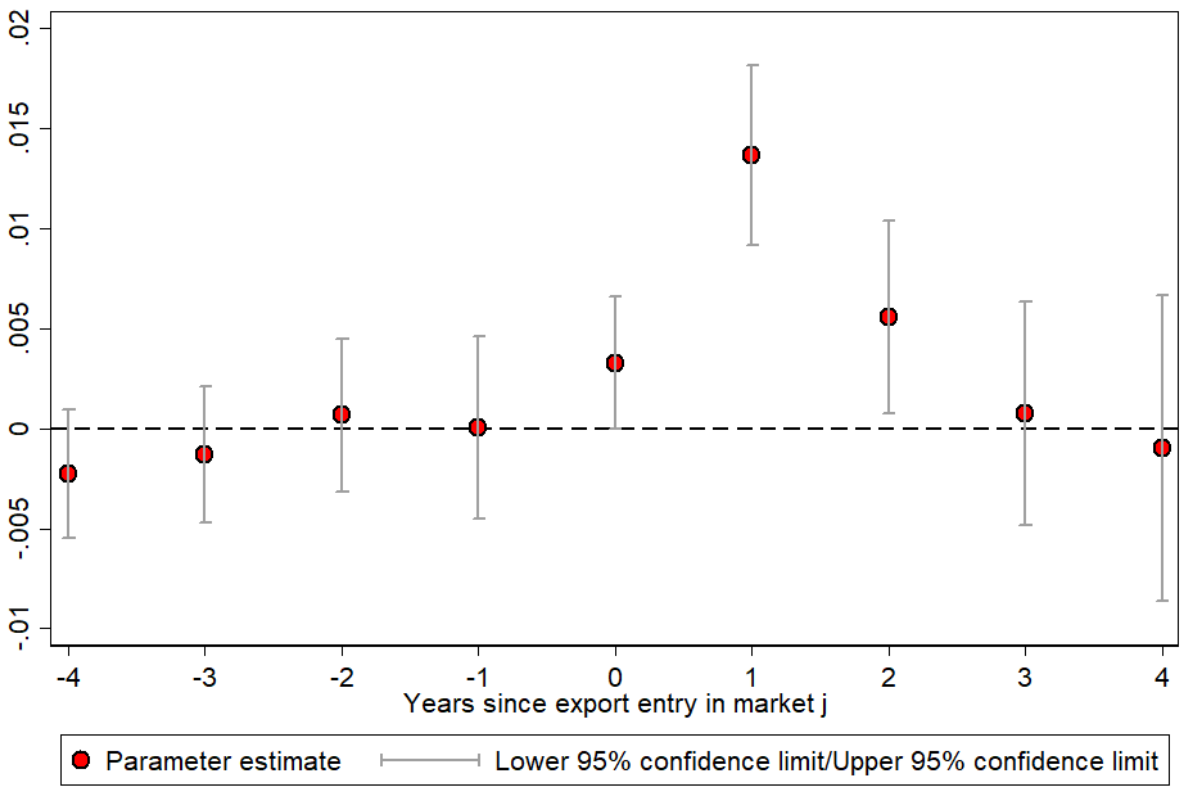
Table 3.3: Probability of importing from a new market

	$Pr[NewOrigin_{ijt} = 1]$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ExportEntry_{ijt-1}$	0.009***	0.018***	0.015***	0.015***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$log(Exports)_{it}$				0.000***		0.000	
				(0.000)		(0.000)	
$log(Imports)_{it}$				0.007***		0.007***	
				(0.000)		(0.000)	
$log(labor)_{it}$					0.012***	0.004***	
					(0.001)	(0.001)	
Mean dep variable	0.027	0.027	0.027	0.027	0.027	0.027	0.027
Observations	589,703	582,503	582,503	582,503	582,503	582,503	582,503
R-squared	0.074	0.342	0.357	0.380	0.358	0.380	0.452
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Market FE	yes	yes	yes	yes	yes	yes	yes
Firm-Market FE	no	yes	yes	yes	yes	yes	yes
Market-Year FE	no	no	yes	yes	yes	yes	yes
Firm-Year FE	no	no	no	no	no	no	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively.

These results establish that export entry increases the probability of importing from the new export market within the lapse of one year. Is the uncovered fact confined to $s = 1$? Figure 3.1 shows the regression coefficients α for $s = \{-4, -3, -2, -1, 0, 1, 2, 3, 4\}$ under our preferred specification, where negative values are years before export entry. First, note that we do not observe any effect on the probability of new imports the years before the firm reaches market j as an exporter. Now, focus on $s = 0$. Although not significant at 1%, the effect of an export entry manifests within the same year, which indicates a possible simultaneity between both activities in a given market. However, as our data is yearly, we cannot distinguish whether the effect is simultaneous or simply triggered within days, weeks or months after the export entry. Note as well that the coefficient is considerably lower than in the case of $s = 1$. Furthermore, in Table C.7 of the Appendix we show that the association between export entry to a market and start sourcing from that market is less robust when confined to the same year. We take a lower estimate and the lack of robustness as suggestive evidence that the effect of export entry requires some time to manifest. Finally, we note that the peak of the effect takes place when $s = 1$, as the estimate is lower two years after export entry ($s = 2$), and vanishes after three years ($s = 3$ and when $s = 4$). For this reason, we focus on the case of $s = 1$ from now on.

Figure 3.1: Estimated α for $s = \{-4, -3, -2, -1, 0, 1, 2, 3, 4\}$



3.4 Model

In this section, we develop a model of import and export decisions. The main goal is to derive our main fact as a theoretical prediction. We also use this framework to derive and test predictions for the main alternative mechanisms behind importing and after exporting: a productivity process or import costs savings.

Environment

Firms produce final goods that can be sold to J foreign markets and combine in production inputs that can be sourced domestically or from foreign markets. Since foreign suppliers are more efficient (or deliver higher quality) at producing some of the varieties, firms may be willing to demand imported inputs as a vehicle to reduce the marginal cost of production.

Demand

We assume that in each market j there is a demand for final goods given by a standard CES:

$$U_j = \left[\int_i s_{ij}^{1/\sigma} q_{ij}^{\sigma-1/\sigma} di \right]^{\sigma/\sigma-1},$$

where $\sigma > 1$ is the elasticity of substitution.[15] s_{ij} summarizes the taste for firm i's good in destination j. We let s_{ij} depend on two components: $s_{ij} = a_j \mu_{ij}$. a_j denotes the average taste of consumers in market j for goods produced by Argentinian firms. μ_{ij} is a taste component specific to the link between firm i and market j. We refer to this component as firm-market profitability. Note that the presence of this component implies that a firm may change its export decisions when facing a demand shock to μ_{ij}, even in absence of any variation of productivity.

Supply

On the supply side, there is a measure N of final-good producers, all of each produce a single differentiated product. Firms are characterized by an heterogeneous attribute φ that, for concreteness, is interpreted as core productivity. Just like in Melitz (2003), this parameter is exogenously drawn from a probability distribution $\xi(\varphi)$ and revealed to the firms once they start to produce.

There is a set of products K and a set of markets J, from which the foreign inputs can be sourced. Varieties are differentiated by their market of origin within the same product class. The difference between products and varieties is embedded in the technology. In particular, we assume that the production function takes the following nested form:

$$y = q(z) = \varphi \left[\sum_k x_k^{\frac{\theta-1}{\theta}} \right]^{(\theta/\theta-1)} \quad with \quad x_k = max[z_{dk}; \eta_{1k} z_{1k}; ...; \eta_{mk} z_{mk}]$$

where η_{jk} represents the quality of product k sourced from market j, z_{jk} denotes the quantity of product k sourced from market j. $\theta > 1$ is the elasticity of substitution between inputs. Within an intermediate product k, input varieties are perfectly substitutable, so the firm optimally selects only one source for each intermediate product. This feature is borne out in the data as for a given product at HS6-digit level, 80% of firms import it from only one source (see Figure C.2 in Appendix).

Importing k from j involves a fixed cost. A novel aspect of the framework is that import costs can also vary across firms according to their trading experience in market j. This feature of the model delivers multi-dimensional heterogeneity in productivity and firm-market-specific trade experience.[16] Formally, the fixed cost of importing product k from market j is

[15] The main conclusions remain unchanged if we let σ_j vary across markets.

[16] On exporting, Albornoz, Fanelli, and Hallak (2016), Morales, Sheu, and Zahler (2019), Das, Roberts, and Tybout (2007) also allow export costs to vary with experience or knowledge.

given by $F^M_{ijk} = \kappa_{jk} g\left(\left\{\mathbb{I}^X_{ij,(t-s)}; s = 0, 1, ..., T\right\}\right)$. $I^X_{ij,(t-s)}$ are indicators that take value 1 if firm i exported to market j in year $t-s$ and, for convenience, we denote $h_{ij} = \left\{\mathbb{I}^X_{ij,(t-s)}; s = 0, 1, ..., T\right\}$ the history of export status of firm i in market j. We assume that $g(h_{ij}) \in [0, 1]$ is weakly decreasing in the firm's experience in export market j, $g'(h_{ij}) \leq 0$. Intuitively, if there are import cost savings associated with exporting experience, then we expect to find that $g'(h_{ij}) < 0$. In this section, we do not specify the source of the cost reduction and focus on testing whether $g'(h_{ij}) < 0$ or $g'(h_{ij}) = 0$. We give more structure to this function in section 3.5. In equilibrium, each firm is characterized by a vector $(\varphi_i, \kappa_{dk}(g(h_{id})), ..., \kappa_{mk}(g(h_{im})))$. We further assume that firms take the set of input prices (including variable transport costs) $[p_{jk}]_{jk}$ as given.

Firm's decisions

We briefly study decisions in steady-state. It is convenient to define a sourcing strategy Ω as the subset of input varieties (j, k), such that the firm imports these varieties. Similarly, we define an exporting strategy Ω^X as the subset of destinations j, such that exports are positive.[17] To characterize the firm's decision, we proceed in three steps. First, conditional on the sourcing strategy Ω and the export strategy Ω^X, we characterize the intensive margin of imports from active sources, the minimum cost function, and derive the optimal revenues in each active market. Second, conditional on the sourcing strategy, we characterize the exporting strategy. Third, we characterize the sourcing strategy.

Step 1: Optimal amount of imports, cost function and revenues conditional on sourcing and exporting strategy

We begin by solving the optimal minimum variable cost. To do so, we compute the intensive margin for each variety in the sourcing strategy set (z^*_{jk}); the minimum marginal cost function $c(\Omega)/\varphi$; and optimal prices and revenues.

Conditional on the sourcing strategy, the intensive margin of imports is fully determined by the solution to the cost function,

$$z^*_{jk}(\varphi, \Omega, y) \equiv arg \min_{z_{jk}} \sum_{(j,k)\in\Omega} p_{jk} z_{jk} \text{ s.t } y = \varphi \left[\sum_{(j,k)\in\Omega} (\eta_{jk} z_{jk})^{\frac{\theta-1}{\theta}}\right]^{(\theta/\theta-1)}. \tag{3.2}$$

This yields that the value of imports of intermediate k from market j is given by :

$$p_{jk} z^*_{jk}(\varphi, \Omega, y) = \frac{y}{\varphi} \frac{\left(\frac{\eta_{jk}}{p_{jk}}\right)^{\theta-1}}{\left[\sum_{(j,k)\in\Omega} \left(\frac{\eta_{jk}}{p_{jk}}\right)^{\theta-1}\right]^{\theta/(\theta-1)}} \qquad \forall (j, k) \in \Omega, \tag{3.3}$$

[17] Note that both sourcing and export strategy are firm-year specific.

Once we have the intensive margin of imports for any potential sourcing strategy, it is straightforward to obtain the minimum unit cost function for a given sourcing strategy:

$$\frac{c(\Omega)}{\varphi} = \frac{1}{\varphi}\left[\sum_{(j,k)\in\Omega}\left(\frac{\eta_{jk}}{p_{jk}}\right)^{\theta-1}\right]^{-\frac{1}{\theta-1}}.$$

To derive optimal prices, each firm chooses its price in each market to maximize profits subject to a downward-sloping residual demand curve with constant elasticity of substitution. From the first-order condition, the equilibrium price for each variety is a constant mark-up over marginal costs. This constant mark-up implies the typical relationship between productivity and prices. The difference imposed by considering importing is that prices also depend on the firm's sourcing strategy. In particular, local prices are given by:

$$p = \frac{\sigma}{\sigma-1}\frac{c(\Omega)}{\varphi}.$$

Thus, revenues for a firm i exporting to market j, paying an iceberg cost equal to τ_j are given by,

$$r_{ij}(\Omega^X, \Omega, \varphi) = \left[\frac{\varphi_i}{c(\Omega_i)}\right]^{(\sigma-1)} A_j\mu_{ij},$$

defining A_j as destination specific appeal: $A_j = \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}(1+\tau_j)^{1-\sigma}P_j^{\sigma-1}X_j a_{j\cdot}$., where τ_j are iceberg costs to reach destination j and P_j is the price index in destination j.

It follows that total revenues for a firm with sourcing strategy Ω and export strategy Ω^X are given by,

$$R_i = \left[\frac{\varphi_i}{c(\Omega_i)}\right]^{(\sigma-1)} B_i(\Omega^X),$$

where $B_i(\Omega^X) = \sum_j I_{ij}^x A_j\mu_{ij}$ is a firm specific variable that summarizes different components of the demand. For concreteness, we refer to this variable as demand scale.

Step 2: Exporting Strategy

Conditional on the sourcing strategy and the optimal unit cost $c(\Omega_i)$, a firm will export to market j if the benefits outweigh the fixed costs of exporting to that market (F_j^x):

$$r_{ij}(\Omega^X, \Omega, \varphi) = \left[\frac{\varphi_i}{c(\Omega_i)}\right]^{(\sigma-1)} A_j\mu_{ij} \geq F_j^x,$$

Note that there are three determinants of export entry to a market. As usual, firms with higher core productivity (φ) are more likely to export to any destination j. Furthermore, firms are more likely to export to markets with higher A_j. Importantly, firms are more likely to export to destinations with higher firm-market profitability, μ_{ij}.[18]

Conditional on productivity, a positive shock to market profitability of a firm i in market j, μ_{ij}, increases the probability of export entry in market j.

This remark is crucial to justify our empirical preferred specification, reported in column (7) of Table 3.3. As we include firm-year fixed effects, we control for shocks to core productivity of a firm. In addition, market-year fixed effects control for any shock in time specific to the destination. Therefore, in our empirical analysis, we exploit variability in export entry coming from shocks to the firm's profitability in a given market.

Step 3. Sourcing strategy

Note that for a given sourcing strategy (Ω) and optimal export strategy (Ω^{X*}), profits are:

$$\pi_i(\Omega^{X*}, \Omega, \varphi) = \left[\frac{\varphi_i}{c(\Omega_i)}\right]^{(\sigma-1)} B_i(\Omega_X^*) - \sum_{(j,k)\in\Omega} \kappa_{jk} g(h_{ij}) - \sum_{(j)\in\Omega^{X*}} F_j^x, \tag{3.4}$$

Equation 3.4 implicitly contains the basic ingredients to determine the extensive margin of imports. The first term represents variable profits, which are increasing in the quality of the variety within each intermediate product k, and also in the number of products k combined in production. Intuitively, quality-differences and love for variety reduce marginal costs, generating incentives to import inputs. The second term corresponds to the import costs associated with the sourcing strategy. Importantly, we allow these costs to vary with experience as exporter in market j. Note that $g'(.)$ being negative could be interpreted as complementarity between both activities. Alternative, a negative $g'(.)$ could reflect reduction in import costs associated with trading experience (e.g. export entry). For example, reaching a new export market may reduce informational costs associated with finding new input suppliers.

We can now define the optimal sourcing strategy. A sourcing strategy Ω^* is the firm's optimal strategy if and only if $\pi(\Omega^{X*}, \Omega^*, \varphi) > \pi(\Omega^X, \Omega, \varphi) \quad \forall \quad \Omega \neq \Omega^*$. Explicitly, this condition implies,

[18] Notice that our setting could incorporate exporting-to-learn; defined as firms internalizing the effect of exporting on the probability of importing when deciding their exporting strategy. Exporting-to-learn would carry no implications on our analysis. If firms could export-to-learn, some firms would find it optimal to export with smaller revenues to learn about suppliers in the destination market (similar to Albornoz et al. (2012)). However, since exporting-to-learn lowers the entry cutoff of exporting to j at every point in time, the decision of a non-exporter to start exporting in response a shock to its profitability in a market will not depend on the degree of exporting-to-learn. Put it differently, exporting-to-learn would be similar to a lower fixed costs of exporting F_j^x. Although not the main focus of the paper, we explore in Appendix whether there are patterns in the data that suggest that firms export-to-learn. In particular, if firms export-to-learn, we should observe that firms with and without previous import experience should enter the import market with different sizes (proxy by total export values). Results reported in Table C.3 of Appendix C.2 suggest that this does not seem to be the case.

$$\frac{R(\Omega^{X*},\Omega^{*},\varphi)}{\sigma}-\sum_{jk\in\Omega^{X*}}F_j^X-\sum_{jk\in\Omega^{*}}\kappa_{jk}g\left(h_{ij}\right)>\frac{R(\Omega^{X},\Omega,\varphi)}{\sigma}-\sum_{jk\in\Omega^{X}}F_j^X-\sum_{jk\in\Omega}\kappa_{jk}g\left(h_{ij}\right) \quad (3.5)$$

for all $\Omega \neq \Omega^*$. If $g'(h_{ij}) < 0$, Equation 3.5 highlights that export experience in a market increases the likelihood of this market to be included in the sourcing strategy. Furthermore, if $g'(h_{ij}) < 0$, a shock to export profitability in a market (μ_{ij}) inducing entry in new export markets may trigger imports of new varieties from those markets. This feature is important for our empirical strategy (see equation 3.1).[19]We summarize the main predictions of the model in the next subsection.

