Scalable Expertise*

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Abstract

We document that aggregate or sectoral demand shocks have disproportionately bigger effects on larger firms. Changes in *scope*, the number of products/locations, plays a significant role in this heterogeneity. Motivated by these facts, we present a theory of firm size, where both *scope* and *expertise* (which determines revenues and profits) are chosen endogenously. The extent to which expertise is scalable (applicable to multiple products), as opposed to local (specific to a particular product), is also chosen by the firm. The model predicts rich heterogeneity in responses to a sector-wide demand shock: firms with higher revenue per product (conditional on scope) adjust their scope by less, while those with higher scope (conditional on revenue per peroduct) adjust by more. Using data on multi-product and multi-establishment firms, we provide empirical evidence in support of these predictions. We also construct a proxy for the scalability of the firm's expertise and show that the predictions of the model with respect to the scalability of firm-level expertise, both in the cross-section and in response to shocks, are also consistent with the patterns observed in the data.

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1 Introduction

The distribution of firm sizes in the aggregate economy and how it responds to shocks and other changes in the economic environment is a central question in modern macroeconomics. The canonical framework of Hopenhayn (1992) and Melitz (2003) has rather stark predictions: firm size is pinned down by idiosyncratic productivity (or demand) and aggregate (or sector-wide) shocks have a disproportionate effect on small firms (which are less productive and closer to an exit threshold). Empirical support for these predictions is rather mixed. First, several papers have documented that the correlation between size and productivity is far from perfect. Second, we document new evidence showing that larger firms exhibit greater sensitivity to aggregate demand shocks. Our analysis also shows that changes in 'scope' – the number of locations/establishments/products operated by a firm – play an important role in this heterogeneous response. In other words, large firms adjust their scope (relatively more than small firms) in response to changes in demand.

Guided by these findings, we lay out a simple theory of firm size, where scope (the number of 'units') as well as profitability are chosen endogenously. The latter is modeled as resulting from *expertise*, an accumulated stock of knowledge that allows the firm to conduct its operations more efficiently. Importantly, in our framework, such knowledge can either be 'scalable' or 'local'. The former can be applied to all units within a firm, while the latter is specific to a particular unit. Replication, i.e. adding a product or location, allows the firm to exploit its scalable expertise more intensively but is costly. Firms, heterogeneous in their ability to accumulate expertise, optimally choose scope, overall expertise and its scalability to maximize total profits. The rich structure of heterogeneity in turn generates a rich pattern of scope and expertise in the cross-section.

The theory makes a number of predictions. The first set of predictions pertain to the cross-sectional distribution of scope, expertise and scalability. *Ceteris paribus*, a firm with a larger number of units will have relatively more scalable expertise (conditional on the level of expertise). Intuitively, higher scope (conditional on profitability) is associated with a comparative advantage in accumulating scalable expertise. Also, more profitable firms are predicted to be less scalable.

The second set of predictions relate the responses of firms to an aggregate shock, specifically a shift in sectoral demand. The model predicts that the elasticity of scope with respect to the shock is increasing in scope (conditional on profitability) and decreasing in profitability (conditional on scope). In other words, a firm operating a larger number of units adjusts its scope by more than one with a relatively smaller number of equally profitable ones. Similarly, among firms of a given scope, less profitable ones are more responsive to the shock. Intuitively, the marginal value of a unit (i.e. of adjusting scope) is more sensitive to a change in demand when it is small to begin with. This occurs when either profitability is low or the marginal cost of adding a unit is high (since costs are convex, firms with larger scope face higher marginal costs). These patterns apply both to the choice of scope as well as the scalability of the firm's expertise.

We test the theory under two different interpretations of scope: the first focuses on the number of *establishments* and uses longitudinal data covering the universe of US businesses from the NETS survey, while the second interprets scope as number of *products* and uses data on the Consumer Packaged Goods sector from the Kilts-Nielsen database. In order to test predictions with respect to responsiveness to shocks, we construct multiple proxies for sectoral demand shocks. First, we exploit cross-regional variation in home prices during the housing boom and bust cycle in the 2000s, following Mian and Sufi (2011, 2014). Our second proxy is based on the intensity of competition from Chinese imports, following Autor et al. (2013). In all these cases - across different interpretations of scope and various shocks – we show that the data support the central prediction of the theory: the elasticity of scope is increasing in scope, conditional on profitability (proxied with revenue per unit) and decreasing in profitability, conditional on scope.

Next, we exploit the detailed information about attributes of products in the Kitts-Nielsen dataset to construct firm-level measures of expertise scalability. Intuitively, this measure is based on the extent to which products within a firm have common characteristics. We then confront the model's predictions with respect to the scalability of expertise, both in the cross-section and in response to shocks.

Finally, we use the product-level data to document a connection between the scalability and diffusion. Our results suggest that knowledge that diffuses more easily within the firm also spills over to other firms in the industry. This is consistent with the idea that scalability is achieved by organizing and codifying knowledge in order to make it more readily usable across multiple products within the firm. But, such codification also makes it easier for the knowledge to be used outside the boundaries of the firm where it originated. This positive association between scalability and diffusion has important implications, both normative and positive. First, it creates an externality, since firms do not internalize benefits accruing to other firms from their expertise choices. Second, changes to the firms' incentives to alter the mix of expertise (e.g. due to aggregate demand shocks) have additional aggregate consequences.

Related Literature: Our paper contributes to a number of different strands. On the empirical front, it documents new facts about the heterogeneous impact of shocks, complementing the well-known studies of, e.g., Mian and Sufi (2011, 2014), and Autor et al. (2013). Our focus on heterogeneity is shared by a few other papers including Moscarini and Postel-Vinay (2012), Fort et al. (2013) and Baldwin and Gu (2009). On the theory side, we contribute to the firm dynamics literature in the tradition of Hopenhayn (1992) and Melitz (2003) with a novel theory of endogenous firm size. Apart from breaking the counterfactual tight link between size and productivity, our framework also provides a deeper understanding of the firm size distribution by focusing on scope and scalability. Our theoretical contribution is also related a few papers in the international trade literature, such as Nocke and Yeaple (2014) and Dhingra (2013). Our analysis also complements work on multi-product firms in international trade by Bernard et al. (2010) and Bernard et al. (2011).

The rest of the paper is organized as follows. Section 2 documents the basic facts about heterogeneity responses of firms to aggregate shocks. Section 3 presents our theoretical framework model and its predictions, which are confronted with the data in Section 4. Section 5 concludes.

2 Firm Size and Responsiveness to Shocks

In this section, we use detailed firm and product-level data to study the effect of aggregate demand shocks on firm's size. We use two distinct datasets and construct two proxies for demand shocks. Our results indicate that large firms are more affected by these shocks. Moreover, this larger response of large firms is driven both by the extensive margin (measured by number of establishments or products) and by the intensive margin (size per unit). These results are robust to multiple alternative specifications and various measurement issues.

2.1 Data

We use two distinct datasets: the National Establishment Time Series (NETS) covering employment and sales for nearly the majority of the private sector; and the Nielsen Retail Measurement Services (RMS) covering a large share of sales and products in the consumer goods sector.

2.1.1 NETS

The NETS data set consists of longitudinally linked Dun & Bradstreet establishment-level data.[1] NETS provides yearly employment and sales information for 'lines of business' in a specific location (similar to the definition of an establishments) over the period 1990-2016.[2] Each establishment is assigned a data universal numbering system (DUNS) identifier that makes it possible to track its sales and employment over time. For each establishment, we know location, industry classification, and parent company. In our main analysis we characterize the industry of establishments at the 4-digit level of Standard Industrial Classification (SIC) and the locations are mapped to Metropolitan Statistical Areas (MSAs).

We mostly explore changes in size over time at the firm-level within sector. To do so, we create for each parent $\times$ industry variables capturing total employment (or total sales), the number of establishments, and the average employment (sales) per location, and study how these variables evolve over time. We also use geographic information when creating measures of shocks and various measures capturing entry and exit of parents and establishments.

[1]The data is provided by Walls & Associates. Appendix C.1 provides detailed information on the data.

[2]A more detailed description of NETS can be found in Barnatchez et al. (2017); Rossi-Hansberg et al. (2018); Crane and Decker (2019). We use samples and produce robustness exercises to address the inclusion of non-employee firms on NETS and imputed observations.

2.1.2 Nielsen

The product data comes from the Nielsen RMS, generated by point-of-sale systems in retail stores covering the period 2006–2015.[3] Each individual store reports weekly sales volume and quantities sold of every barcode that had any sales volume during that week.[4] The data also provided us with detailed information about each product such as its brand, volume, color, flavor, and size. The data cover a wide range of products both in terms of type (e.g. from non-durables such as food to semi-durables like small appliances) and in terms of revenue share.

We link firms and products with information obtained from GS1 US, the single official source of barcodes. This link allows us to perform the analysis at the parent company level rather than at the level of the manufacturing firm. Given that the GS1 US data contains all of the company prefixes generated in the US, we combine these prefixes with the barcodes in the RMS. By combining these two datasets, we identify the revenue, price, and quantity of each product in a firm's portfolio and we aggregate them to the level of the firm and product sector.

We define sector using information on the type of product. The original data consist of more than one million distinct products identified by barcodes, organized into a hierarchical structure. Each barcode is classified into one of the 1070 product modules, that are organized into 104 product groups, that are then grouped into 10 major departments.[5] For example, a 31-ounce bag of Tide Pods (UPC 037000930389) is mapped to product module "Detergent-Packaged" in product group "Detergent", which belongs to the "Non-Food Grocery" department. We follow Hottman et al. (2016) and Argente et al. (2019) and define sectors based on the classification of product group.

For each firm $\times$ sector, we measure total sales, total products and average sales per products. We also make use the MSA location of the stores when creating measures of shocks and various measures capturing entry and exit of firms and products.

2.2 Sectoral Demand Shocks

We use two distinct shocks. Our first shock is firm and sector-specific and exploits cross-regional variation in home prices during the housing boom and bust cycle in the 2000s, following Mian and Sufi (2011, 2014), and the pre-existing exposure of firms to different locations. Our second shock is a sector-specific and capture different exposure to the intensity of competition from Chinese imports, following Autor et al. (2013).

[3] The data is provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. Appendix C.1 provides detailed information on the data.

[4] A barcode is a 12-digit Universal Product Code (UPC) consisting of 12 numerical digits that is uniquely assigned to each specific good available in stores. UPCs were created to allow retail outlets to determine prices and inventory accurately and improve transactions along the supply chain distribution (?).

[5] The ten major departments are: Health and Beauty aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise).

2.2.1 House Price Shock

In this section, we provide an overview of our empirical strategy for identifying the impact of house price changes on firm growth. We use across-MSA variation in housing supply elasticity as an instrument for house price changes in order to uncover the causal relationship between house-price-induced demand shocks and firm growth. This approach isolates differences in house price growth that are plausibly orthogonal to other factors that might directly influence firms' performance.

We follow an extensive literature that exploits across-MSA variation in housing supply elasticity to instrument for house price changes. The intuition for this instrument is that for a fixed housing demand shock during the housing boom, house prices should rise more in areas where housing supply is less elastic. During the housing bust, it is then precisely those areas where house prices rose most that see the largest declines in house prices. Saiz (2010) uses information on the geography of a metropolitan area to measure the ease with which new housing can be constructed. The index assigns a high elasticity to areas with a flat topology without many water bodies, such as lakes and oceans. The first stage is given by the following equation:

$$\Delta \log(\text{HousePrice})_m^\tau = \rho \, \text{SupplyElasticity}_m + \delta X_m + \varepsilon_m \tag{1}$$

The unit of observation is an MSA, denoted by m, and separately for the housing boom (2001-2006) and bust (2007-2011), denoted as τ. X_m is a vector of controls that include the change in the number of retail establishments, the change in all establishments, the change in the construction share of employment, the change in the retail share of employment, and the change in the share of employment in the non-tradable sector. The housing supply elasticity from Saiz (2010) is our instrument for house price changes. We obtain house price indices at both the MSA level from the FHFA House Price Index. Table A.III in Appendix presents results from the first-stage regression. The instrument is highly predictive of house price changes over both periods, with low-elasticity MSAs experiencing larger house price gains during the housing boom, and larger house price drops during the housing bust.