Predictions on the extensive and intensive margin of importing

We solve for firms' optimal responses to shocks in productivity (φ_i) and in market-profitability (μ_{ij}). How does importing after exporting emerge in this framework? On the one hand, it is a established fact that exporting is related to productivity and productivity is related to importing (e.g. Halpern et al. (2009), Antras et al. (2014), Blaum et al. (2019)). Thus, export entry to market j could reflect unobservable productivity shifts that may also affect the probability of importing. On the other hand, export entry can reduce the cost of importing. In this subsection, we derive predictions that clarify the effect of export entry on the extensive and intensive margins of importing according to whether entry reflects productivity gains or import cost savings.

Export entry and the extensive margin of imports

Importing from a new source may be driven by multiple forces. Some of these drivers are also determinants of exporting to new markets. In particular, productivity (or any change that affect the scale of the firm) can affect entry in export markets and also the firm's sourcing strategy. Conversely, market-specific profitability shocks are confined to the decision to export. If these shocks induce export entry in a market, and exporting to a market reduces the cost of importing from that market, then export entry may affect the subsequent decision to source specifically from the new export destination; and not necessarily from other markets. We summarize this logic in the following proposition:

[Extensive margin]

1. **Import cost savings** Conditional on productivity (φ) and demand scale ($B(\Omega^X)$):

   A. (import cost savings) If $g'(h_{ij}) < 0$, export entry in market j, increases the probability of sourcing from market j.

[19] Antras et al. (2014) remark that assuming homogeneous fixed costs across firms is at odds with the data. We provide one rationale for those differences: firm experience in export markets can affect costs of importing.

B. (import cost savings) If $g'(h_{ij}) < 0$ and export entry in market j is not followed by new imports from j, the probability of importing from other sources $m \neq j$ remains unchanged.

2. **Productivity:**

A. (scale effects) Export entry in market j driven by a productivity (φ_i) shock (or any scale shock), increases the probability of sourcing from **any** potential source (the effect of a productivity shock is not confined to a particular market).

Proof. See Appendix. □

Part 1.A. of this proposition delivers as a prediction the fact that we uncover in Section 3.3: after controlling for firm-year FE (productivity and scale), export entry in market j leads to an increase in the probability of start sourcing from that market. Part 1.B. and Part 2.A. are related to the effect of reaching a new export destination on importing from any other potential source. These parts provide contrasting predictions on the extensive margin in other markets, according to whether export entry is related to productivity gains or to import cost savings.

If export entry in market j does not affect costs through the acquisition of new inputs from that market, then there is no reason to expect new import sources, unless export entry changes the scale of the firm or reflects a productivity shock; in which case new imports should come from any potential market. Put it differently, if importing after exporting is related to import costs savings, through the function g(.), we should not observe any effect on new imports from third markets. In contrast, if importing after exporting is related to a shift in productivity or a considerable increase in the firm's scale after entry, then we expect an increase in the probability of start importing from every market. In order to test these implications, we estimate the probability of start sourcing from m following export entry in market j, controlling for employment as a proxy for productivity.[20] Formally,

$$New\ Origin_{ijt} = \alpha Export\ Entry(-j)_{i,t-1} + \beta log(labor)_{i,t} + \{FE\} + \mu_{ijt} \tag{3.6}$$

where $Export\ Entry(-j)_{i,t-1}$ is an indicator that takes value 1 if the firm started to export to any market $m \neq j$ the previous year.

We display the results in Table 3.4. We present results for the overall sample and for each market separately. Consistent with the import cost savings explanation, export entry in destination m carries no impact on the probability of start sourcing from market $j \neq m$. Additionally, as expected, an increase on firms' productivity/scale (proxied by labor) is associated with an increase in the probability of importing from every market.

[20] Results are qualitatively unchanged if we use other proxies of productivity (e.g. total exports, employment growth, among others).

Table 3.4: The effect of export entry in market k on importing from market j≠k

	$Pr[NewOrigin_{ijt} = 1]$						
Panel A	**All**	**Outside the Americas**					
Market (j)	All	ASEAN	RAsia	UE	REu	Africa	Australia
$Export\ entry(-j)_{it-1}$	0.000	0.001	0.003	0.001	-0.000	0.000	0.001
	(0.001)	(0.004)	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)
$log(labor)_{it}$	0.024***	0.037***	0.019***	0.054***	0.014***	0.004**	0.003**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)	(0.001)
Observations	512,783	50,449	52,163	46,619	52,826	53,457	53,626
R-squared	0.468	0.434	0.469	0.433	0.520	0.492	0.470
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Market-Year FE	yes	no	no	no	no	no	no
Firm-Market FE	yes	no	no	no	no	no	no

Panel B	**The Americas**			
Market (j)	Mercosur	RAme	North Am.	CA
$Export\ entry(-j)_{it-1}$	0.004	-0.004*	0.001	-0.000
	(0.004)	(0.002)	(0.003)	(0.001)
$log(labor)_{it}$	0.039***	0.023***	0.043***	0.003***
	(0.004)	(0.002)	(0.003)	(0.001)
Observations	48,039	52,306	49,650	53,648
R-squared	0.440	0.470	0.468	0.489
Firm FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively. Column 1 includes firm-market and market-year fixed effects. Remaining columns include firm and year FE.

Export entry and the intensive margin of imports

In this section, we examine how export entry affects the intensive margin of imports. The following proposition summarizes firms' responses on the intensive margin, depending on whether export entry is associated with productivity gains or with a decline in import costs.

[Intensive margin]
Conditional on the sourcing strategy,

A. **Conditional on productivity and scale,** if $g'(h_{ij}) < 0$, export entry does not affect the value of imports from pre-existent sources.

B. Export entry associated to a positive productivity shock (or a scale shock) increases the value of imports from every pre-existent source.

Proof. See Appendix

□

We can use these predictions to obtain further evidence about whether importing after exporting reflects an increase in productivity or a reduction in import costs through the function $g(.)$. According to Proposition 2, conditional on the sourcing strategy, export entry should affect the intensive margin of imports only if it relates to productivity or scale gains. Conditional on scale, when export entry into market j is driven by a market profitability shock, we should not observe a rise in the value of imports from pre-existent sources. By contrast, when export entry into a market is related to positive productivity shocks or scale gains, we expect an increase in the value of imports from every pre-existent source. In order to assess how export entry affects the value of imports from pre-existent sources, we hold constant the sourcing strategy and estimate:

$$log(Imports_{ijt}) = \alpha Export\ Entry_{i,t-1} + \beta log(labor_{i,t}) + \delta_{ij} + \delta_{jt} + \mu_{ijt}, \tag{3.7}$$

where $Imports_{ijt}$ is firm i's value of imports from market j at year t, $Export\ Entry_{i,t-1}$ is a dummy indicating whether firm i entered to a new destination in $t-1$ for the first time. We also include firm-market fixed effects (δ_{ij}) and market-year fixed effects (δ_{jt}). Since we are interested in the intensive margin of imports, we only consider active markets in $t-1$ ($imports_{ij,t-1} > 0$).

Results of the estimation of equation 3.7 are reported in Table 3.5. As Part A of Proposition 2 predicts, we do not find a significant effect of export entry on the value of imports from pre-existent sources. In contrast, as expected, labor (as a proxy for productivity) positively affects the value of imports from all pre-existent sources.[21]

We take these results on the intensive margin, together with results regarding the extensive margin, and the fact that the main effect remains after controlling for firm-year fixed effects as indicative that the effect of export entry on new imports is associated with a fall in import costs.[22]

[21] We find similar results when we focus in the change in $log(imports_{ijt})$ from existent sources as outcome.

[22] We further discard other explanations related to productivity in Section 3.8.

Table 3.5: Intensive margin: The effect of an export entry on the value of imports from pre-existent sources

	Conditional on Sourcing Strategy	
	$log(imports)_{ijt}$	$log(imports)_{ijt}$
$Export\ Entry_{it-1}$	0.040	0.026
	(0.060)	(0.057)
$log(labor)_{it}$		2.045***
		(0.200)
Firm-Market FE	yes	yes
Market-Year FE	yes	yes
Cond Sources	yes	yes
Observations	35,549	35,549
R-squared	0.676	0.681

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

3.5 Cost complementarity versus trading experience

Our previous analysis shows that reaching a new export destination affects the probability of importing by reducing import costs. As shown by Halpern et al. (2009); Amiti and Konings (2007), import costs play a crucial role in determining sourcing decisions. But, what are these costs? While there is indirect evidence of the existence of import costs, little is known about their nature. We consider two types of import costs. One category includes import costs that are complementary with export costs. Both activities may share the same concurrent fixed costs. For example, the cost of setting-up a trade division belongs to this category. The second category includes import costs that depend on trading experience in a market. For example, the presence of a firm in a market facilitates setting up intermediate networks, learning about potential suppliers, building commercial relationships or specifying particular attributes of the goods to be acquired.

Our empirical strategy will be based on deriving distinct implications for how complementarity in import-export costs and how trading experience affect import sourcing. In our model, the effect of exporting on import costs is captured by changes through the function $g(.)$. We proceed by first shutting down the effect of cost complementarities to focus exclusively on the effect of trading experience. More specifically, we let function $g(.)$ depend only on knowledge of the firm about a market j (K_{ij}). We further assume $g'(K_{ij}) < 0$ and

$g''(K_{ij}) > 0$. Under this specification, trading experience acquired by export entry in market j affects import costs by increasing K_{ij}. Since $g''(.) > 0$, we expect a stronger effect on importing in situations where the firm is less informed about the characteristics of the market and the inputs to be sourced. Intuitively, gaining trading experience is more relevant when the market is relatively unknown or the inputs to be imported are relatively rare. We establish these intuitions formally:

If $g'(K_{ij}) < 0$ and $g''(K_{ij}) > 0$, export entry that reduces the cost of acquiring information implies:

I Market previous knowledge *DOES* matter for import decisions: stronger effect in less explored markets.

II Product specificity *DOES* matter for import decisions: stronger effect when imports involve non-homogeneous goods or higher technological content

III Export survival DOES not matter for import decisions: start sourcing from market j after export entry to j *DOES NOT* require export survival.

Proof. See Appendix □

Alternatively, there may be a potential association between exporting and importing given by cost complementarity (as emphasized by Kasahara and Lapham (2013), for example). For instance, we could define the function $g(.)$ as $g(.) = \Gamma * \mathbb{I}^{x}_{ij}$, where Γ captures the cost complementarity between importing and exporting. Note that this specification assumes the effect of trading experience away (i.e: Γ does not depend on the knowledge that the firm has about each market (K_{ij})).[23] Besides, an explanation based on complementarity in import-export costs requires export survival upon entry in a new market, since the possibility of cost savings requires both activities to be carry out simultaneously. On this score, each part of Proposition 3 provides a contrasting prediction that allows us to distinguish between the empirical relevance of each competing explanation. We examine the validity of each prediction in the following sections.

Market previous knowledge

Learning about suppliers is a possible channel through which trading experience in an export destination reduces the cost of importing from that market. If this is the case, the occurrence of importing after exporting should depend on previous knowledge about the market. In

[23] Note that, in part, we have already ruled out some explanations related to operational costs since most of the operational costs complementarities are not confined to the same market. In addition, most of stories related to complementarity in costs would usually require a simultaneous relation between importing and exporting. However, it is still possible that the observed sequence of export entry followed by new sourcing from the same market to be explained by cost complementarity. In this section, we note that if this were case, it would be unlikely that the magnitude of the effect varies according to a firm's previous knowledge about the market and the specificity of the product.

this section, we design different exercises to explore the empirical relevance of this potential channel. How do we proxy for previous knowledge about a market? We explore different possibilities.

Previous knowledge might have been acquired in a previous export experience. If this is the case, and previous knowledge is relevant, then re-entry should be associated with a smaller increase in the probability of sourcing from that the market. To test this hypothesis, we exploit the fact that a considerable number of the firms in our sample are re-entrants to export markets. These are firms that did not export at $t-2$, but did so before $t-2$ and export again at $t-1$.[24] The underlying hypothesis is that a firm that re-enters a market already has already acquired relevant experience in the past. For this reason, we expect re-entry to have a weaker effect on import sourcing.

We estimate $Pr[NewOrigin_{ijt} = 1]$ as a function of $Re-entrant_{ijt-1}$; a variable that takes value 1 if the firm entered as exporter to market j in t, but already had experience as exporter in that market before $t-1$. Table 3.6 reports the results. Consistent with experience being a driver of sourcing decisions, we do not observe a significant effect on the probability of new imports when the firm starts exporting to a market that the firm has already served in the past.[25]

Table 3.6: Exporting does not affect importing if the export market is not new

	$Pr[NewOrigin_{ijt} = 1]$		
	(1)	(2)	(3)
$Re-entrant_{ijt-1}$	0.005	0.004	0.000
	(0.005)	(0.005)	(0.005)
$log(labor)_{it}$		0.013***	
		(0.001)	
Observations	615,787	615,787	615,614
R-squared	0.354	0.355	0.463
Firm-Market FE	yes	yes	yes
Market-Year FE	yes	yes	yes
Firm-Year FE	yes	yes	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

[24] As shown in Table C.1 of the Appendix, about 25% of firms entering to a new destination are re-entrants.

[25] Notice that, even if self-selection into re-entry may bias our estimates, the fact remains that re-entry in an export market is likely a more informed decision that first-entry (Albornoz et al., 2012, 2016), which provides further evidence in favor of the experience-based channel.

Arguably, the fact that re-entry does not affect sourcing rules out the possibility of "importing after exporting" being explained by complementarity in import-export costs. If our results reflected cost complementarity, the reduction in import costs should be associated with all types of export activities, not only with export-entry.

Furthermore, previous knowledge (K_{ij}) should also vary across markets, making the potential gains from new trading experience differ across markets. And this is indeed the case. We run our baseline estimation for each market j, including firm and year fixed effects, as well as employment to control for productivity.[26] Results are reported in Table 3.7. Clearly, the effect of exporting on importing is stronger for markets outside the Americas; such as Asean+3, EU, RAsia, while the association between exporting and importing disappears in nearby markets such as Mercosur and the rest of the American continent. For example, export entry to the European Union rises the probability of starting to import from a country within European Union by 6,4%. For Mercosur, new export activity has no such effect. Furthermore, if we split the sample into Non-Americas' markets (Asean+3, RAsia, EU, REurope,Australia,Africa) and The Americas' markets (Mercosur, RSA, North America and CA) and perform a separate estimation for each sub-sample, we find that export entry is only associated with new imports from the same source in Non-Americas' markets.

Table 3.7: Region specific importing after exporting

$Pr[NewOrigin_{ijt} = 1]$	**Non-Americas Markets**	ASEAN	RAsia	EU	REu	Africa
$Export\ Entry_{ijt-1}$	0.031***	0.046***	0.026**	0.041***	0.030***	0.018***
	(0.005)	(0.017)	(0.011)	(0.012)	(0.010)	(0.007)
Observations	363,880	55,145	61,054	42,504	64,601	69,697
Mean dep variable	0.027	0.061	0.032	0.074	0.016	0.003
$Pr[NewOrigin_{ijt} = 1]$	**The Americas Markets**	Mercosur	RSA	North America	CA	
$Export\ Entry_{ijt-1}$	0.005*	0.004	0.005	0.002	0.005*	
	(0.003)	(0.005)	(0.003)	(0.008)	(0.003)	
Observations	218,623	44,560	54,810	50,775	68,478	
Mean dep variable	0.026	0.045	0.018	0.048	0.002	
Firm FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Firm-Market FE	yes	no	no	no	no	no
Employment proxy	yes	yes	yes	yes	yes	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

Of course, it could still be the case that this result may be driven by destination-specific

[26] Results are qualitatively similar if we include other proxies for productivity such as amount of exports/imports, or growth of these variables. These estimations are available upon request.

complementarity in costs between exporting and importing. An alternative interpretation of this finding is that trading experience matters more to source from markets where Argentinian firms lack of relevant information about potential suppliers.[27] This explanation can be tested further. We generate a measure that proxy knowledge about potential suppliers in a market at the firm level before export entry to a destination. For each input variety (a combination of product k at the HS 6-digit level and origin j), we define whether it is "known" or "unknown" according to the following rule:

Let N_{vjk} denote the number of firms that import the variety (j,k) in sector v (at the ISIC 4-digit level). Then, define an unknown variety for sector v at year 2003 as:

$$Unknown\ Variety_{vjk} = \begin{cases} 1, & \text{if } N_{vjk,0} < Median_v\left[N_{vjk}\right] \\ 0, & \text{if otherwise} \end{cases}$$

We can use $Unknown\ Variety_{vjk}$ to generate two types of imported inputs:

$$u = \{known, unknown\}$$

Thus, for each firm, we can distinguish imported inputs according to $Unknown\ input_{iju}$, which takes the value of 1 for imports of unknown varieties and 0 otherwise.[28] This variable allows to explore, for a given firm, whether the probability of a new sourcing following an export entry in the same market depends on the type of input. Implicitly, even when a firm had never imported a variety (jk), knowledge about potential suppliers increases for varieties that are known in the sector where the firm belongs. Put it differently, we assume that knowledge available about a particular variety increases with the number of firms belonging to the same sector importing that variety. To test this, we estimate:

$$NewOrigin_{ijut} = \beta_1 ExportEntry_{ij,t-1} + \beta_2 ExportEntry_{ij,t-1} * Unknown\ Input_{iju} + \{FE\} + \epsilon_{iujt},$$

where the vector of fixed effects includes our baseline FE combined with the type of input u.