We generate the predicted change in price index $\Delta \log(\widehat{\text{HousePrice}})_m^\tau$. Using $\Delta \log(\widehat{\text{HousePrice}})_m^\tau$, we build the firm-specific shocks separately for the housing boom (2001-2006) and bust (2007-2011) as follows

$$\Delta D_{ij\tau}^{\text{Size}} = \sum_{m=1}^{M_{ij\tau_0}} \frac{\text{Size}_{ij\tau_0 m}}{\sum_{m=1}^{M_{ij\tau_0}} \text{Size}_{ij\tau_0 m}} \Delta \log(\widehat{\text{HousePrice}})_m^\tau \tag{2}$$

where i refers to firms, j to sectors, and m to the MSA location. The variable Size_{ijts} refers to measures of size in the baseline years τ_0 2001 and 2007. Size is measured as total employment in the NETS data and total sales in the Nielsen data. For the NETS data we cover both the housing boom and bust, while for the NETS data we only cover the bust period. We report the results to each period and dataset independently, and we change the sign of the shock in the bust period to make the shock consistent with a positive demand shock.[6]

2.2.2 China Import Penetration Shock

Our measures of trade exposure follow closely Autor et al. (2013) and Acemoglu et al. (2016) by capturing the change in the import penetration ratio. For all sectors j in the consumer goods sector, we collect data on imports from China into the US, $M_{j,t}$, exports, $E_{j,t}$, and industry shipments, $Y_{j,t}$, from UN Comtrade, NBER-CES and UNIDO.[7] Our baseline measure of the change in the Chinese import penetration ratio for a given sector over the period 2006–2015, is defined as

$$\Delta IP_{j,06-15} = \frac{M_{j,15} - M_{j,06}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100 \tag{3}$$

We use 2006 as the baseline year since it is the earliest period for which we have simultaneously trade and firm data. Intuitively, the measure $\Delta IP_{j,06-15}$ captures group-level changes in imports from China. In order to address endogeneity concerns, we also work with an alternative measure that uses imports in other high income countries as an instrument, following Acemoglu et al. (2016). The motivation for the instrument is that high-income economies are similarly exposed to a Chinese supply shock, but are unaffected by US-specific shocks that affect US import demand.[8]

We map the import penetration measures to changes in demand for equivalent products produced by US firms. Thus, we define the shocks of the different sectors as the inverse of the import penetration measures to proxy a positive demand shock. Figure C.2.2 in Appendix shows the measure of Chinese import penetration by sector. There is a substantial amount of heterogeneity within the consumer product industry. As expected, on average, sectors that produce semi-durables products were more affected by import penetration of China products and thus have more negative demand shocks than sectors related to food products.

2.3 Heterogeneous Response to Demand Shocks

We explore how the sensitivity to demand shocks varies by firm size by using regression analysis. We use lower case letters to refer to variables in logs (e.g. $\ln(X) = x$) and we refer to the demand shocks, either house price shocks, ΔD, or the China import penetration shock, ΔIP, as Δg and implement the following specification:

$$\Delta zn_{ij,\tau} = \beta_0(\Delta g_{ij,\tau} zn_{ij,\tau_0}) + \alpha \Delta g_{ij,\tau} + \gamma_0 zn_{ij,\tau_0} + \sigma_{j\tau} + \epsilon_{ij,\tau} \tag{4}$$

[6] In Appendix, we provide more details on the distribution of these shocks.

[7] For the NETS data we use standard SIC mapping to trade data. For the Nielsen data, We link sectors to trade data by using the concordance developed by Bai and Stumpner (2019). We provide more details on the data sources in Appendix D.1.

[8] See Appendix D.1 for more details on the instrument $\Delta IP_{j,06-15}$ and measures of import penetration for other time periods.

where the dependent variable $\Delta zn_{ij,\tau}$ is the log change in the total employment/sales of firm i in sector j in the period τ (multiplied by 100). In the specifications using the NETS data, we use employment as our benchmark measure of size.[9] In the specifications using the Nielsen data our measure of size is the total sales of a firm in a given sector. $\Delta g_{ij,\tau}$ stands for the demand shock, either the housing price shock or the China import penetration shock. The control variables zn_{ij,τ_0} is log of total sales/employment measured in the beginning of period τ_0 (standardized within j and τ) and $\sigma_{j\tau_0}$ are year sector-specific fixed-effects. The coefficient of interest β_1 estimates how the effect of changes in exposure varies with the size of the firm measure by employment or sales.

Table A.VI shows our estimates for β_1 using both the NETS data (Columns 1-3) and the Nielsen data (Columns 4-5) and for both the housing price shock (Column 1 for the boom and Column 2-4 for the bust) as well as the China import penetration shock (Columns 3 and 5). For both data sets and both shocks, the table shows that larger firms show greater sensitivity to demand shocks.

Table 1: Heterogeneous Response to Demand Shocks - Size

Δzn	(1)	(2)	(3)	(4)	(5)
$\Delta g \times zn$	0.049***	0.047***	0.191***	0.666***	0.126***
	(0.001)	(0.001)	(0.049)	(0.145)	(0.012)
Observations	580,946	569,328	34,583	27,930	23,812
R-squared	0.096	0.076	0.112	0.088	0.152
Sector	Y	Y	Y	Y	Y
Shock	Housing	Housing	China	Housing	China
Period	2001-2006	2007-2011	2006-2015	2006-2011	2006-2015
Data	NETS	NETS	NETS	Nielsen	Nielsen

Note: The table reports the results of estimating equation 14. The dependent variable is the log change in the total employment/sales of firm i in sector j in the period τ. The reported coefficient is the effect of changes in exposure to demand shocks by firm size. The first three columns use the NETS data and the last two the Nielsen data. Column 1 uses as demand shock the housing price shock from 2001-2006, Columns 2 and 4 the housing price shock from 2006-2011, and Column 3 and 5 the China import penetration shock. All the specifications include sector effects.

Next, we explore whether the greater sensitivity we observe in large firms comes from changes in scope – the number of locations/establishments/products – operated by a firm or by changes in their expertise – the total employment (sales) per plant (product). To do so, we estimate equation 14 using either the change in the number of plants/products of firm i in sector j in period τ as dependent variable ($\Delta n_{ij,\tau}$) or the change in the the employment/sales per plant/product ($\Delta z_{ij,\tau}$).

[9] In Appendix D.2.1 we show that using total sales rather than employment does not affect our findings.

As before, the coefficient of interest β_1 estimates how the effect of changes in exposure varies with employment (sales) per plant and the number of plants (products) respectively.

The results are presented in Table A.VII. As before, the table is divided by data sets, shocks, and periods. For example, Column 1 shows how the response of the employment/sales per plant/product to a demand shock varies by size, where the shock in this case is the housing price shock during the boom and that data used is NETS. Similarly, Column 2 shows the response of the number of plants/products for the same shock and data set. Since $\Delta zn_{ij,\tau} = \Delta n_{ij,\tau} + \Delta z_{ij,\tau}$, summing the coefficients reported in Columns 1 and 2 equals the total effect on employment/sales ($\Delta z_{ij,\tau}$) reported in Table A.VI.

Columns 1-6 shows that larger firms exhibit greater sensitivity to demand shocks than smaller firms in both margins – employment per plant and number of plants – regardless of the shock. Column 7-10 shows a similar story for firms in the Nielsen data where both margins are measured by the total sales per product and the number of products. These results are consistent using both housing price shocks (either during the boom or during the bust) or using the China import penetration shock. Larger firms adjust both their scope (relatively more than small firms) in response to changes in demand as well as their employment (sales) per plant plant (product).

Table 2: Heterogeneous Response to Demand Shocks - Extensive and Intensive Margins

	(1) Δz	(2) Δn	(3) Δz	(4) Δn	(5) Δz	(6) Δn	(7) Δz	(8) Δn	(9) Δz	(10) Δn
$\Delta g \times zn$	0.018***	0.031***	0.022***	0.025***	0.155***	0.036	0.600***	0.066*	0.115***	0.011***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.043)	(0.023)	(0.130)	(0.036)	(0.011)	(0.004)
Obs.	580,946	580,946	569,328	569,328	34,583	34,583	27,930	28,137	23,812	23,812
R-squared	0.067	0.057	0.041	0.062	0.088	0.049	0.087	0.031	0.145	0.067
Sector	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sample	Housing	Housing	Housing	Housing	China	China	Housing	Housing	China	China
Period	2001-2006	2001-2006	2007-2011	2007-2011	2006-2015	2006-2015	2007-2011	2007-2011	2006-2015	2006-2015
Data	NETS	NETS	NETS	NETS	NETS	NETS	Nielsen	Nielsen	Nielsen	Nielsen

Note: The table reports the results of estimating equation 14. The dependent variables are the change in the number of plants/products of firm i in sector j in period τ ($\Delta n_{ij,\tau}$) or the change in the the employment/sales per plant/product ($\Delta z_{ij,\tau}$). The reported coefficient is the effect of changes in exposure to demand shocks by firm size. The first six columns use the NETS data and the last three the Nielsen data. Column 1 an 2 use as demand shock the housing price shock from 2001-2006, Columns 3,4,7, and 8 the housing price shock from 2006-2011, and Column 6 and 9 the China import penetration shock. All the specifications include sector effects.

3 Model

This section presents our theoretical framework, motivated in part by the patterns documented in the previous section. Firms, heterogeneous in the abilities to accumulate expertise, optimally choose the scope and size of their operations. The theory makes a number of implications – in particular, for the response of scope and *scalability* to shocks – which we take to the data in the following section.

The economy comprises many infinitesimal sectors, indexed by j, aggregated into a final good using a Cobb-Douglas function:

$$Y = \int \alpha_j \ln Y_j dj \qquad \Rightarrow \qquad P_j Y_j = \alpha_j Y_j \ .$$

Each sector has a continuum of domestic firms (indexed by i) as well as a continuum of foreign firms (indexed by f). The sectoral good Y^s is a CES aggregate of the goods sold by both sets of firms:

$$Y_j \ = \ \left[\int (Y_{ij})^{1-\frac{1}{\theta}} di + \int \left(Y^*_{jf}\right)^{1-\frac{1}{\theta}} df \right]^{\frac{\theta}{\theta-1}} \ ,$$

where Y^s_i denotes the (composite) good of firm i and θ is the elasticity of substitution across firms. This in turn is an composite of a continuum of products (or varieties), with substitution elasticity ϵ:

$$Y_{ij} \ = \ \int^{N_{ij}} (Y^s_{ij})^{1-\frac{1}{\epsilon}} \ ds \ ,$$

where Y^s_{ij} denotes the quantity of product s and N_{ij} the (endogenous) measure of products.

For simplicity, we will assume that the measure of foreign products is fixed and all of them are available at the same price of P^*_j. Normalizing the price of the economy-wide final good to 1, we obtain the sectoral price index as a composite of the domestic and foreign price indices:

$$P_j^{1-\theta} = \left(P^d_j\right)^{1-\theta} + \left(P^*_j\right)^{1-\theta} \qquad \text{where} \qquad \left(P^d_j\right)^{1-\theta} = \int (P_{ij})^{1-\theta} \, di$$

This structure implies that the following demand function for product s:

$$Y^s_{ij} = \left(\frac{P^s_{ij}}{P_{ij}}\right)^{-\epsilon} \left(\frac{P_{ij}}{P_j}\right)^{-\theta} Y_j \ .$$

Production is linear in labor input, i.e.

$$Y^s_{ij} = Z^s_{ij} L^s_{ij} \ ,$$

where Z_{ij}^s denotes productivity (we will connect this to the expertise of firm i later). Given the economy-wide wage W, the optimal price is a constant markup over marginal cost, i.e.

$$P_{ij}^s = \frac{\epsilon}{\epsilon - 1} \frac{W}{Z_{ij}^s} \qquad\qquad (P_{ij})^{1-\epsilon} = \int^{N_{ij}} \left(P_{ij}^s\right)^{1-\epsilon} ds \ .$$

Let $\mathcal{F}(N_{ij})$ denote the fixed cost of operating N_{ij} products. The total operating profits of firm i across all products are given by

$$\Pi_{ij} = \int_0^{N_{ij}} \left(P_{ij}^s - \frac{W}{Z_{ij}^s} \right) Y_{ij}^s ds - \mathcal{F}(N_{ij})$$

Substituting and imposing symmetry across products ($Z_{ij}^s = Z_{ij}$, a conjecture that will be shown to hold at the optimum), this can be expressed as

$$\Pi_{ij} = \underbrace{\frac{(\theta-1)^{\theta-1}}{\theta^\theta} P_j Y_j \left(\frac{P_j}{W}\right)^{\theta-1}}_{G_j} (N_{ij})^{\frac{\theta-1}{\epsilon-1}} \quad (Z_{ij})^{\theta-1} \qquad \equiv \qquad \Pi(G_j, N_{ij}, Z_{ij}) \tag{5}$$

where G_j is a common (i.e. sector-wide) equilibrium coefficient that scales firms' profits.