The estimated coefficients are reported in Table 3.8. The results are eloquent. Column 1 and Column 2 show that the effect of export entry on the likelihood of importing from the same market crucially depends on whether the firm has previous knowledge about the market. In particular, consistent with the experience channel, export entry has a stronger effect on import entry when the newly imported variety is relatively unknown in the sector where the firm operates.

[27] In general, Argentine firms have more experience with some markets than others. For example, even if a firm never exported to Mercosur, we expect that it has good enough information about inputs available there. In contrast, a firm that had never established trade with the European Union or ASEAN+3 might have less information about those markets, and thus more to learn.

[28] Results are qualitatively similar is we use amount of imports, instead of number of firms and are available upon request.

Table 3.8: Importing after exporting: Stronger effect when new import variety is relatively unknown

	$Pr[NewOrigin_{ijut} = 1]$	
	(1)	(2)
$ExportEntry_{ij,t-1}$	0.004*	0.002
	(0.002)	(0.002)
$ExportEntry_{ijt-1} * UnknownInput_{iju}$	0.008***	0.008***
	(0.003)	(0.003)
$log(labor)_{it}$	0.010***	
	(0.001)	
Observations	1,126,308	1,126,308
R-squared	0.328	0.399
Firm-Market-unknown FE	yes	yes
Market-Year-unknown FE	yes	yes
Firm-Year FE	yes	yes
Mean dep variable	0.018	0.018

The dataset is at the firm-market-year-product type level. Where unknown takes values 0 or 1 for unknown and known varieties, respectively. Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

Product specificity

In this section, we exploit the fact that certain types of inputs may be more likely to require previous knowledge about specific suppliers. For example, homogeneous goods do not require a specific supplier and are sold in relatively competitive markets, where information is more likely to be conveyed by the price. By contrast, non-homogeneous goods are differentiated across different attributes, such as quality, and typically require more information about the specific supplier. Similarly, low-technology inputs are easier to acquire than high-tech goods, for which knowledge about suppliers may be more valuable.

We consider two ways to distinguish between different inputs: product differentiation and technology differentiation. For product differentiation, we use the classification proposed by Rauch (1999). To distinguish products according to their technological content, we use the OECD classification. Thus, we generate two types to classify imported inputs:

$$u = \{\text{Differentiated, Non-Differentiated}\}$$

or alternatively,

$$u = \{\text{High-tech, low-tech}\}$$

We then run our baseline regression distinguishing between the differential effect of export entry on new imports, depending on whether the newly imported product is differentiated ($Diff_u$=1), or not ($Diff_u$=0) for both definitions of u:

$$NewOrigin_{ijut} = \beta_1 ExportEntry_{ij,t-1} + \beta_2 ExportEntry_{ij,t-1} * Diff_u + \{FE\} + \epsilon_{iujt},$$

where the vector of fixed effects includes those of our baseline regression, interacted with the input type u. In this case, we are interested in estimating β_2, which captures the effect of interacting $ExportEntry$ with the type of imported input.

Results are reported in table 3.9. We can observe that the effect of export entry on the probability of start importing is remarkably higher when the newly imported input is differentiated (columns 1 and 2). We obtain similar conclusions if we focus on technology differentiation of the newly imported input (columns 3 and 4).

Table 3.9: Product specificity: stronger effect for differentiated and med-high tech inputs

	$NewOrigin_{ijut}$			
	Product Differentiation (Rauch)		Technology Differentiation (OECD)	
$ExportEntry_{ijt-1}$	0.001*	0.002**	0.003*	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
$ExportEntry_{ijt-1} * Diff_u$	0.014***	0.014***	0.011***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
$log(labor)_{it}$	0.009***		0.009***	
	(0.001)		(0.001)	
Observations	1,139,030	1,139,030	1,139,030	1,139,030
R-squared	0.271	0.324	0.269	0.322
Firm-Market-Diff FE	yes	yes	yes	yes
Market-Year-Diff FE	yes	yes	yes	yes
Firm-Year-Diff FE	no	yes	no	yes

The dataset is at the firm-market-year-differentiated level. Diff takes value 1 for differentiated inputs. Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

Importing after exporting does not require export survival

Finally, a more clear-cut distinction is given by observing that operational cost complementarity in exporting and importing requires both activities to be carried out concurrently. In contrast, the effect of experience may last, regardless on whether the firm continues serving the market as an exporter or not. We explore whether the effect of export entry on new imports depends on the firm survival in the export market.[29] Formally, we begin by estimating the following version of equation 3.1,

$$NewOrigin_{ijt} = \alpha_1 ExportEntry_{ij,t-1} + \alpha_2 Exporter_{ijt} + \alpha_3 ExportEntry_{ij,t-1} * Exporter_{ijt} + \{FE\} + \mu_{ijt},$$

where $Exporter_{ijt}$ is an indicator that takes value one if the firm exports positive amount to market j in year t. The key parameter is α_3, which indicates how relevant is export survival for our main fact. If the effect is related to concurrent complementarity in import-export costs, then we expect a positive estimate for the interaction term, indicating that export survival is required. In contrast, if the effect operates through newly acquired trading experience (e.g: acquisition of information about suppliers), then the interaction term would not be relevant. As we report in Table 3.10, consistent with the trading experience channel, surviving in the export market is not required to trigger new sourcing after export entry.

Table 3.10: Does the persistence of the export relationship matters?

	$Pr[NewOrigin_{ijt} = 1]$	
$ExportEntry_{ijt-1}$	0.014***	0.016***
	(0.003)	(0.003)
$Exporter_{ijt}$	0.008***	0.006***
	(0.002)	(0.002)
$Export\ Entry_{ijt-1} * Exporter_{ijt}$	**0.001**	**-0.004**
	(0.005)	**(0.005)**
$log(labor)_{it}$	0.012***	
	(0.001)	
Observations	582,503	582,503
R-squared	0.358	0.452
Firm-Market FE	yes	yes
Year-Market FE	yes	yes
Firm-Year FE	no	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

Taken together, the results presented in this section suggest that firms gain experience after export entry, and this experience is associated with lower import costs.

[29] We exploit variability coming from the fact that a considerable number firms exit the export market just after export entry (see Table C.1 of the Appendix).

On the direction of the effect

If experience as an exporter is a way to reduce import cost, it is possible that experience as an importer helps a firm to gain access to a particular market. In principle, it is possible that the activities associated with finding and maintaining links with new foreign suppliers could be conducive to reaching new consumers. For example, a firm can learn about the demand for their products in a market from interacting with a supplier. We are agnostic about this possibility as the role experience on importing does not require the opposite channel to be true. For example, it is plausible that, by selling a car a firm acquires information about steel suppliers, while importing steel from the same country may not reveal relevant information about the demand for cars in that country. For this reason, we consider the possibility of exporting after importing as an empirical question that we test for completeness.

We estimate the probability of a firm starting to export to a new destination ($ExportEntry_{ij,t}$) on a indicator variable $NewOrigin_{ij,t-1}$ that takes the value of 1 if the firm started to source from market j in the previous year, and our battery of fixed effects. As reported in Table C.8, sourcing from a new market does not affect the probability of exporting there the following year. This fact remains both in the whole sample and also doing the estimation market by market.

This finding does not contradict the effect of experience of export entry on importing. Note however that it is indeed inconsistent with the alternative explanation based on cost complementarities between exporting and exporting. In that case, the relationship should definitely be bidirectional. We consider this last finding as further indirect evidence in favour of our preferred interpretation.

3.6 Backing up Fixed costs and Fixed cost savings g(.)

According to our model, our fact reflects a reduction in the fixed cost of importing after export entry. Although unobservable, we approximate the fixed costs of importing and estimate the savings in import costs that are associated with recently acquired experience in a new export destination.

The estimation requires the additional assumption of time being continuous. This implies that a firm starts to import from a new source as soon as the gains from importing are equal to the fixed costs of importing from that market. Thus, the fixed cost of importing from market j can be approximated by the variation in the firm's total revenues between $t-1$ and t at the moment the firm starts importing from j, controlling for new operations in other markets.

This strategy entails two sources of bias. First, as time is discrete, the change in revenues at entry constitutes an upper bound for the fixed costs of importing. Second, revenues at t depend on decisions taken after export entry. For these reasons, the main aim of this exercise is not to come up with a precise estimation of the level of the fixed costs of importing, but rather to give an idea of the magnitude of the reduction associated with previous export experience.

Following the model, we let fixed costs depend on the firm's previous status as exporter in a given market. Hence, by comparing the predicted fixed costs for firms with no previous export experience in a market with the predicted fixed costs for firms that started to export the year before starting to import, we can infer the magnitude of the fixed cost savings: $\left[\frac{g(I^X_{ij,t-1}=1)}{g(0)}\right]$ (see equation 3.5).

Formally, normalize $g(0) = 1$ the cost savings when the firm has no export experience and recall that $g'(.) < 0$ is decreasing with experience in a market. For simplicity, we suppress the product k dimension and write fixed costs of importing from j as κ_j. Now consider a firm that starts importing from market j in year t.

The difference in revenues before and after sourcing from a new market is given by:

$$R_{it}\left(\varphi_{it}, \Omega^{X*}_{it}, \Omega_{it-1} \cup j\right) - R_{it-1}\left(\varphi_{it-1}, \Omega^{X*}_{it-1}, \Omega_{it-1}\right) = (1 - \mathbb{I}^X_{jt-1})\kappa_j + \mathbb{I}^X_{jt-1}\kappa_j g(.),$$

where we denote $\Omega_{it-1} \cup j$ the subset that combines the sourcing strategy at $t-1$ with sourcing from a new market j. The equation above indicates that the cost savings can be estimated by comparing the change in revenues for a firm that starts to import after export entry (denoted by MaX) relative to a similar firm that starts to import with no export experience ($No - MaX$).Taking logs and rearranging,

$$lng(.) = ln\frac{\left[R_{it}\left(\varphi_{it}, \Omega^{X*}_{it}, \Omega_{it-1} \cup j\right) - R_{it-1}\left(\varphi_{it-1}, \Omega^{X*}_{it-1}, \Omega_{it-1}\right)\right]^{MAX}}{\left[R_{it}\left(\varphi_{it}, \Omega^{X*}_{it}, \Omega_{it-1} \cup j\right) - R_{it-1}\left(\varphi_{it-1}, \Omega^{X*}_{it-1}, \Omega_{it-1}\right)\right]^{No-MAX}}, \tag{3.8}$$

In order to take this object to the data, we need to make two additional assumptions. First, we assume that the change in total exports in response to a reduction in costs is proportional to the change in revenues. This feature is consistent with our theoretical framework and is common to standard trade models. Second, in order to avoid a mechanic increase in total exports for firms that started exporting to market j in $t-1$, our dependent variable excludes exports to j in the estimation.[30]

Rearranging equation 3.8, we can now estimate the cost saving $g(.)$ with the following linear model:

$$ln\left(Exports_{it} - Exports_{it-1}\right) = \beta ExportEntry_{ijt-1} + X_{it} + \gamma_i + \gamma_{sjt} + \epsilon_{ijt}, \text{for } NewOrigin_{ijt} = 1.$$

We include market-year-sector fixed effects and control for different sourcing strategies by including the number of previous sources of the firm. The estimate β approximates the savings in import costs due to recently acquired export experience: $\beta = ln(g(.))$.

As shown in Table C.9 of the Appendix, the coefficient of the regression is -0.5 and it is statistically significant at the 1%. We predict the outcome value for new importers and

[30] Since exports upon entry to a market are usually low, results remain almost unchanged if we include exports to j.

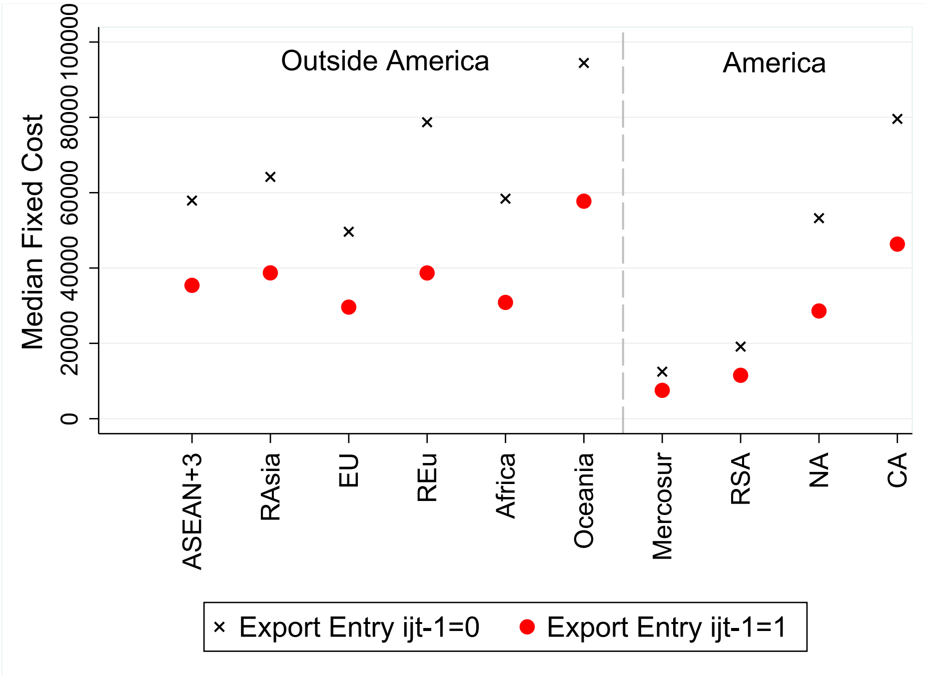
summarize the main estimations in Table 3.11. The median firm fixed cost of importing is 50,000 dollars. However, previous export entry reduces these costs by a factor of $1 - g(.) = 0.46$, leading to a fixed cost of 26,700 dollars for firms that start importing after export entry. The estimated values are within the range $(15,000; 60,000)$ estimated in Antras et al. (2014) and contrast well with Halpern et al. (2009), where fixed costs of importing for local firms are compared to those for foreign firms in Hungary. According to their estimates, foreign firms pay 60% lower fixed costs of importing than local firms. Our findings suggest that export experience acquired after after export entry reduces fixed costs of importing by 50%. Notably, we find that the entire distribution of import fixed costs is below for firms that start importing after export entry.

Table 3.11: Fixed costs and Fixed Costs savings

Percentile of Fixed Cost	Fixed Cost: $ExportEntry_{ijt-1} = 0$	Fixed Cost: $ExportEntry_{ijt-1} = 1$	g(.)
10th	14264.93	6966.60	0.49
25th	36870.61	11107.93	0.30
50th	49636.65	26663.95	0.54
75th	71124.48	36730.27	0.52
90th	91817.04	51351.67	0.56

As a further exploration, we can replicate the previous exercise and estimate the fixed cost of importing for each market. We report the median fixed costs in each market in Figure 3.2. Note that, as expected, fixed costs are lower for nearer markets. For instance, while the fixed cost of importing from Mercosur for a median firm with no export experience is 15,000 dollars, the fixed cost of importing from Rest of Asia is around 62,000 dollars. Second, we confirm that export entry reduces import fixed costs in every market. Interestingly, consistent with our previous findings, fixed costs savings are also systematically higher in markets outside the American continent.

Figure 3.2: Median fixed cost of importing by market and export experience



3.7 Implications

Our findings emphasize the complexity of the importing activities. Importing requires experience in the foreign market and exporting can help the firm acquire that experience. For example, acquiring export experience may also generate information about import sources, which facilitates the process of finding suppliers. On this ground, our findings highlight the relevance of informational barriers that firms face to find suppliers abroad and how experience gained by exporting may help firms overcome these barriers. In this section, we discuss broader economic implications of importing after exporting.

First, interpreting the findings of this paper through the lens of our model indicates that the effect of acquiring export experience is higher for relatively unknown and differentiated import varieties. On this ground, new export markets become a channel through which firms improve input quality and production efficiency.