Expertise The key economic forces in our model stem from the accumulation and allocation of *expertise*. We interpret expertise rather broadly to encompass all forms knowledge that allows the firm to operate more efficiently and extract more value from its inputs.[10] Formally, the productivity of product s in firm i is a combination of two types of expertise – *scalable* (or firm-wide) or *local* (j-specific). The former, denoted x_i, aims to capture expertise that is applicable to all the products of the firm, while the latter, denoted y_i^s, reflects knowledge that is unique to a particular product. We adopt the following specification for Z_{ij}

$$Z_{ij}^s = \left[(x_i^s)^{\frac{\sigma-1}{\sigma}} + (y_{ij})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \qquad \equiv \qquad Z(x_{ij}, y_{ij})$$

where the parameter σ indexes the elasticity of substitution between the two types of expertise. We will refer to the ratio $\frac{x_i}{y_{ij}}$ as *scalability* of the firm's expertise.

Cost of expertise: For now, we specify a general cost function, $\mathcal{C}_{ij}(x_{ij}, N_{ij}, \{y_{ij}^s\})$. Note that the function is indexed by i, so firms are heterogeneous in their expertise accumulation costs.

[10] In Appendix B, we present a information-based micro-foundation in a dynamic setting.

The firm's problem Firm i solves

$$\max_{N_{ij},x_{ij},y_{ij}} \quad \Pi(G_j, N_{ij}, Z(x_{ij}, y_{ij})) - \mathcal{F}(N_{ij}) - \mathcal{C}_{ij}(x_{ij}, N_{ij}, y_{ij}) \tag{6}$$

3.1 A Special Case

We first solve (6) for a tractable special case with $\theta = \epsilon = 2, \mathcal{F}(N_{ij}) = FN_{ij}$ and the cost function takes the form of a capacity constraint, i.e.

$$\begin{aligned} \mathcal{C}_{ij}(x_{ij}, N_{ij}, y_{ij}) = 0 \quad & \text{if} \ \ \frac{x_{ij}}{a^x_{ij}} + \frac{N_{ij}y_{ij}}{a^y_{ij}} \ \leq \ 1 \\ = \infty \quad & \text{otherwise.} \end{aligned} \tag{7}$$

where a^x_{ij} and a^y_{ij} denote the firm's skill in accumulating scalable and local expertise, respectively.

The solution is characterized by the following first-order conditions:

$$x_{ij}: \qquad N_{ij}G_jZ_x(x_{ij}, y_{ij}) = \frac{\lambda_{ij}}{a^x_{ij}} \tag{8}$$

$$y_{ij}: \qquad G_jZ_y(x_{ij}, y_{ij}) = \frac{\lambda_{ij}}{a^y_{ij}} \tag{9}$$

$$N_{ij}: \qquad G_jZ(x_{ij}, y_{ij}) - F = y_{ij}\frac{\lambda_{ij}}{a^y_{ij}}\ , \tag{10}$$

where λ_{ij} is the Lagrange multiplier on the capacity constraint (7). The expressions on the left hand side of (8)-(10) represent the marginal benefit to the firm from increasing scalable expertise (x_{ij}), non-scalable expertise (y_{ij}) and scope N_{ij} respectively. The expressions on the right are the associated marginal costs. Equation (8) shows that the benefit from x_{ij} is scaled by the measure of products N_{ij}, reflecting its scalable nature. On the other hand, since scope affects both the benefits and costs of increasing y_{ij}, it does not appear in(9).

Combining and re-arranging the conditions yields

$$(8) + (9) \quad \Rightarrow \quad \underbrace{\frac{x_{ij}}{y_{ij}}}_{\text{Scalability}} = \left(N_{ij}\frac{a^x_{ij}}{a^y_{ij}}\right)^{\sigma} \tag{11}$$

$$(9) + (10) \quad \Rightarrow \quad \underbrace{\frac{G_jZ(x_{ij}, y_{ij}) - F}{G_jZ(x_{ij}, y_{ij})}}_{Profitability} = \underbrace{\frac{y_{ij}G_jZ_y(x_{ij}, y_{ij})}{G_jZ(x_{ij}, y_{ij})}}_{\frac{mpy}{apy}} = \left(\left(\frac{x_{ij}}{y_{ij}}\right)^{\frac{\sigma-1}{\sigma}} + 1\right)^{-1} \tag{12}$$

$$(11) + (12) \quad \Rightarrow \quad Z(x_{ij}, y_{ij}) = \left[1 + \left(N_{ij}\frac{a^x_{ij}}{a^y_{ij}}\right)^{1-\sigma}\right]\frac{F}{G_j}\ . \tag{13}$$

The following result is immediate.

Lemma 1. *Suppose $\sigma > 1$. Then, scalability of expertise $\left(\frac{x_{ij}}{y_{ij}}\right)$ is decreasing in profitability Z_{ij}, or equivalently revenue per product.*

The above relationship holds when the two types of expertise are quite substitutable, i.e. $\sigma > 1$ (as we will see, this turns out to the empirically relevant case). Then, (12) directly implies that per-product profitability $Z(x_i^s, y_i^s)$ is negatively related to scalability in the cross-section. To see the intuition, note that each additional product generates $G_j Z(x_{ij}, y_{ij}) - F$ of profits but requires y_{ij} units of non-scalable expertise. Thus, the marginal benefit to the firm from a unit of capacity spent on raising increasing scope is the product of net profitability $\frac{G_j Z(x_{ij}, y_{ij}) - F}{G_j Z(x_{ij}, y_{ij})}$ and the average profit per unit of non-scalable expertise, $\frac{G_j Z(x_{ij}, y_{ij})}{y_{ij}}$. At an interior optimum, this must be equal to the marginal benefit from allocating a unit of capacity to increasing y_i^s, i.e. to the marginal product of y_{ij}. Now, both *mpy* and *apy* are increasing in scalability $\frac{x_{ij}}{y_{ij}}$. But since $\sigma > 1$, i.e. the two forms of expertise are relatively substitutable, the marginal product rises more slowly than the average product, so the ratio $\frac{mpy}{apy}$ is decreasing in scalability. In other words, firms with more scalable expertise are less profitable on a per-product basis. In Section 4.3, we construct a measure of scalability using product-level data and test this prediction (more precisely, a generalized version).