Second, we have shown that export entry provides firms with experience that may help them operate as importers. For example, the experience gain as exporter could allow the firm to resolve part of the uncertainty about suppliers in the foreign market. In this case, as sourcing decisions are made with more accurate information, we expect import relationships generated after export entry to last longer. This would be reflected in higher survival rates.[31] To test this implication, we compare the likelihood of being active in the import market for

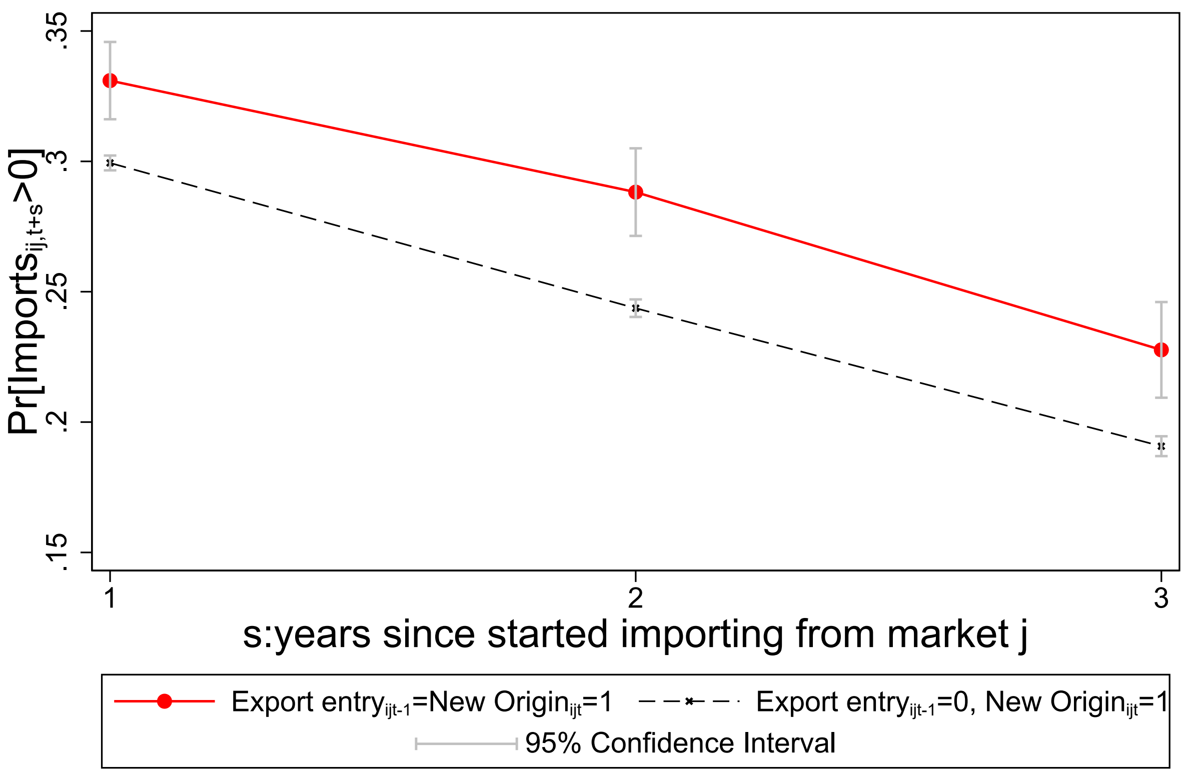
[31] For example, Besedeš (2008) shows that duration of relationships increases for more reliable suppliers.

firms that start importing after export entry, relative to firms that start importing with no previous export experience in the market. Formally,

$$ImportStatus_{ij,t+s} = \beta_1 NewOrigin_{ij,t} + \beta_2 NewOrigin_{ij,t} * ExportEntry_{ij,t-1} + \delta_{ij} + \delta_{jt} + \delta_{it} + \epsilon_{ijt}$$

for $s = \{1, 2, 3\}$, where s denotes years after the initial year of importing from j. We report β_1 and $\beta_1 + \beta_2$ for different values of s in Figure 3.3. We observe that one year after start sourcing from a market, the probability of being active in the market is 11% higher for firms that started to import after export entry. This initial difference remains stable even three years after import entry. Higher survival rates indicate that importing after exporting generates longer and more stable trading relationships.

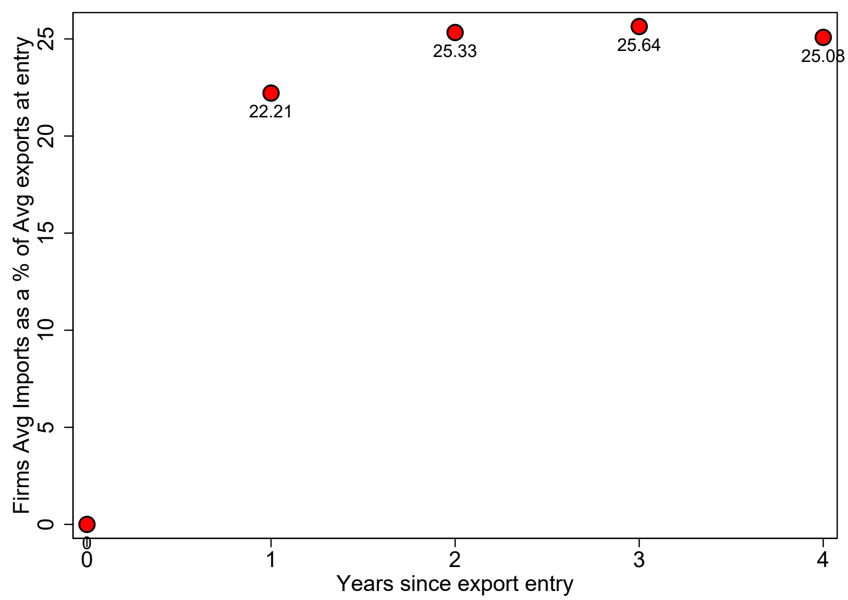
Figure 3.3: Importers after exporting are more likely to remain active in the import market



Notes: we report estimations of β_1 and $\beta_1 + \beta 2$ for different values of s according to equation 3.7 including firm-market, market-year and firm-year fixed effects.

Third, importing after exporting has an effect on trade balances. In figure 3.4, we focus on firms that start importing after exporting and report the total value of imports from market j as a percentage of total exports to that market at the moment of entry. According to our calculations, one year after reaching a new destination, total imports from market j account for 22% of exports to market j at entry. As expected, this new flow of imports generated after export entry continues over time. This entails implications for policy. For example, if export promotion policies were motivated by the goal of reducing trade imbalances, our findings warn against the effectiveness of this policies. On the other hand, the fact that export entry generates experience in the foreign market that also facilitates importing activities might serve as a novel rationale for export promotion if firms do not internalise the effect of export experience on import costs.

Figure 3.4: Average imports as a % of Average Exports at the moment of entry to market j



Sub-sample of firms that start importing after exporting.

Taken together, a substantial part of new exports is translated on new imports from that market within a year. In addition, import relationships that are established after having exported to a market involve relatively unknown and differentiated inputs and are more likely to persist overtime.

3.8 Further discussion on alternative explanations

To conclude the exhaustive examination of alternative explanations, we briefly explore two other potential channels: i) market-specific similarity in fixed costs for exporting and importing; and ii) customization.

i) **Market-specific similarity in fixed costs for exporting and importing:** Despite including firm-year fixed effects to control for firm specific changes in productivity, and showing that exporting only affects the probability of importing in the same market, there is still a remaining possibility in which firm-year shocks (e.g.: productivity shocks) can affect the probability for a firm to start exporting to and importing from the same market. If there was a positive correlation between export and import costs across countries, or whether export profitability in a market potential is also correlated with cost savings from importing, then it is still possible that a productivity shock can induce export entry in and new sourcing from the same market. In this section, we show patterns observed in the data that contradicts this alternative explanation.

First, recall that we include market-year fixed effects in our preferred specification. This rules out firm-invariant variability across markets in any given year; which eliminates potential issues related to a market being, on average, easier to reach by Argentinian firms. Second, we find evidence that is inconsistent with a positive correlation between import and export entry costs. Such a correlation would imply that, on average, the easiest export destination markets should also be the easiest markets to source from. This would imply that firms that start exporting (or start sourcing from) a given market should have a similar hierarchical ranking of sources and destinations. We test this in two ways. First, in Table 3.12, we display the average number of export (import) markets to (from) where the firm was exporting (importing) before it started to export (import) to (from) a new market. This exercise ranks import and export markets according to how hard it is to reach them. We observe that the hierarchy of markets based on export entry is very different to the hierarchy based on new sourcing. This suggests that the ranking of import and export fixed costs differ. For example, on average, before reaching ASEAN+3 as exporter, a firm usually exports to 3.3 other markets (ranked 6th). In contrast, firms that import from ASEAN+3 only need to import from 1.2 markets before starting to source from there (ranked 3rd). Second, we rank the firms according to their size (number of employees) at the moment of reaching a new destination or at the moment of start sourcing from a new origin. In Table 3.13, we report the results. Reassuringly, we observe a similar pattern. Note also that the average size when the firm enters as exporter to a market is remarkably different to the average size when the firm enters as importer; suggesting that the import and export entry thresholds are considerably different. For example, firms with an average of 53 employees are able to source from UE, while firms with 129 employees are able to reach UE as exporters.[32]

[32] As a robustness check, we arrive to similar conclusions if we approximate size with total exports.

Table 3.12: Previous exportimport market experience when a firm reaches a market

Rank	New exporter to	# of previous export markets	Rank	New importer from	# of previous import markets
1	Mercosur	0.71	1	Mercosur	0.71
2	RAme	0.74	2	UE	1.10
3	NA	1.86	3	ASEAN	1.22
4	UE	1.99	4	NA	1.25
5	CentralAm	2.52	5	RAsia	1.91
6	ASEAN	3.30	6	RAme	2.25
7	RAsia	3.32	7	REuropa	2.63
8	REuropa	3.40	8	Africa	3.78
9	Africa	3.60	9	Aus	4.07
10	Aus	4.24	10	CentralAm	4.16

Table 3.13: Employment when a firm reaches a new market

Rank	New exporter to	# of workers	Rank	New importer from	# of workers
1	Merc	43.8	1	EU	53.5
2	RSA	47.7	2	Merc	73.1
3	NA	98.7	3	NA	75.2
4	CA	121.3	4	ASEAN+3	80.8
5	EU	129.8	5	RAsia	109.6
6	REu	168	6	RSA	154.4
7	RAsia	189.1	7	REu	166.3
8	Africa	193.9	8	Africa	311.9
9	ASEAN+3	215.8	9	CA	357.1
10	Aus	241.9	10	Aus	370.9

ii) **Customization:** Finally, it is possible that, in order to export to a market, firms might need to adapt their products by importing inputs from that market.

If the firm realizes the benefits of customization after the first export experience, we would observe a sequence that is similar to the one uncovered by this paper. In a way, customization is a special case of learning about suppliers. Notice, however, that if our results were mainly driven by customization, importing would require continuous exporting to the export market. However, we show that importing after exporting does not require survival in the export market. This implies that the newly imported input from market j is used by the firm to produce a good for many markets and not specifically for the export market j.

3.9 Conclusion

In this paper, we document a novel fact about the interrelationship between exporting and importing. Exporting to a specific market increases the probability of importing from that market within a year. We develop a framework where firms make decisions on exporting and importing that accounts for different aspects of import behavior and allows us to rationalize our main fact, clarify the channels through which exporting affects importing, and establish qualitative and quantitative implications.

Our paper sheds new light on import behavior that motivates future research and the design of policies. We emphasize the complexity of the importing activities. Importing requires knowledge about available inputs and potential suppliers. This knowledge is not readily available and depends on a firm's experience in foreign markets. Our paper shows that acquiring export experience help firms to reduce their costs of importing. For example, export experience may generate important information about suppliers in the foreign market, which, in turn, may facilitate the process of importing. We estimate that the import cost savings associated with export entry are, on average, around 50% and are higher in markets beyond the Americas. On this ground, our results encourage future research on the determinants of import costs, the role of informational barriers and the policies that may help firms overcome these barriers.

Furthermore, we show that the duration of the import relations for firms that start importing after exporting is longer. This suggests that importing relations that start with better information are more likely to succeed. This fact is important to design policies oriented to provide information about foreign markets to importers. We leave for future research understanding what factors determine the duration of the import relation.

Finally, if access to better quality foreign inputs fosters development, our finding that exporting eases the process of reaching the right suppliers open a new set of questions related to the effectiveness of export promotion policies.

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Appendix A

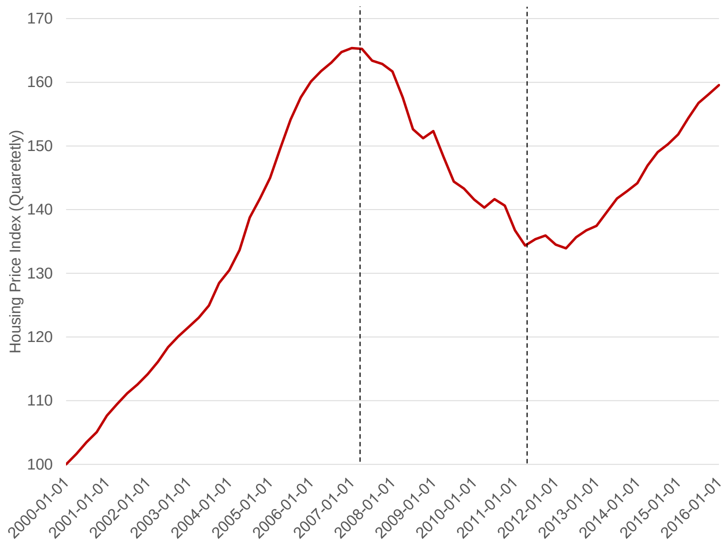
Appendix: Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail

A.1 Data

House prices Data

Figure A.1 depicts the evolution of the national house price index. We can observe the collapse in house prices started in the beginning of 2007. House prices continued declining until the second semester of 2011. Throughout that period, house prices dropped 18%.

Figure A.1: Evolution of House Price Index



Note: av

Differences between counties in sample and out of sample

For my main analysis, I only consider counties for which I have information on change in house prices (2208), Nielsen Scanner Data (2300), and Wharton Land Regulation Index (910). Hence, in my baseline specification, I consider only 910 counties for which I have information about the WLRI. In Table A.1, I show that these 910 counties represent 70% of the population and 70% of the sales in the Nielsen Data. These counties where hit slightly more by the crisis and had a smaller initial unemployment rate.

Table A.1: Counties with and without data on Wharton Land Regulation Index

Data on WLRI avaiable	Counties #	Population Total (millions)	Sales Total (millions)	$\Delta Log(HP)^{2007-2011}$ % (mean)	Unemployment rate (mean)
No	1298	86.64	13798.59	-10.50	5.07
Yes	910	200.21	33638.94	-13.41	4.83
Total	2208	286.86	47437.53	-11.71	-4.97

A.2 Price Indices: Main analysis.

As the main focus of the paper is on a) prices of existing products that are similar within chain across stores, and b) variation of price indices across time, we include an item only if it has positive sales in 2007 and 2011. We track the price of identical items (UPC-store combinations) across time, so that changes in quality or issues with comparing nonidentical products are less relevant for our results.

We construct two price indices, at two different levels of aggregation: A) A price index for each County (P_{ct}), and a retail chain by county price Index (P_{rct}). I describe them in detail in next sections.

County level Price index

We construct county-level price index in two steps. We first construct a product-module level price index. Ignoring the introduction of new varieties, the exact price index of the CES utility function for product module m in county c is as in Sato (1976) and Vartia (1976):[1]

$$P_{mct} = \Pi_{u \in I_{mc}} \left(\frac{P_{umct}}{P_{umct-1}} \right)^{w_{umct}},$$

where

$$w_{ucmt} = \frac{(s_{umct} - s_{umct-1})/(ln(s_{umct}) - ln(s_{umct-1}))}{\sum_{v \in I_{mc}} (s_{vmct} - s_{vmct-1})/(ln(s_{vmct}) - ln(s_{vmct-1}))} \quad ; \quad s_{umct} = \frac{P_{umct} Q_{umct}}{\sum_{v \in I_{mc}} P_{vmct} Q_{vmct}},$$

and I_{mc} is the set of varieties in product module m in county c that are consumed in both years (continuers). The weights w are ideal log-change weights and they are county specific to allow for spatial variation the relative weight of an item. [2]

I then construct an overall county-specific price index by weighting these category price indices by the revenue share of a particular product module in the initial year,

$$P_{ct} = \Pi_m \left(\frac{P_{mct}}{P_{mct-1}} \right)^{w_{mct-1}},$$

where

$$w_{mct-1} = \frac{\sum_{u \in m} Sales_{umct-1}}{\sum_u Sales_{uct-1}}$$

[1]This price index is consistent with the following utility function:

$$U_c(y_c) = \prod_{m \in R_c} \left[\sum_{u \in R_{mc}} q_{umc}^{\frac{\sigma_m(y_c)-1}{\sigma_m(y_c)}} \right]^{\alpha_{mc} \frac{\sigma_m(y_c)}{\sigma_m(y_c)-1}}$$

Consumer behavior features multi-stage budgeting in two stages. In the first stage, consumers in a county decide which of 1000 product modules to buy from based on the product module price index. In the second stage, conditional on the product module, consumers decide which variety to purchase; where variety is defined as a store-barcode combination (eg. 12 oz. Coke in 7-eleven).

[2]Note that they are always bounded between the shares of spending in period t and period t-1.

In figure A.2, I report the histogram of county-level inflation rate between 2007 and 2011. There is substantial heterogeneity in inflation rates by county in the US. The population-weighted average inflation rate of the counties in our sample is 11.09%, which contrast well with the variation in the food at home official CPI from BLS. Table A.2 reports inflation rate for the 10 counties with highest inflation rate and for the 10 counties with the lowest inflation rate (excluding outliers in the top/bottom 1 percent).

Figure A.2: Histogram: County's percentage change in retail prices between 2007 and 2011

Table A.2: Counties with lowest and highest inflation rate

County	County's Δ Log Price Index 07-11
Lowest Inflation Rate	
Contra Costa County, California	0.067
Bonner County, Idaho	0.067
Letcher County, Kentucky	0.068
Prowers County, Colorado	0.068
Buchanan County, Virginia	0.068
Leelanau County, Michigan	0.068
San Francisco County, California	0.068
Marin County, California	0.069
Sonoma County, California	0.069
Pike County, Alabama	0.069
Highest Inflation Rate	
Richmond County, North Carolina	0.180
Ben Hill County, Georgia	0.180
Jasper County, Iowa	0.180
Grundy County, Iowa	0.181
McCormick County, South Carolina	0.181
Lawrence County, Arkansas	0.182
Atkinson County, Georgia	0.182
Terrell County, Georgia	0.184
Chautauqua County, New York	0.185
Dickinson County, Iowa	0.185
U.S population-weighted average	0.111

Retail chain by county Price Index

Similarly, we construct a price index at the retail chain by county level.

First, we first construct a product-module level price index within retail chain in a county.

$$P_{mrct} = \Pi_{u \in I_{mrc}} \left(\frac{P_{umrct}}{P_{umrct-1}} \right)^{w_{umrct}},$$

where

$$w_{umrct} = \frac{(s_{umrct} - s_{umrct-1})/(ln(s_{umrct}) - ln(s_{umrct-1}))}{\sum_{v \in I_{mrc}} (s_{vmrct} - s_{vmrct-1})/(ln(s_{vmrct}) - ln(s_{vmrct-1}))} \ ; \ s_{umrct} = \frac{P_{umrct} Q_{umrct}}{\sum_{v \in I_{mrc}} P_{vmrct} Q_{vmrct}},$$

and I_{mrc} is the set of varieties in product module m, sold by retailer chain r that are consumed in both years (continuers). The weights w are ideal log-change weights and they are retailer chain specific to allow for variation in the importance of items in different retailer chains.

We then construct a retail chain by county price index by weighting these category price indices by the revenue share in $t-1$ of a particular product module in the retail chain in the county.

$$P_{rct} = \Pi_m \left(\frac{P_{mrct}}{P_{mrct-1}} \right)^{w_{mrct-1}},$$

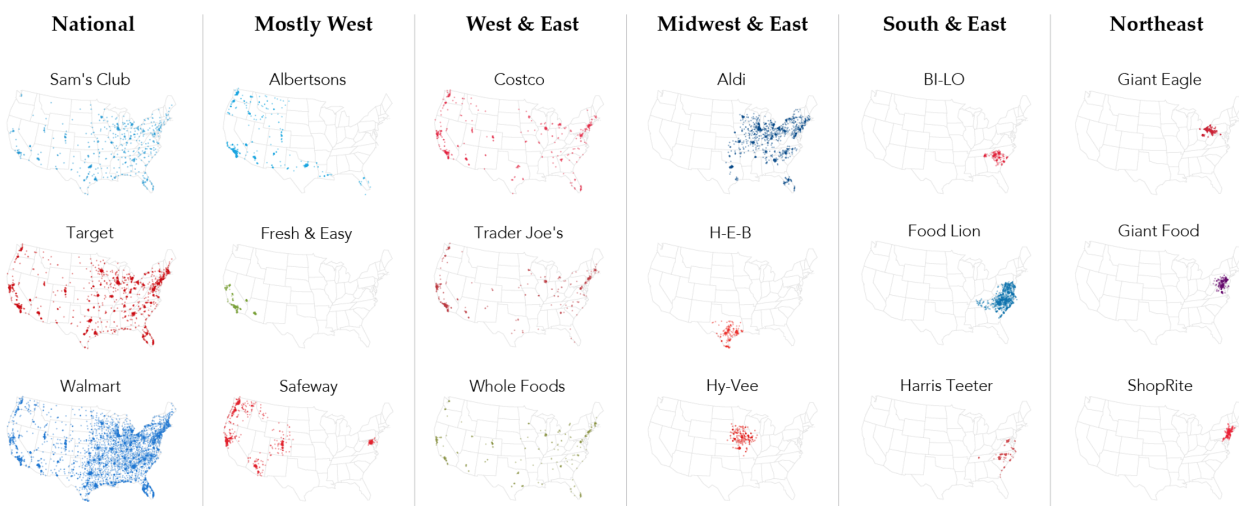
where

$$w_{mrct-1} = \frac{\sum_{u \epsilon m} Sales_{umrct-1}}{\sum_u Sales_{urct-1}}$$

A.3 Geographic Distribution of Retail Chains

Nielsen does not disclose the names of the chains in the data. In order to to provide a broad view of the geographic distribution of retail chains, in Figure A.3 I use AggData from 2006 to illustrate the geographic distribution of some popular retail chains .[3]

Figure A.3: Geographic Distribution of retail chains



Source: AggData for 2006

A.4 Empirical Analysis

Robustness Checks

Alternative county-level controls

I begin by exploring whether the main IV estimates are stable across specifications with different county-level controls. Results are reported in Table A.3. Reassuringly, the coefficient

[3] Some of these chains are in my data, while some of them are not. This is an illustrative example.

associated with chain-linked percentage change in house prices in other counties remains stable across different specifications. This suggests that, once I control for county's house price growth, the instrument is not correlated with other county-level variables in the error term.

Table A.3: Validity of identification assumption: Adding controls to IV estimations

Dep Variable: County's Δ Log Price Index						
	IV: WLRI instrument					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.074**	0.075**	0.078**	0.076**	0.070	0.057
	(0.034)	(0.036)	(0.038)	(0.037)	(0.045)	(0.046)
Chain-linked Δ Log HP (other counties)	0.129***	0.128***	0.132***	0.135***	0.138***	0.147***
	(0.039)	(0.041)	(0.041)	(0.040)	(0.042)	(0.045)
County's Δ Log Wages		-0.002	0.005	0.031**	0.032**	0.024*
		(0.016)	(0.013)	(0.014)	(0.014)	(0.013)
County's Δ Log # Establishments			-0.036	-0.020	-0.020	-0.018
			(0.025)	(0.026)	(0.025)	(0.022)
County's Δ Log Employment				-0.028*	-0.028**	-0.029**
				(0.014)	(0.014)	(0.013)
County's Log Retail Sales in 2007					-0.000	-0.000
					(0.001)	(0.001)
County's Log Market Access 2007						-0.006
						(0.004)
Panel B: First Stage						
F-stat	22.100	20.746	14.286	14.479	13.172	13.223
Observations	910	910	910	910	910	910
R-squared	0.059	0.062	0.048	0.060	0.077	0.096

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the percentage change in the county price index between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (1) to (6) report results, after instrumenting county exposure to house price shocks through the network of retailer chains with county exposure to WLRI through the network of retailer chains. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Test of Overidentifying assumptions: Saiz Housing Supply elasticity instrument

As a further check, I explore whether the main results change if I use another common instrument in the literature. In particular, I instrument county's percentage change in house price with housing supply elasticity (HSE, hereafter) constructed by Saiz (2010). Saiz (2010) uses geographic information of the metropolitan area to measure how easy is constructing new houses (e.g: areas with a flat topology are assigned with a higher elasticity). Naturally, I also use the Saiz HSE and the weights ω_{ck} to construct an instrument for network-weighted percentage change in house price in other counties.[4] Results are reported in Table A.4. The first two columns present OLS coefficients. Column (3) and (4) reports results using the WRLI instrument, as in my main specification. Columns (5) and (6) instrument the endogeneous variables with the Saiz HSE. The main coefficient increases modestly. Columns (7) and (8) present results including the 4 instruments. Again, throughout specifications, the coefficient remains stable between 0.129 and 0.146. In addition, I cannot reject the hypothesis that the coefficients obtained by using the different instruments are different.

Table A.4: Validity of identification assumption: Saiz (2010) housing supply elasticity instrument

	Dep Variable: County's Δ Log Price Index					
	IV: WLRI instrument		IV: HSE (Saiz) instrument		IV: All instruments	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.074**	0.076**	0.042*	0.040	0.054**	0.055*
	(0.034)	(0.037)	(0.023)	(0.026)	(0.027)	(0.031)
Chain-linked Δ Log HP (other counties)	0.129***	0.135***	0.139***	0.145***	0.140***	0.146***
	(0.039)	(0.040)	(0.037)	(0.039)	(0.035)	(0.036)
Panel B: First Stage						
First Stage F-stat	18.642	14.756	13.868	10.525	11.558	8.787
Observations	910	910	903	903	903	903
R-squared	0.082	0.074	0.183	0.185	0.143	0.140
County controls	no	yes	no	yes	no	yes

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retail chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

[4] Saiz HSE is at the MSA level so I have less variability. In addition, it is available for a lower number of counties. For this reason, the WLRI instrument is my baseline specification.

Robustness Checks: Controlling for similarity-weighted house price changes in other counties

In Table A.5, I provide another test for the possibility of common regional shocks at the county-level. Following the strategy in Giroud and Mueller (2019), I control for similarity-weighted house price changes in other counties. The weights place more weight on those counties that have a smaller absolute difference with respect to the county, based on different county-level covariates. The idea is that counties which are more similar in population, income, household debt and education are more likely to be exposed to the same county-level shocks and co-move in retail prices.

Table A.5: Controlling for similarity-weighted shocks

	Dep Variable: County's Δ Log Price Index				
	IV: WLRI instrument				
	(1)	(2)	(3)	(4)	(5)
Panel A: Second Stage					
County's Δ Log HP	0.079**	0.063*	0.062*	0.063*	0.064*
	(0.035)	(0.032)	(0.034)	(0.032)	(0.033)
Chain-linked Δ Log HP (other counties)	0.135***	0.136***	0.134***	0.136***	0.129***
	(0.033)	(0.032)	(0.032)	(0.032)	(0.036)
Population-weighted Δ Log HP (other counties)		0.029			
		(0.036)			
Income-weighted Δ Log HP (other counties)			-0.034		
			(0.051)		
Education-weighted Δ Log HP (other counties)				-0.032	
				(0.042)	
HH debt-weighted Δ Log HP (other counties)					0.010
					(0.020)
Panel B: First Stage					
F-statistic	13.814	13.582	13.230	13.755	13.254
Observations	910	910	910	910	910
R-squared	0.060	0.093	0.097	0.092	0.089
County controls	yes	yes	yes	yes	yes

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retail chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (5) control for similarity-weighted changes in house prices. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Robustness Checks: Different assumptions to construct the Price Index

In my baseline specification, I choose the CES exact price index for continuing varieties to construct the price index. In this section, I show that my main results remain qualitatively unchanged under different assumptions to construct the price indices. In particular, I repeat my main analysis with Laspeyers, a Paasche and a Fisher price index. Results are reported in Table A.6. We can observe that main results hold under these alternative county-level price indices.

Table A.6: Robustness Check: Other Price Indices

	Dep Variable: County's Δ Log Price Index			
	Exact CES	Laspeyeres	Pasche	Fischer
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.068*	0.069	0.082**	0.075*
	(0.040)	(0.043)	(0.040)	(0.041)
Chain-linked Δ Log HP (other counties)	0.135***	0.140***	0.098**	0.120***
	(0.040)	(0.040)	(0.041)	(0.040)
Observations	922	922	922	922
R-squared	0.060	0.043	0.072	0.071
County controls	yes	yes	yes	yes
Panel B: First Stage				
F-stat	14.756	14.756	14.756	14.756

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors clustered at the state level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Robustness Checks: Alternative period of analysis: 2007-2009

In my baseline specification, I choose the period between 2007 and 2011. In this section, I show that my main results remain qualitatively unchanged when I choose other period of analysis. Table A.7 replicates main table 1.1 for the period 2007 to 2009.

Table A.7: Propagation of house price-induced local demand shocks across counties through the network of retailer chains: 2007-2009

	Dep Variable: County's Δ Log Price Index (2007-2009)					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.044	0.023	0.012	0.121***	0.073*	0.069
	(0.027)	(0.026)	(0.027)	(0.043)	(0.044)	(0.046)
Chain-linked Δ Log HP (other counties)		0.074**	0.081***		0.110***	0.117***
		(0.030)	(0.030)		(0.037)	(0.037)
Panel B: First Stage						
F-stat				20.757	14.378	13.437
Observations	910	910	910	910	910	910
County controls	no	no	yes	no	no	yes

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the percentage change in the county price index between 2007 and 2009. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2009, where the weights are defined as $\omega_{c,k}$ in the main text. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with WLRI. I instrument county exposure to house price shocks through the network of retailer chains with county exposure to WLRI through the network of retailer chains. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Robustness Checks: Alternative market definitions: three digit Zip Code level

In my baseline specification, I choose the county as the relevant market. In this section, I check the robustness of my results to a different market definition. In particular, I define markets as a three digit zip code.

Robustness Checks: Region fixed effects

I explore the sensitivity of results to different combinations of region fixed effects. Throughout specifications, the main coefficient remains positive and significant. Note that once I include state fixed effects, the instrument becomes weak as reflected in the first stage F-statistic; so the coefficients in column (4) should be interpreted with caution.

Table A.8: Robustness Check: Region fixed effects

	County's Δ Log Price Index			
	(1)	(2)	(3)	(4)
County's Δ Log HP	0.065*	0.073*	0.091***	0.203***
	(0.036)	(0.038)	(0.045)	(0.078)
Chain-linked Δ Log HP (other counties)	0.112***	0.124***	0.115***	0.083***
	(0.037)	(0.034)	(0.037)	(0.031)
County controls	yes	yes	yes	yes
4-Regions FE	no	yes	-	-
9-Divisions FE	no	no	yes	-
State FE	no	no	no	yes
First Stage F-stat	20.746	19.026	13.718	4.782
Observations	922	922	922	922
R-squared	0.062	0.059	0.020	0.043

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k\neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors clustered at the state level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Clientele Effects

It is possible that common regional shocks bear different effects on different type of stores, even within a county. For example, a store of a retail chain that caters to richer consumers might be affected differently compared to a store of a retail chain that caters to poorer consumers. To account for this, I construct a variable at the retail chain level that captures whether the retail chain is mostly present in rich counties or in poor counties, based on county-level median household income.

I define the indicator variable, Clientele, that takes value one if the retail chain is above the median, and 0 otherwise. And then run the main specification at the county-by-store level, but now including County by Clientele fixed effects. Thus, I compare stores within a county, catering to similar demographic groups.

Results are presented in Table A.9. The main conclusions remain unchanged.

Table A.9: Robustness Check: Clientele effects at the retail chain by county-level

	Dep Variable: Chain's Δ Log Price in county c			
	OLS		IV: WLRI instrument	
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
Store $\Delta \log HP(others)_{rc}$	0.094***	0.079***	0.183***	0.191***
	(0.032)	(0.033)	(0.037)	(0.061)
Panel B: First Stage				
F-statistic			19.932	16.221
Retail chain controls	yes	yes	yes	yes
County FE	yes	-	yes	-
County-Clientele FE	no	yes	no	yes
Observations	3,747	3,747	3,747	3,747
R-squared	0.612	0.738	0.497	0.568
# retailers	84	84	84	84
# counties	910	910	910	910

Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Robustness check: Excluding California

I check the robustness of my results to excluding the largest state in the sample, California.

Table A.10: Robustness Check: excluding CA

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.047***	0.029**	0.019	0.126***	0.072*	0.078
	(0.014)	(0.013)	(0.014)	(0.034)	(0.041)	(0.050)
Chain-linked Δ Log HP (other counties)		0.077**	0.079***		0.165***	0.174***
		(0.030)	(0.029)		(0.038)	(0.037)
Panel B: First Stage						
F-stat				20.527	16.695	11.933
Observations	881	881	881	881	881	881
County controls	no	no	yes	no	no	yes

This table repeats Table 1.1, but excluding Caliornia (the largest state) from the analysis. Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Robustness check: Trade Flows

Alternatively, I construct a variable that accounts for the trade flows between county c and county k:

$$\text{trade-weighted}\Delta\log(HP)_c^{others} = \sum_{k\neq c}\gamma_{ck}^{trade}\Delta\log(HP)_k^{07-11},$$

where

$$\gamma_{ck}^{trade} = \frac{tradeflow_{ck}}{\sum_k tradeflow_{ck}}$$

where $trade_{ck}$ is the trade flow (exports and imports) between the state where county c is located and the state in which county k is located.[5] Intuitively, the more county c and county k trade with each other and the bigger county k is, the more a shock in county k will affect county c.

I add this term to my main Equation 1.5, estimate it and obtain the following results for the coefficients of interest:

Inference with correlated errors in shift-share design

In a recent paper, Adao et al. (2019) shows that in shift-share designs, regression residuals can be correlated across regions with similar shares, independent of their geographic location. This implies that even though I cluster at the state-level in my main analysis, there could still be remaining issues with the standard errors.

In this section, I follow Adao et al. (2019) methodology to take this into account. In particular, their methodology provides inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. I present results in table A.11.

[5] This data was obtained from Bureau of Transportation Statistics, Office of Secretary And Federal Highway Administration U.S. Department of Transportation combining data from the 2012 Commodity Flow Survey(CFS) and other trade data from the Census Bureau.