Scalability is also positively related to scope (conditional on relative skill), as equation (11) shows. Intuitively, the benefit of x_{ij} is scaled by N_{ij}, while that of y_{ij} is not. This force is more powerful when the two forms of expertise are relatively substitutable, i.e. σ is high. Combined with 1, this implies a negative relationship between scope and profitability – equation (13). Taken together, these equations show how a firm could be large (in terms of total sales or employment) but relatively unprofitable (on a per product basis). As we will see, this will play a crucial role in the response to shocks. Note, however, that equations (11) and (13) are not directly testable in the cross-section, even with a measure of scalability: unobserved heterogeneity in relative skill $\frac{a_{ij}^x}{a_{ij}^y}$ creates endogeneity.

3.1.1 Response to Aggregate/Sectoral Shocks

We now characterize heterogeneity in the response to a sector-wide demand shock, interpreted as a change in G^s. This is a simple way to capture the sectoral changes analyzed in Section 2. Using the solution to the firm's problem characterized above, the comparative statics with respect to G^s can be easily obtained and are stated in the following result.

Proposition 1. *The elasticity of scope (N_{ij}) and scalability $\left(\frac{x_{ij}}{y_{ij}}\right)$ with respect to G_j are decreasing in profitability Z_{ij}, or equivalently, revenue per product.*

Thus, all firms cut back on their product scope and scalability in response to a fall in demand, but the effects are heterogeneous. A sufficient statistic for the response of a firm is profitability, $G_j Z_{ij}$ (given our CES demand system, this is equivalent to conditioning on revenue per product). Firms which sell more (on a per-product basis) make smaller adjustments to their scope and scalability.

Intuitively, the profit margin per product is $\frac{G_j Z_{ij} - F}{G_j Z_{ij}}$ is less sensitive to changes G_j at higher levels of profitability. This means that firms with higher Z_{ij} see a smaller change in their incentives to add products or accumulate scalable expertise. In other words, what matters for the firm's decision is not the overall size of the firm but the profitability of its product lines. A large firm with a number of marginally profitable product lines will adjust its scope more dramatically relative to a smaller, more profitable firm.

3.2 The general case

Now, we turn to a more general specification of the firm's problem:

$$\max \qquad G_j (N_{ij})^{\phi} Z(x_{ij}, y_{ij})^{\psi} - F(N_{ij})^{\omega} - H \cdot \left[\frac{(x_{ij})^{\mu}}{a^x_{ij}} + \frac{N_{ij}(y_{ij})^{\mu}}{a^y_{ij}} \right]^{\gamma} .$$

Note that this nests the special case analyzed in the previous subsection with $\phi = \psi = \omega = 1$ and $\gamma = \infty$. This specification allows for arbitrary elasticities of substitution both across products of a given firm as well as across composite goods of different firms within a sector (not necessarily equal to each other: this implies $\phi = \frac{\theta - 1}{\varepsilon - 1} \neq 1$) as well as a flexible specification for the fixed operating costs, $\mathcal{F}(N_{ij})$ and the cost of expertise. This generality comes at the expense of complicated, less intuitive expressions for the objects of interest, so we relegate them to the Appendix and directly present the generalized versions of the results. The following proposition generalizes Lemma 1 on the cross-sectional relationship between scalability and other variables.

Proposition 2. *Suppose $\sigma > 1$. Then, scalability of expertise $\left(\frac{x_{ij}}{y_{ij}}\right)$ is*

(i) decreasing in Z_{ij}, conditional on N_{ij}.

(ii) increasing in N_{ij}, conditional on Z_{ij}.

The intuition for this result is similar to that of the special case, suitably modified for the curvature of the profit function in scope (in the special case, operating profits were linear in N_{ij}). The inverse relationship with profitability and scalability continues to hold, albeit conditional on a given scope. Curvature in N_{ij} also leads to a new implication: a cross-sectional positive relationship between scope and scalability, conditional on profitability Z_{ij}.

Next, we generalize Proposition 1 on the response of scope and scalability to a sector-wide demand shock.

Proposition 3. *The elasticity of scope and scalability w.r.t. G_j are*

(i) decreasing in Z_{ij}, conditional on N_{ij}.

(ii) increasing in N_{ij}, conditional on Z_{ij}.

(iii) increasing in scalability (if $\sigma > 1$).

The underlying intuition is the same: what matters for responsiveness is not the size of the firm but profitability of its products. The additional curvature here relative to the special case serves to make profitability a decreasing function of scope (e.g. because $\mathcal{F}' = F\omega(N_{ij})^{\omega-1}$). As a result, the first prediction (how the response varies with Z_{ij}) requires conditioning on scope. The curvature also generates another prediction: firms with higher scope adjust both scope and scalability by more in response to a sector-wide shock.

4 Validating the theory

In this section, we confront the predictions of the model with data used in Section 2. First, we show that the predictions of Proposition 3 are in line with observed patterns in the data. First, we test the predictions with respect to the responsiveness of scope in both the establishment-level (NETS) and product-leve (Nielsen) data. Next, we leverage the detailed information on product-level attributes in the Nielsen data to construct a measure of scalability, which allows us to validate the model's implications on that front as well.

4.1 Mapping model to data

Scope We explore two different interpretations of scope. In the NETS data, we define N_{ijt} as the total number of establishments a firm i in sector j in year t operates. In the Nielsen data, $Scope_{ijt}$ is defined as the total number of barcodes sold across all stores by firm i in sector j in year t. Barcodes are, by design unique, to every product – changes in any attribute of a good (e.g. forms, sizes, package, formula) result in a new barcode.

Expertise In the theory, both revenue and employment per unit scope are tightly linked to expertise. We exploit this connection and employment (or sales) per establishment (or per product) to proxy for the average expertise of the firm. Specifically, in the NETS data, expertise $Z_{ij,t}$ is defined as the total employment per establishment. In the Nielsen data, expertise is approximated by the total revenue per product. We combine all sales at the national and annual level and for each firm i in sector j in year t, we define total revenue as the total sales across all stores and weeks in the year.