Table A.11: Adao et al. (2019) Robust Standard Errors

	Dep Variable: County's Δ Log Price Index			
	OLS		IV: WLRI instrument	
	(2)	(3)	(5)	(6)
Panel A: Second Stage				
Chain-linked Δ Log HP (other counties)	0.088***	0.089***	0.129***	0.135***
	(0.036)	(0.037)	(0.054)	(0.059)
Panel B: First Stage				
F-stat			16.642	12.756
Observations	910	910	910	910
County controls	no	yes	no	yes
Demeaned by $\Delta LogHP_c$	yes	yes	yes	yes

This table repeats Columns (1), (2), (3) and (4) of Table 1.1 using shift-share robust standard errors proposed by Adao et al. (2019) to conduct valid inference under arbitrary cross-regional correlation in the residuals. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Extensive Margin Adjustments

In the main analysis, we have focused on the propagation of shocks to prices of continuing varieties. However, retail chains might also adjust their extensive margin in response to shocks. For instance, they might close stores or discontinue products.

In this section of the appendix, I explore this possibility. In my previous analysis, I showed that county level prices are sensitive to shocks in distant regions linked by the retail chains' network. This can imply changes in average markups of the county, leading to entry or exit of stores. For example, a county exposed to negative shocks in other county will experience a drop in its retail prices. This, in turn, will make competition tougher in the county. Therefore, we may observe more exit of stores due to tougher competition in counties that were linked to counties more affected by the house price drops.

In order to study the effect on the extensive margin at the county level, I begin by running my main specification with counties' percentage changes in number of stores, barcodes and varieties as dependent variable. I present results in Table A.12. Although significant only at 10%, there is some suggestive evidence of exit of stores and barcodes in counties served by retail chains more exposed to drops in house prices in other counties.

Table A.12: Retailer chain's extensive margin responses

VARIABLES	(1) $\Delta Stores$	(2) $\Delta Stores$	(3) $\Delta Products$	(4) $\Delta Products$	(5) $\Delta Varieties$	(6) $\Delta Varieties$
County's Δ Log HP	0.024	-0.095	0.271	0.135	0.093	-0.122
	(0.151)	(0.187)	(0.175)	(0.230)	(0.246)	(0.296)
Chain-linked Δ Log HP (others)		0.316*		0.361		0.570*
		(0.179)		(0.297)		(0.317)
Observations	910	910	910	910	910	910
R-squared	0.001	0.030	0.006	0.003	0.004	0.026
County controls	yes	yes	yes	yes	yes	yes
First Stage F-stat	13.358	13.862	13.358	13.862	13.358	13.862

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k\neq c}\omega_{c,k}\Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

Previous table shows how the Great Recession and the geographic distribution of retailer chain's stores affected the varieties available for consumers. Given that consumers have a taste for variety, an increase in the range of available varieties should lead to a decrease in the price index. Translating the increase in product variety into welfare gains requires structural assumptions. Following Feenstra (1994) and Broda and Weinstein (2006) I assume a CES utility function to infer the infra-marginal consumer surplus created or destroyed by changes in product variety from the observed spending shares on new and exiting products. I also decompose entry and exit of barcode-stores into two terms:[6] In particular, I decompose the Feenstra Ratio into two margins of adjustments:

1. Store-level Feenstra Ratio: captures consumer surplus by changes in stores available.
2. Barcode-level Feenstra Ratio: captures consumer surplus created by entry or exit of barcodes in existing stores.

I then construct an exact CES price index that considers entry and exit of new varieties:

$$\left[\Pi_{bs\in I_{mc}}\left(\frac{P_{bsmct}}{P_{bsmt-1}}\right)^{w_{bsmct}}\right]\left[\Pi_{s\in I_{mc}}\left(\frac{\lambda_{smct}}{\lambda_{smct-1}}\right)^{\frac{w_{smct}}{\sigma_s-1}}\right]\left(\frac{\lambda_{mct}}{\lambda_{mct-1}}\right)^{\frac{1}{\sigma_m-1}}$$

The first multiplicative term in brackets is the the CES price index for continuing products between t and $t-1$, as described in the body of the paper. We refer to the second term

[6] To do so, I assume that consumers first choose the store in which they will shop and then choose the barcodes.

as the barcode-level Feesntra Ratio. The higher the expenditure share of new varieties within a product module and store, the lower λ_{smct}, implying a lower adjusted inflation rate. Intuitively, conditional on the number of stores, the adjusted inflation rate is going to be lower if consumers spend more in new varieties. The third term is the store-level Feenstra Ratio. The higher the expenditure in new stores, the lower λ_{mct}, implying a lower adjusted inflation rate. The price index also depends on the module-specific elasticity of substitution σ_m between stores and module-store specific elasticity of substitution σ_s between barcodes in a product-module-store. As these elasticities grow, the additional terms converge to one and the bias in the price index goes to zero. The intuition is that when existing varieties are close substitutes to new or disappearing varieties, price changes in the set of existing products perfectly reflect price changes for exiting and new varieties.

Now, I estimate my main specification with each of the terms above as dependent variable. Table A.13 report the results. Columnn (1) report results for the price index for continuing varities, as in the main analysis of the paper. Column (2), reports the effect of retailer chains networks on changes in product variety within existing stores. Column (3) report results for the effect on changes in available stores. Finally, column (4) provides the exact price index combining the three terms. We do not observe any effect of the network of retail chains on entry and exit of stores and barcodes. However, in column (4), we observe that the main conclusions of the paper remain when we adjust the price index to account for entry and exit of varieties.

Table A.13: County level Price Index adjusted for entry and exit of varieties

	Δ Log Price Index (continuers)	Feenstra Ratio (barcodes)	Feenstra Ratio (stores)	Δ Log Price Index (adjusted)
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.069*	-0.034	0.035	0.071
	(0.040)	(0.025)	(0.034)	(0.067)
Chain-linked Δ Log HP (other counties)	0.119***	0.034	-0.008	0.147**
	(0.039)	(0.034)	(0.033)	(0.071)
Observations	922	922	922	922
County controls	yes	yes	yes	yes
First Stage F-stat	14.479	14.479	14.479	14.479

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the Nielsen data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k\neq c}\omega_{c,k}\Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from Nielsen Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008b), Housing supply elasticity is obtained from Saiz (2010).

A.5 Model

National costs and error term

In this section, I discuss the the implication for identification in the model, when costs are at the retail level.

$$dlogP_{ct} = \beta^H \left[\sum_{r\in\Omega_c}\theta_{rc}S_{rc}\right] dlogHP_c + \beta^H \sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\theta_{rk}dlogHP_k + \sum_{r\in\Omega_c} l_{rc}dlogC_r \tag{A.1}$$

As the cost of retail chain is not observed, it lies in the error term. Hence, the exogeneity assumption to identify β^H is given by,

$$E\Big[\sum_{r\in\Omega_c} l_{rc}dlogC_r \Big| \Big(\sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\theta_{rk}dlogHP_k\Big)\Big] = 0 \tag{A.2}$$

This simply reflects that, conditional on own house price changes, the evolution of the marginal cost in county c cannot be correlated with the weighted average of the change in house prices in other counties k. For exposition, define $\Delta C_r = \sum_c \lambda_{rc}\Delta A_c$ as a weighted average of unit costs (A_c) across counties in the U.S; where λ_{rc} are the share of costs of retail r that comes from county c (e.g.: wholesale products that buys in c). The threat is common shocks to costs to regions in which the retail chain operates that also correlate with house price changes. Then there are a couple of intuitive *Sufficient conditions* to satisfy Condition A.2.

1. If $Cov(\Delta A_k, \Delta log(HP)_k) = 0$, then Condition A.2 is satisfied. *However, house price shocks could be correlated with productivity shocks in the county.*

2. If $Cov(\lambda_{rc}, \theta_{rc}) = 0$, then Condition A.2 is satisfied. Stroebel and Vavra (2019) present a range of evidence suggesting that the location where retail sell their products (θ_{rk}) differ from the locations where the retail buy their products from wholesales. In line with this, Hyun and Kim (2019), show that most of sales of manufacturing firms come from markets that are not where they have their plants.

In case sufficient conditions (1) and (2) do not hold, I rely on the housing supply elasticity instrument. The assumption then becomes:

$$E\Big[\sum_{r\in\Omega_c} l_{rc} dlogC_r \Big| \Big(\sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\theta_{rk} WLRI_k\Big)\Big] = 0 \tag{A.3}$$

Note that now a sufficient condition for A.3 to hold is that: $Cov(\Delta A_k, WLRI_k) = 0$. This assumption mimics the identification assumption of papers that analyzed the local effect of the house price slump (e.g: Mian and Sufi (2011), Stroebel and Vavra (2019)). Hence, given that this condition is sufficient (but not necessary), my empirical design relies on milder assumptions.

Alternative assumptions for costs: local costs

In the main analysis, I solved the model for the case in which the retail chain has national costs $c_{rc} = c_r$. Here, I explore the case in which retail chain has local costs in each market (c_{rc}).

Solving the optimization problem, we get the optimal price in the situation where the retail chains' costs are local:

$$P_{rc} = \bar{p}_r = \frac{\sum_k \mu_k c_{rk}(\sigma_k - 1)S_{rk}}{\sum_k S_{rk}(\sigma_k - 1)} \tag{A.4}$$

where $\mu_k = \frac{\sigma_k}{\sigma_k - 1}$ is the markup in market k. From equation A.4 it is clear that the price under uniform pricing is a weighted average of the conditions (costs and markups) in the different markets that a retail chain serve.

Following the steps in the main section to aggregate the price index and total differentiate the aggregate price index to observe the sources of variation, we get:

$$dlogP_{ct}^{U} = -\left[\sum_{r\in\Omega_c} l_{rc}\tilde{\theta}_{rc}\psi_{rc}\right] dlog\sigma_c - \sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\tilde{\theta}_{rk}\psi_{rk} dlog\sigma_k + \sum_{k\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rk}\sigma_k c_{rk}}{\sum_k \sigma_k S_{rk} c_{rk}} dlogc_{rk} \tag{A.5}$$

where I define θ as in the main analysis

$$\tilde{\theta}_{rk} = \frac{S_{rk}\sigma_k}{\left[\sum_{k\in\Omega_r} S_{rk}\sigma_k c_{rk}\right]\left[\sum_{k\in\Omega_r} S_{rk}(\sigma_k - 1)\right]},$$

and,

$$\psi_{rc} = c_{rc}\sum_k S_{rk}\left(\sigma_k \frac{c_{rc} - c_{rk}}{c_{rc}} - 1\right)$$

Compared with the case of national costs in the main analysis, now the weights also adjust for initial differences in costs across markets (ψ_{rk}). In addition, local shocks can affect the cost term of the equation.

In the next section, I explore how propagation of cost shocks would look like.

Propagation of local cost shocks

In order to be consistent with previous papers that emphasize the demand channel of the house price shock, in the main analysis I assumed that the the house price shock affected the elasticity of demand. However, to study propagation of shocks through the network of retail chains, one could be agnostic about whether the shock is demand-driven or cost-driven.

In this section, I discuss theoretically the propagation of local shocks through the network of retail chains. Assume that σ_k is constant and the shocks are to the local costs of the firm. That is $\beta^{H-Costs} = \frac{\partial logc_{rc}}{\partial logHP_c}$. Then, Equation A.6 becomes:

$$dlogP_{ct}^{U} = \beta^{H-Costs}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rc}\sigma_c c_{rc}}{\sum_k \sigma_k S_{rk} c_{rk}} dlogc_{rc} + \beta^{H-Costs}\sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rk}\sigma_k c_{rk}}{\sum_k \sigma_k S_{rk} c_{rk}} dlogc_{rk} \tag{A.6}$$

The last term corresponds to the propagation of local shocks through the network of retail chains. Note that the importance of a market is also increasing on S_{rk}. This makes more meaningful the weights ω_{ck} in the reduced form that can be used to proxy weights for both cost shocks and demand shocks.

Quantitative analysis

Table A.14: σ by quartile of population (From Hottman, 2014)

City Size Dist:	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
σ_c	3.9	3.9	4.5	4.8

Table A.15: Propagation of local shocks through the network of retails chains (weights adjusted by σ)

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.056***	0.050***	0.050***	0.125***	0.093**	0.096**
	(0.014)	(0.013)	(0.015)	(0.027)	(0.034)	(0.037)
Chain-linked Δ Log HP (other counties)		0.049***	0.048***		0.116**	0.126**
($\sigma_{adjusted}$)		(0.017)	(0.017)		(0.050)	(0.054)
Panel B: First Stage						
F-stat				21.358	11.660	10.810
Observations	910	910	910	910	910	910
County controls	no	no	yes	no	no	yes

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k\neq c} \theta_{ck} \Delta log(HP_k)$) as defined in Equation 1.14. Columns (1) to (3) report results for OLS estimations. County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments and changes in log employment. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k\neq c} \theta_{ck} \Delta log(HP_k)$) in other counties with network-weighted WLRI in other counties ($\sum_{k\neq c} \omega_{ck} WLRI_k$).Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

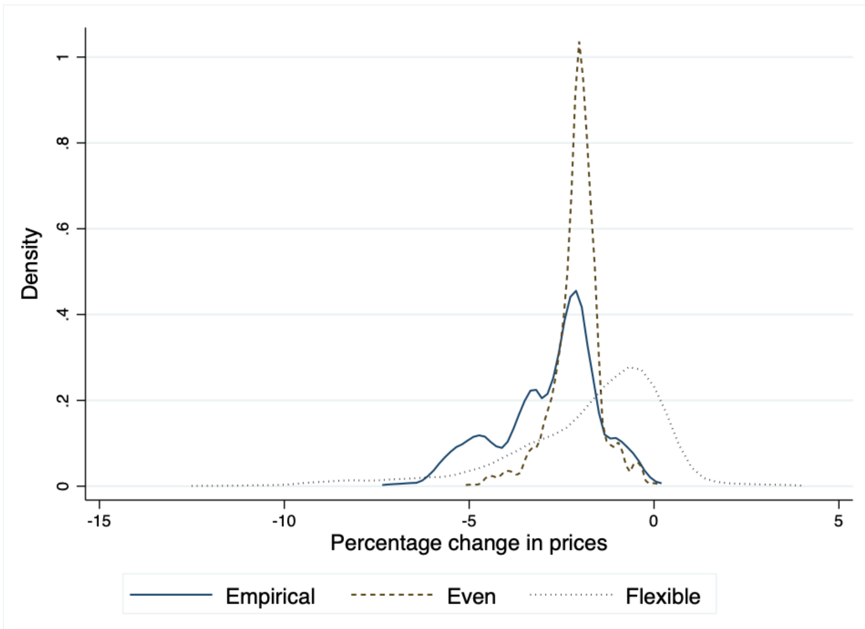
A.6 Counterfactuals

Cross-county dispersion in inflation rate: Alternative scenarios

Figure A.6 plots the distribution of house price changes under three alternative scenarios. Uniform pricing and empirical distribution of sales (benchmark), Uniform pricing and even distribution of sales, and flexible pricing. We can observe that the dispersion is much smaller under uniform pricing.

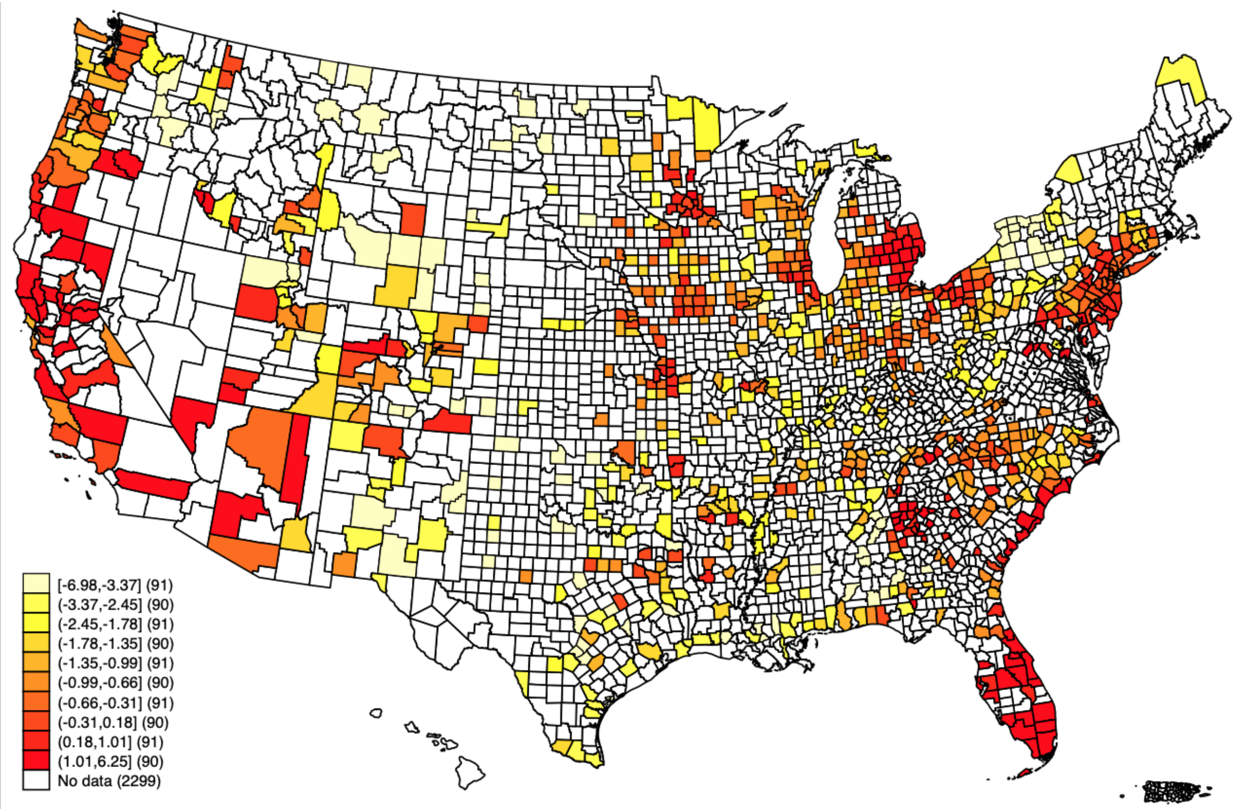
Figure A.4: Cross-county dispersion in inflation rate: Alternative scenarios

Figure A.5: Densities



Distributive effects of uniform pricing

Figure A.6: Regional Redistribution of shocks: $\Delta\log(P_c^U) - \Delta\log(P_c^{flex})$



Note: Heat map for the difference between inflation rate under uniform pricing and inflation rate under flexible pricing for each county ($\Delta\log(P_c^U) - \Delta\log(P_c^{flex})$). The numbers are in %. The map is divided into deciles of $\Delta\log(P_c^U) - \Delta\log(P_c^{flex})$. Red indicates high values for this difference. That is, counties that were negatively affected by uniform pricing since their prices decrease less than under a counterfactual of flexible pricing.

A positive shock of 20% to Los Angeles' house prices

In this section, I will be simulating a positive house price shock of 20% in Los Angeles, California. I evaluate how the pricing strategies and the geographic distribution of the stores has implications on the effect of the shock. I choose Los Angeles because it is the county whose shocks have on average the biggest effect on other counties, and at the same time is in the top 20% richest counties in the United States.

Table A.16 shows the results for the different pricing strategies. For this shock, I calculate the welfare implications measured as price changes under different price settings: uniform pricing and flexible prices. In particular, I decompose the aggregate effect on U.S. inflation in two different ways. First, In Panel A, I decompose the aggregate inflation into geographic categories: changes in local prices, changes in prices of counties in the same state and changes in prices out of state. Second, in Panel B, I decompose the aggregate inflation into income quintiles. Each county's inflation is weighted by the population of the county, so number represent the contribution of counties in that group to aggregate inflation.

Lets focus first in Panel A of Table A.16. While the weighted average inflation rate is similar under uniform and flexible prices, the existence of uniform prices creates redistribution from the county affected by the shock to counties connected by the network of retail chains. In particular, under uniform pricing Los Angeles *export* half of the inflation rate to other counties. An increase of 20% in Los Angeles' house prices implies an increase of 0.14% average inflation rate in the U.S under uniform pricing. 0.07% of that inflation rate is explained by price changes in L.A, 0.05% is explained by propagation to counties outside California and 0.02% is explained by propagation to other counties within California.

When collapsed to five per capita expenditure quintiles on panel B of Table A.16, I find that the richer the counties are, the bigger average effect relative to poorer counties. Two effects might play a role here. On the one had, richer counties are more connected than poor counties, so they are more likely affected by a shock somewhere else. On the other hand, retailers in richer counties depend less on other counties to set up their prices given that the sales on their own county are highly relevant. The former effect might be dominating. Moreover, the fact that the effect in weighted by population, and riches counties tend to have higher population density, contributes to getting a higher average effect for richest quintiles.

In Table A.17, I report results for alternative distributions of the stores of the retail chains. The first column is the effect on national inflation rate under the current distribution of retail chains. Column (2) analyzes an increase in retail chains' geographic dispersion of sales. The effect of the shock becomes smaller at the national level. Intuitively, relative to the current distribution, retail chains become smaller in big counties; while relatively larger in small counties. As S_{rk} are equal, retail chains in L.A. export the inflation rate in equal proportions to every county. Hence,the population weighted average inflation rate for the U.S. declines considerably. In the third column, we increase competition within a county by letting all retail chains in the county have equal shares. The national effect of the shock is slightly smaller. This evidences that the key for the propagation of shocks is the importance of each county for the retail chain. The forth column contains both equal distribution in counties and equal importance of counties for a chain. This situation is closely to full integration and implies that the effect of a shock in L.A would impact 60% less the average inflation rate in the U.S. Finally, the last column the case of a monopoly in each of the counties. For each county, I pick the retail chain with the highest sales in the county and assign $l_{rc} = 1$ to it and zero to other retail chains in the county. The effect average national effect increases. A potential explanation for this is that when the biggest retailers in the country behave as monopolists in their counties, the propagation of the shocks increases the most. The prices are controlled by a few chains that are most likely present in Los Angeles and a lot of other counties around the United States.

Table A.16: 20% shock in Los Angeles under alternative pricing rules

Panel A: Effect by Geographic Location		
Welfare \ Price Choice	Uniform	Flexible
Δ in Prices(average)	0.1440%	0.1368%
Δ in Local Prices	0.0732%	0.1368%
Δ Prices in-state	0.0215%	0.0000%
Δ Prices out-of-state	0.0494%	0.0000%
Panel B: Effect by Income Quintile		
Welfare \ Price Choice	Uniform	Flexible
Δ in Prices(average)	0.1440%	0.1368%
Δ in Local Prices	0.0732%	0.1368%
Δ in Poorest Quintile	0.0023%	0.0000%
Δ in Second Poorest Quintile	0.0035%	0.0000%
Δ in Middle Quintile	0.0090%	0.0000%
Δ in Second Richest Quintile	0.0246%	0.0000%
Δ in Richest Quintile	0.0315%	0.0000%

Note: Effects in each county are weighted by population. As Los Angeles is on the richest quintile, we subtract the local average effect from the effect on the richest quintile.

Table A.17: 20% shock in Los Angeles under alternative distributions

Welfare \ Distribution	**Current**	**Competition: Even Distribution**			**Monopoly**
		$S_{rk} = 1/\#c$	$L_{rk} = 1/\#r$	Both	$L_{rk} = 1$
Δ in Prices(average)	0.144%	0.027%	0.122%	0.063%	0.154%
Δ in Local Prices	0.073%	0.019%	0.085%	0.049%	0.119%
Δ Prices in-state	0.021%	0.004%	0.021%	0.011%	0.014%
Δ Prices out-of-state	0.049%	0.004%	0.015%	0.004%	0.209%

Appendix B

Appendix: Multi-destination Exporters, Market Power and the Elasticity of Markups across Destinations

B.1 Appendix: Data construction

Market Share

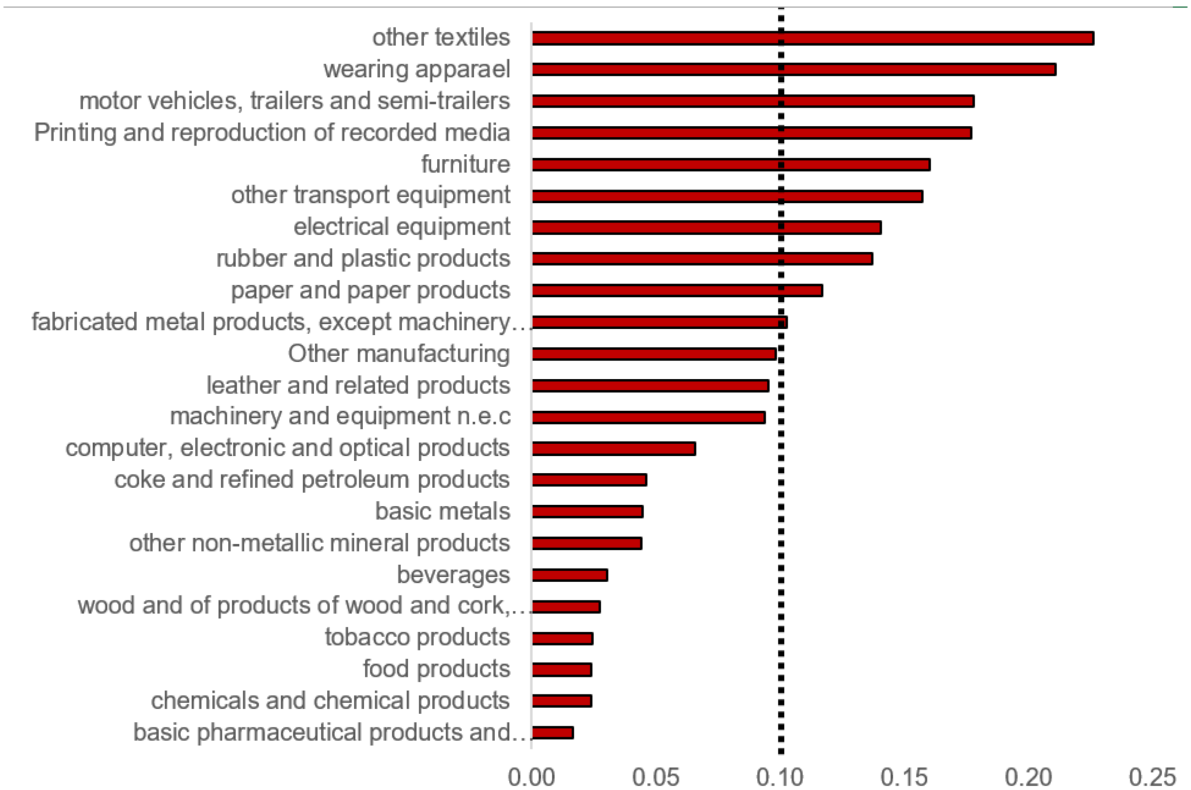
Distribution of Market share variable S_{iskt}

Table B.1: Market Share distribution. Year 2006

percentile	S_{iskt}
p10	0.004
p25	0.038
p50	0.299
p75	2.043
p99	9.633
Average	4.163

NAILs by sector

Figure B.1: Average firm's share of imports corresponding to affected inputs (2011), by sector CLAE 2 digits



Appendix C

Appendix: Importing after Exporting

C.1 Descriptive statistics

Variability in type of export-market relation

We classify firm-market exports into 4 categories: Continuers, Exiters, Entrants and Re-entrants. Continuers are firms that export to a market in t and t-1. Exiters are firms that export to a market in $t-1$, but not in t. Entrants are firms that export to a market in t, but were not exporting to that market in $t-1$ and in any previous year. Finally, there is a considerable number of re-entrants: firms that exported to a market at $t-2$ or before, did not export in $t-1$ and export again in t. We summarize the number of firm-market combinations for each of this categories in Table C.1. We can observe that around 25% of export entries into a market are explained by re-entrants.

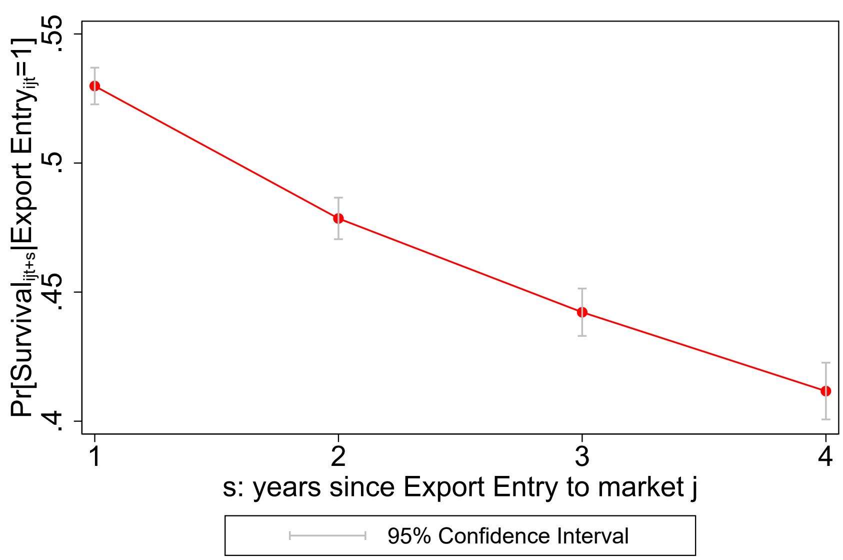
Table C.1: Descriptive: Exporters

Year	*Exporters*	*Continuers*	*Exiters*	*Entrants*	*Reentrants*
2002	10441	0	0	0	0
2003	12137	8318	2123	3819	0
2004	13068	9643	2494	3425	0
2005	14763	10745	2323	3567	451
2006	14806	11365	3398	2752	689
2007	15123	11680	3126	2384	1059
2008	15797	11724	3399	2963	1110
2009	14420	11512	4285	1765	1143

Exporter count the number of active markets for the firms in year t. Continuers are firm-markets for which the firms exported in $t-1$ and also export in t. Exiters are firm-markets that exported in $t-1$, but not in t. Entrants are the number of markets for which the firms never exported and export in t. Re-entrants the are the number of markets for which the firms did not export in $t-1$, but exported before that and re entry at t.

Survival profile after reaching a new destination

Figure C.1: Survival profile after export entry into j



Descriptive: variability in type of importer

Similarly, we summarize information by type of importer.

Table C.2: Descriptive: Importers

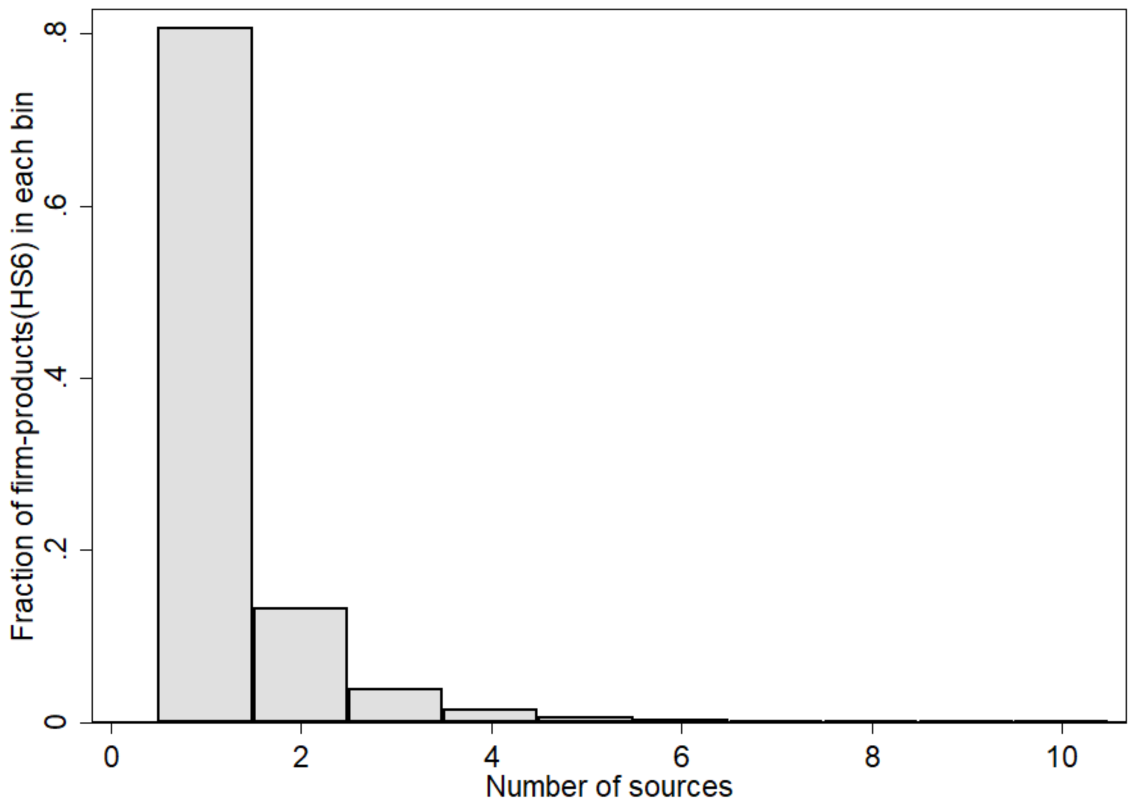
Year	*Importers*	*Continuers*	*Exiters*	*Entrants*
2002	9365	0	0	0
2003	12352	7188	2177	5164
2004	13930	9165	3187	4765
2005	15255	10202	3728	5053
2006	16166	11096	4159	5070
2007	16372	11666	4500	4706
2008	16999	12116	4256	4883

Importers count the number of active markets for the firms in year t. Continuers are firm-markets for which the firms imported in $t-1$ and also import in t. Exiters are firm-markets that imported in $t-1$, but not in t. Entrants are the number of markets from which the firms never imported and start to import in t.

C.2 Theoretical Framework Appendix

Most of the firms import a given product (hs6 digits) from only one source

Figure C.2: Most of the firms import a given product from only one source



Do firms internalize the effect of exporting on importing?

The main prediction of a model in which we let firms anticipate the effect is that the cutoff to start exporting to a market would be lower. Given that exporting has indirect gains through possible import costs savings in the future, firms might find profitable to enter to a market with lower revenues.