4.2 Scope

Recall that Proposition 3 makes two predictions with respect to responses to sectoral shocks:

1. Conditional on expertise, firms with higher scope adjust scope by *more*.

2. Conditional on scope, firms with higher revenue/product adjust scope by *less*.

To test these predictions, we estimate the following specification:

$$\Delta n_{ij\tau} = \alpha + \beta_0 \Delta g_{ij\tau_0} + \beta_1(\Delta g_{ij\tau} \times n_{ij\tau_0}) + \beta_2(\Delta g_{ij\tau} \times z_{ij\tau_0}) + \gamma_1 \; n_{ij\tau_0} + \gamma_2 \; z_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau} \tag{14}$$

where the dependent variable is the change in the (log of) scope of firm i in sector j between τ_0 and τ, i.e. $\Delta n_{ij\tau} \equiv \log N_{ij\tau} - \log N_{ij\tau_0}$, while $\Delta g_{ij\tau}$ denotes the demand shocks constructed in Section 2, either the housing price shock or the China import penetration shock.[11] Finally, $\Delta z_{ij,\tau}$ is the log change in the revenue (or employment) per establishment (or product) of firm i in sector j between τ_0 and τ. We also include sector sector-specific fixed-effects, X_j.

We run five different versions of this regressions for different interpretations of scope and different candidate shocks (housing prices during the boom and bust phases as well as the China import penetration shock). The coefficients of interest are β_1 and β_2, which are reported in Table A.VIII below. The theory predicts $\beta_1 > 0$ and $\beta_2 < 0$.

Table 3: Elasticity of Scope to Aggregate Demand Shocks

	(1)	(2)	(3)	(4)	(5)
Δn					
$\Delta g \times n$	0.022***	0.018***	0.060***	0.104***	0.035***
	(0.000)	(0.000)	(0.013)	(0.039)	(0.004)
$\Delta g \times z$	-0.001	-0.003***	-0.016	0.048	-0.015***
	(0.000)	(0.001)	(0.026)	(0.035)	(0.004)
Observations	580,946	569,328	34,577	28,137	23,812
R^2	0.121	0.114	0.127	0.087	0.137
Sector	Y	Y	Y	Y	Y
Shock	Housing	Housing	China	Housing	China
Period	2001-2006	2007-2011	2006-2015	2006-2011	2006-2015
Data	NETS	NETS	NETS	Nielsen	Nielsen

Note: The table reports the results of estimating equation 14. The dependent variable is the change in the scope of firm i in sector j between τ_0 and τ ($\Delta n_{ij,\tau}$). The reported coefficients are the effects of changes in exposure to demand shocks by the level of scope of the firms or their level of expertise at the initial period. The first three columns use the NETS data and the last two the Nielsen data. Column 1 uses as demand shock the housing price shock from 2001-2006, Columns 2 and 4 the housing price shock from 2006-2011, and Column 3 and 5 the China import penetration shock. All the specifications include sector effects.

Table A.VIII shows support for the theory across all the cases. Specifically, we see that firms with

[11] In what follows, lower-case letters denote the natural log of the corresponding upper case variable, i.e. $n_{ijt} = \ln N_{ijt}, z_{ijt} = \ln Z_{ijt}$ and so on.

higher scope (conditional on expertise) adjust scope by more while those with higher expertise (conditional on scope) adjust scope by less in response to the shock. The magnitude of the former is larger in absolute terms.

4.3 Scalability

Next, we turn to scalability, which is a key object in our theory. Given the central role played by scalability in the theory, it is natural to ask: how well are the predictions with respect to scalability borne out by the data? Unfortunately, scalability is not directly observable from data on revenues, profits and scope. Here, we circumvent this difficulty by constructing a proxy for scalability in our product-level data and use it to provide additional validation for the model.

Recall that the theory offers two sets of implications for scalability. First, in the cross-section, Proposition 2 predicts that scalability is

1. *negatively* related to revenue/product, conditional on scope.

2. *positively* related to scope, conditional on expertise.

Next, we collect the implications of Proposition 3 related to scalability. Specifically, that result states that, in response to a common demand shocks,

1. firms with *higher* scalability adjust scope by *more*.

2. firms with *higher* scalability adjust scalability by *more*.

3. firms with *higher* expertise adjust scalability by *less*, conditional on scope.

4. firms with *higher* scope adjust scalability by *more*, conditional on expertise.

We will show that data are consistent with *all* of these patterns, a remarkable finding for a relatively parsimonious theory. We begin by describing how we construct our scalability measure. We exploit the detailed information on product features in the Nielsen data. Each product has a certain number of "attributes", such as color, size, flavor, formula.[12] These attributes can take different values, which we term "characteristics". Thus, each product is a bundle of characteristics, some of which it shares with other products.

Consider the product module: razor blades. The products in this module have the following five attributes: form, consumer type, scent, skin condition, and generic. The attribute "form" can take the following characteristics: "adjustable", "assorted", "injector", "moving", "pivoting" etc. Powder detergents, on the other hand, are described by the following four attributes: form, container, type, and generic. The attribute "form" for detergents could be "pack", "pod", "refill", "table".

The distinguishing feature of scalable expertise is its applicability to multiple products, in contrast to 'local' or product-specific expertise. In line with this interpretation, we map the scalability of expertise of

[12] We use a total of 20 distinct attributes. Each product module has between 4 and 8 active attributes.

firm i to the fraction of common attributes across its product portfolio. In particular, the Scalability Index of firm i in sector j in product module m at time t is defined as follows:

$$\mathcal{SI}_{mijt} \equiv 1 - \frac{\text{Unique}_{mijt}}{N_{mijt} \times \text{NumAttributes}_{mjt}} ,$$

where the variable Unique_{mijt} counts the number of distinct characteristics in the portfolio of products of the firm in module m. This is normalized by the total number of attribute-cells to be filled, i.e. module-level scope N^m_{ijt} times the number of attributes for each product in that module $\text{NumAttributes}_{mjt}$. In other words, the index captures the share of common characteristics within the portfolio of products of the firms, i.e. the likelihood that the characteristics of products are shared within the portfolio of a given firm. If no characteristic is repeated across the products of a firm, the Scalability Index equals 0. For example, a single-product firm will have a number of different attributes equal the number of distinct characteristics. By contrast, when products of a single firm share many characteristics, the Scalability Index converges to 1.[13] Note that the index is a relative measure, intended to measure the *composition* of expertise, not its *level*. This leads us to the following mapping between the Scalability Index (or more precisely, a simple transformation thereof) to scalability in the theory:

$$S_{mijt} = \frac{x_{mijt}}{y_{mijt}} \equiv \frac{\mathcal{SI}_{mijt}}{1 - \mathcal{SI}_{mijt}} .$$