To test this, we compare export values when a firm start to export to a market for two types of firms. By comparing these two types of firms, we assess whether firms internalize the effect of exports on the probability of importing. The first group are firms that start exporting to a market from where they haven't imported. The second group are firms that start exporting to a market where they already import. Intuitively, for the first group start exporting to market j increases the probability of importing from there in the future. In contrast, the second group has no indirect gains from exporting. Therefore, if firms anticipate that exporting might lead to importing, we expect the amount of exports to market j at the moment of entry to be lower for the first group. Results are reported in Table C.3. We demeaned the variables by market-year-industry and include different combinations of fixed effects in order to compare amount of exports to market j at the moment of entry: a) across firms with similar characteristics (column 1); b) within a firm, across markets and years (column 2); and c) within a firm-year, across markets (column 3). Throughout the specifications, we find no conclusive evidence of firms changing their export decisions in order to internalize the effect on the probability of importing in the future.

Table C.3: Does firms anticipate the effect of exporting on importing?

	(1)	(2)	(3)
	$log(Exports)_{ijt-1}$		
$Imported\ Before_{ijt-1}$	-0.081	-0.093	-0.068
	(0.056)	(0.067)	(0.111)
Observations	16,894	13,900	5,582
R-squared	0.265	0.629	0.761
Firm FE	no	yes	yes
Firm-Year FE	no	no	yes
Market-Year-Sector FE	yes	yes	yes
Controls	yes	yes	yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Proofs

Proof: proposition 1.1.A. Assume a fixed costs draw $\kappa = \{\kappa_d, \kappa_1, ..., \kappa_{j^*}, ..., \kappa_m\}$ such that the firm optimal sourcing strategy (Ω_{-j^*}) does not include market j^*. Also assume that the optimal export strategy does not include j^* ($\Omega^X_{-j^*}$).
By definition, we know that the optimal sourcing strategy (Ω_{-j^*}) yields higher benefits than Ω_{j^*} for any strategy that contains j^* as a sourcing market. This implies:

$$\frac{R(\Omega_{-j^*}, \varphi, \Omega^{X_*}_{-j^*})}{\sigma} \left\{ \left[\frac{c(\Omega_{-j^*})}{c(\Omega_{j^*})} \right]^{\sigma-1} - 1 \right\} < \sum_{(j,k)\in\Omega_{j^*}} \kappa_{jk} g(h_{ij}) - \sum_{(j,k)\in\Omega_{-j^*}} \kappa_{jk} g(h_{ij})$$

Now assume a shock to μ_{ij} that induces export entry to j. If $g'(h_{ij^*}) < 0$, then the right-hand side becomes smaller for every sourcing strategy Ω that includes j^*. Therefore, it is now more likely that the firm chooses a sourcing strategy that includes source j^*. □

Proof: proposition 1.1.B. Assume a fixed costs draw $\kappa = \{\kappa_d, \kappa_1, ..., \kappa_{j^*}, ..., \kappa_m\}$ such that the firm optimal sourcing strategy (Ω_{-j^*}) does not include market j^*. Also assume that the optimal export strategy does not include j^* $(\Omega^X_{-j^*})$.

Now assume export entry into j; such that fixed costs of the firm are now given by $\hat{F} = \{\kappa_d, \kappa_1, ..., \kappa_j, g(h_{ij^*} + \Delta h_{ij^*})\kappa_{j^*}, ..., g(h_{im}\kappa_m\}$. Given $g'(.) < 0$, fixed costs of importing from j^* are now lower, while fixed costs of importing from other markets remain unchanged. Now consider a different optimal sourcing strategy that still does not include j^*: Ω'_{-j^*}. This implies that for old fixed costs we have:

$$\frac{R(\Omega'_{-j^*}, \varphi, \Omega^{X*})}{\sigma}\left\{\left[\frac{c(\Omega'_{-j^*})}{c(\Omega_{-j^*})}\right]^{\sigma-1} - 1\right\} \leq \sum_{(j,k)\in\Omega'_{-j}} g(h_{ij})\kappa_{jk} - \sum_{(j,k)\in\Omega_{-j^*}} g(h_{ij})\kappa_{jk},$$

and for new fixed costs we have,

$$\frac{R(\Omega'_{-j^*}, \varphi, \Omega^{X*})}{\sigma}\left\{\left[\frac{c(\Omega'_{-j^*})}{c(\Omega_{-j^*})}\right]^{\sigma-1} - 1\right\} \geq \sum_{(j,k)\in\Omega'_{-j}} g(h_{ij})\kappa_{jk} - \sum_{(j,k)\in\Omega_{-j^*}} g(h_{ij})\kappa_{jk}.$$

Since $j^* \notin \Omega_{-j^*}$ and $j^* \notin \Omega'_{-j^*}$, and since there is a unique profit maximizing strategy, the two inequalities above holds only if $\Omega_{-j^*} = \Omega'_{-j^*}$. Then, if the firm does not import from j^* after export entry, it does not change its sourcing strategy at all. □

Proof: Proposition 1.2.A. Assume two different draws of productivity $\varphi\prime > \varphi$. Consider two sourcing strategies Ω and $\hat{\Omega}$. Assume that Ω is optimal for a firm with productivity φ. Then, the extensive margin condition (3.5) implies:

$$\varphi_i^{(\sigma-1)} B_i(\Omega^{X*})\left\{\left[\frac{c(\Omega)}{c(\hat{\Omega})}\right]^{\sigma-1} - 1\right\} < \sum_{(j,k)\in\hat{\Omega}} g(h_{ij})\kappa_{jk} - \sum_{(j,k)\in\Omega} g(h_{ij})\kappa_{jk}$$

Now Consider a shock that increases the productivity from φ to $\varphi\prime$. In order to prove the proposition, we will proceed in two steps. First, we will show that the cost function is decreasing in productivity. Second, we will show that productivity directly increase the LHS of equation above.

Step 1: Assume that $c(\hat{\Omega}) > c(\Omega)$. From equation above, we can see that, all else equal, the LHS becomes decreasing in productivity, since $\left\{\left[\frac{c(\Omega)}{c(\hat{\Omega})}\right]^{\sigma-1} - 1\right\} < 0$. Therefore, if a sourcing strategy $\hat{\Omega}$ has higher marginal costs and is not optimal for φ, then it is not optimal for higher productivity $\varphi\prime$ either.

Step 2: it is straight-forward to see that there is a direct positive effect on the LHS from higher productivity.

Step 3: Therefore, higher productivity implies higher LHS directly and even higher LHS through changes in the sourcing strategy towards a lower cost function. Hence, higher productivity can induce the firm to select a new sourcing strategy $\hat{\Omega}$, increasing the probability of observing new imports from any different markets.

Note that it is straight-forward to show that the response of a firm to a any scale shock ($B_i(.)$) is qualitatively equivalent to the response of a firm to a productivity shock. □

Proof: proposition 2.A. Consider a firm with productivity φ and a vector of fixed costs $\kappa = \left\{\kappa_d, g(h_{ij'})\kappa_{j'}, ..., g(h_{im})\kappa_m\right\}$ that optimally chooses sourcing strategy Ω. It can be shown that firm's optimal output is given by: $y = c(\Omega)^{-\sigma}\varphi^{\sigma}B_i(\Omega^X)\frac{\sigma-1}{\sigma}$. Plugging y into intensive margin equation (3.3), the total amount of imports from market j' is then given by:

$$\sum_{j'k\in\Omega} p_{j'k}z_{j'k} = \frac{\varphi^{\sigma-1}}{c(\Omega)^{\sigma-\theta}}\sum_{j'k\in\Omega}\left(\frac{\eta_{j'k}}{p_{j'k}}\right)^{\theta-1} B_i(\Omega^X)\frac{\sigma-1}{\sigma}$$

.

Now assume export entry to j such that $\hat{F_i^M} = \{\kappa_d, g(h_{ij} + \Delta h_{ij})\hat{\kappa_j}, ..., g(h_{im})\kappa_m\}$. Note that $g'(h_{ij}) < 0 \Rightarrow g(h_{ij} + \Delta h_{ij})\kappa_j < g(h_{ij})\kappa_j$. Assume that the fixed costs of importing from other markets remain unchanged.

> It is straight-forward to show that, holding constant productivity, scale and the sourcing strategy (Ω), the equation above remains unchanged with the new configuration of fixed costs. Therefore, if export entry is associated with fixed costs savings, the amounts of imports of active sources should be unaffected if the firm does not start importing from market j after export entry to j.

□

Proof: proposition 2.B. Consider a firm with productivity φ and a vector of fixed costs $\kappa = \left\{\kappa_d, g(h_{ij'})\kappa_{j'}, ..., g(h_{im})\kappa_m\right\}$ that optimally chooses sourcing strategy Ω. It can be shown that firm's optimal output is given by: $y = c(\Omega)^{-\sigma}\varphi^{\sigma}B_i(\Omega^X)\frac{\sigma-1}{\sigma}$. Plugging y into intensive margin equation 3.3, the total amount of imports from market j' is then given by:

$$\sum_{j'k\in\Omega} p_{j'k}z_{j'k} = \frac{\varphi^{\sigma-1}}{c(\Omega)^{\sigma-\theta}}\sum_{j'k\in\Omega}\left(\frac{\eta_{j'k}}{p_{j'k}}\right)^{\theta-1} B_i(\Omega^X)\frac{\sigma-1}{\sigma}$$

.

Holding constant the sourcing strategy (Ω), provided $\sigma > 1$, it is straightforward to derive from equation above that:

$$\frac{\partial log\left(\sum_{j'k\in\Omega} p_{j'k}z_{j'k}\right)}{\partial log\varphi} = \sigma - 1 > 0, \qquad \forall (j', k) \in \Omega.$$

□

C.3 Appendix to Empirical Analysis 3.3

Main fact: Importing after exporting at the country level

In this section, we replicate the main estimation at the country level. We select the 30 main Argentinian partners according to aggregate level of exports and imports. These countries represent roughly 93% of total exports and imports in the manufacturing sector. Results are presented in Table C.4. We can observe that results are qualitatively similar. In our preferred specification, export entry to market j increases the probability of start sourcing from that market by 60% with respect to the unconditional probability.

Table C.4: Probability of importing from a new destination: 30 main partners

	$Pr[NewOrigin_{ij,t} = 1]$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ExportEntry_{ijt-1}$	0.005***	0.011***	0.011***	0.011***	0.011***	0.011***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$log(Exports)_{it}$				0.000***		0.000	
				(0.000)		(0.000)	
$log(Imports)_{it}$				0.002***		0.002***	
				(0.000)		(0.000)	
$log(labor)_{it}$					0.006***	0.003***	
					(0.001)	(0.001)	
Observations	1,932,017	1,932,017	1,932,017	1,932,017	1,932,017	1,932,017	1,932,017
R-squared	0.041	0.335	0.347	0.354	0.348	0.354	0.389
Mean dep variable	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Market FE	yes	yes	yes	yes	yes	yes	yes
Firm-Market FE	no	yes	yes	yes	yes	yes	yes
Market-Year FE	no	no	yes	yes	yes	yes	yes
Firm-Year FE	no	no	no	no	no	no	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively. Columns 5 and 6 have fewer observations because we do not have data on employment for 2008.

Other robustness checks

In table C.5 we check the robustness of our results to other proxies for productivity and to the inclusion of sector-market-year fixed effects. In column (1) and (2) we include the growth rate of total employment, total exports and total imports of the firm. In column (3), we add sector-market-year fixed effects to our preferred specification. This fixed effects also remove shocks specific to a sector-market in a given year such as a country demand increasing in a particular sector. We observe that results remain qualitatively unchanged. Furthermore, the coefficient remains remarkably stable throughout the specifications.

Table C.5: Robustness check: other proxies for productivity and sector-market trends

	$Pr[NewOrigin_{ij,t} = 1]$		
	(1)	(2)	(3)
$ExportEntry_{ijt-1}$	0.017***	0.015***	0.012***
	(0.002)	(0.002)	(0.003)
$log(labor)_{it}$		0.004***	
		(0.001)	
$log(Exports)_{it}$		-0.000**	
		(0.000)	
$log(Imports)_{it}$		0.008***	
		(0.000)	
$\Delta log(Exports)_{it}$	0.000***	0.000***	
	(0.000)	. (0.000)	
$\Delta log(Imports)_{it}$	0.003***	-0.001***	
	(0.000)	(0.000)	
$\Delta log(labor)_{it}$	0.001	-0.000	
	(0.001)	(0.001)	
Observations	582,503	582,503	582,503
R-squared	0.366	0.380	0.473
Firm FE	yes	yes	yes
Year FE	yes	yes	yes
Market FE	yes	yes	yes
Firm-Market FE	yes	yes	yes
Market-Year FE	yes	yes	yes
Market-Year-sector FE	no	no	yes
Firm-Year FE	no	no	yes
Mean dep variable	0.027	0.027	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively.

In table C.6 we check the robustness of our results once we condition to the sub-sample of firms that were already exporters in 2002 (to at least one destination). Again, the effect remains qualitatively unchanged.

Table C.6: Probability of importing from a new destination: sub-sample of already exporters in 2002

	$Pr[NewOrigin_{ij,t} = 1]$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ExportEntry_{ijt-1}$	0.005*	0.020***	0.018***	0.017***	0.018***	0.017***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
$log(Exports)_{it}$				0.001***		0.000***	
				(0.000)		(0.000)	
$log(Imports)_{it}$				0.006***		0.006***	
				(0.000)		(0.000)	
$log(labor)_{it}$					0.019***	0.011***	
					(0.002)	(0.002)	
Observations	145,693	141,953	141,953	141,953	141,953	141,953	141,406
R-squared	0.098	0.359	0.374	0.384	0.375	0.385	0.492
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Market FE	yes	yes	yes	yes	yes	yes	yes
Firm-Market FE	no	yes	yes	yes	yes	yes	yes
Market-Year FE	no	no	yes	yes	yes	yes	yes
Firm-Year FE	no	no	no	no	no	no	yes
Mean dep variable	0.0506	0.0506	0.0506	0.0506	0.0506	0.0506	0.0506

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively.

Testing simultaneous relation

We test whether export entry to market j in a given year is associated with new imports from that market in the same year. Results are reported in table C.7. We can observe that the estimated coefficient is about a third compared to our preferred specification in which we let the relation to manifest after one year. Furthermore, the significance of the effect vanishes in some of the specifications.

Table C.7: Probability of importing from a new market at the same time

	$Pr[NewOrigin_{ijt} = 1]$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Export Entry$_{ij,t}$	0.013***	0.010***	0.009***	0.006***	0.002	0.002	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(exports)				0.000**		0.000	
				(0.000)		(0.000)	
log(imports)				0.007***		0.006***	
				(0.000)		(0.000)	
log(labor)					0.013***	0.007***	
					(0.001)	(0.001)	
Mean dep variable	0.027	0.027	0.027	0.027	0.027	0.027	0.027
Observations	589,378	582,139	582,139	582,139	582,119	582,119	582,139
R-squared	0.074	0.342	0.357	0.380	0.409	0.424	0.469
Firm FE	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes
Market FE	yes	yes	yes	yes	yes	yes	yes
Firm-Market FE	no	yes	yes	yes	yes	yes	yes
Market-Year FE	no	no	yes	yes	yes	yes	yes
Firm-Year FE	no	no	no	no	no	no	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5%, and 10% respectively.

Does new imports trigger export entry within the following year?

If the observed relationship between export entry and new sourcing is driven by common operational costs, there is no reason to think that there is a particular order in this sequence of activities. If a firm starts sourcing from j the cost of exporting there fall and we should observe exporting after importing. If the driver was learning about suppliers, it is hard to establish ex-ante whether importing inputs should reveal relevant information about exporting to the new source country. Our theory is silent about what to expect regarding how importing to a market affect export entry to that market in the following year. Therefore, this is empirical question that we test for completeness. We estimate the probability of a firm starting to export to a new destination ($ExportEntry_{ij,t}$) on a indicator variable $NewOrigin_{ij,t-1}$ that takes the value of 1 if the firm started to source from market j in the previous year, and our battery of fixed effects. As reported in Table C.8, sourcing from a new market does not affect the probability of exporting there the following year. This fact remains both in the whole sample and also doing the estimation market by market.

Table C.8: Exporting does not follow importing in any market

$Pr[NewDest_{ij,t} = 1]$	All	**Non-Americas Markets**	Asean	RAsia	EU	REu
$NewOrigin_{ij,t-1}$	0.001	0.006	0.003	0.006	-0.001	0.000
	(0.003)	(0.007)	(0.004)	(0.007)	(0.006)	(0.010)
$Pr[NewDest_{ij,t} = 1]$		**The Americas Markets**	Mercosur	RSA	North America	CA
$NewOrigin_{ij,t-1}$		0.000	-0.016*	-0.011	0.001	-0.012
		(0.005)	(0.010)	(0.013)	(0.007)	(0.030)
Firm FE	no	no	yes	yes	yes	yes
Year FE	yes	no	yes	yes	yes	yes
Firm-Region FE	yes	yes	no	no	no	no
Employment-proxy	yes	yes	yes	yes	yes	yes

Standard errors in parenthesis are clustered at the firm level. ***,** and * indicates significance at the level 1%, 5% and 10% respectively.

C.4 Appendix to Section 3.6

Table C.9: Difference in revenues at entry to import market

	(1)	(2)
	$\Delta Revenues_{it}$	$\Delta Revenues_{it}$
$ExportEntry_{ijt-1}$	-0.506***	-0.290**
	(0.137)	(0.136)
Constant	10.532***	8.997***
	(0.189)	(0.207)
Observations	6,858	8,734
R-squared	0.830	0.179
Firm FE	yes	no
Year-Market-Sector FE	yes	yes

*** p<0.01, ** p<0.05, * p<0.1