We aggregate this measure to the firm-sector level (denoted S_{ijt}) using revenue-weights. We then run the following regression:

$$s_{ijt} = \alpha + \beta_1 \; z_{ijt} + \beta_2 \; n_{ijt} + \Gamma_{jt} + \varepsilon_{ijt} . \tag{15}$$

where Γ_{jt} is a set of sector $\times$ time fixed effects. The results are presented in Column (3) of Table 4. In line with Proposition 2, we find $\beta_1 < 0$ and $\beta_2 > 0$. The table highlights the importance of including both variables in the regression: columns (1)-(2) shows that unconditionally, scalability is positively associated with both scope and expertise.

[13] A potential concern is that $\mathcal{SI}^m_{ijt}$ is biased towards 1 for firms with a large number of products. We address this issue in Appendix C.3 using a bootstrap procedure to adjust for this potential mechanical relationship between N^m_{ijt} and the Scalability Index. Our results remain robust under this alternative measure.

Table 4: Scope, Scalability and Expertise

s	(1)	(2)	(3)
z	0.19***		-0.02***
	(0.002)		(0.002)
n		0.49***	0.50***
		(0.002)	(0.002)
Observations	293,013	293,151	293,013
R-squared	0.155	0.324	0.324
Period × Sector	Y	Y	Y

Note: The table shows the results estimating equation 15 in the Nielsen data. The dependent variable is (the log of) scalability from (15) and the independent variables are (the logs of) scope, expertise (revenue per product).

Next, we explore how scalability affects the scope adjustment by firms in response to sectoral demand shocks. Proposition 3 predicts that firms with higher scalability adjust scope by more. To test this prediction, we run the following specification:

$$\Delta n_{ij\tau} = \alpha + \beta_0 \, \Delta g_{j\tau} + \beta_1 \, \Delta g_{j\tau} \times s_{ij\tau_0} + \gamma \; s_{ij\tau_0} + \Gamma_j + \epsilon_{ij,\tau} \tag{16}$$

where $g_{j\tau}$ is the China import penetration shock from year 2006 to 2015 for sector j. The coefficient of interest is β_1, which measures the heterogeneous response of firms with different scalability – the theory predicts $\beta_1 > 0$. Table 5, in particular columns (2)-(3), shows that firms with higher scalability do indeed adjust their scope by more in response to a positive demand shock.

Table 5: Response of Scope to Shocks

	(1)	(2)	(3)
Δn			
Δg	0.026**	0.036***	
	(0.012)	(0.004)	
$\Delta g\ \times s$		0.024***	0.024**
		(0.004)	(0.009)
Observations	22,822	18,125	18,125
R-squared	0.002	0.031	0.074
Sector	N	N	Y

Note: The table shows the results of estimating equation 16. The dependent variable is the change in the (log of) scope of firm i in sector j. The dependent variable is the China import penetration shock interacted with the scope of the firm in 2006. Column (3) include sector fixed effects.

Lastly, we explore the response of scalability to demand shocks. Our theory predicts that, in response to common shocks, i) firms with higher scalability adjust scalability by more, ii) firms with higher expertise adjust scalability by less conditional on scope, and iii) firms with higher scope adjust scalability by more, conditional on expertise. We test prediction (i) first using the following specification:

$$\Delta s_{ij\tau} = \alpha + \beta_0\, \Delta g_{j\tau} + \beta_1\, \Delta g_{j\tau} \times s_{ij\tau_0} + \gamma\, s_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau} \tag{17}$$

where Γ_j are sector fixed effects. The results are shown in Table 6. Column (1) shows that scalability responds positively to changes in demand, while column (2) confirms that firms with higher scalability are more responsive to demand shocks (relative to the average firm, whose response is now picked up by the sector fixed effects). Predictions (ii)-(iii) are then tested simultaneously using the following specification:

$$\Delta s_{ij\tau} = \alpha + \beta_0\, \Delta g_{j\tau} + \beta_1\, \Delta g_{j\tau} \times z_{ij\tau_0} + \gamma_1\, z_{ij\tau_0} + \beta_2\, \Delta g_{j,\tau} \times n_{ij\tau_0} + \gamma_2\, n_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau} \tag{18}$$

The coefficients of interest are β_1 and β_2, with the theoretical predictions implying $\beta_1 < 0$ and $\beta_2 > 0$. The results, shown in Column (3) of Table 6, are consistent with the theory.

Table 6: **Response of Scalability to Shocks**

Δs	(1)	(2)	(3)
Δg	0.017***		
	(0.002)		
$\Delta g \times s$		0.006***	
		(0.001)	
$\Delta g \times z$			-0.008***
			(0.003)
$\Delta g \times n$			0.006**
			(0.002)
Observations	16,077	16,076	16,076
R-squared	0.003	0.313	0.083
Sector	N	Y	Y

Note: Columns (1) and (2) show the results of estimating equation 16. The dependent variable is the change in scalability from 2006-2015. The independent variable in Column (1) is the China import penetration shock. In Column (2) the same shock is interacted with the baseline level of scalability in year 2006. In Column (3) and (4) the same shock is interacted with the levels of both expertise and scope in 2006 respectively.

Taken together, the tests in this section provide strong support for our theory. Our arguably parsimonious model is able to go quite far in terms of capturing the heterogeneity, both in the cross-sectional distribution as well as in the responses to common shocks.

4.4 Diffusion

Lastly, in this subsection, we document an interesting link between scalability and diffusion of knowledge across firms. The underlying hypothesis is an intuitive one: scalable expertise, i.e. knowledge that can be more readily used across different products of a given firm is also more likely to be useful to other firms in the industry. One interpretation of this assumption is that scalability is the result of practices that enhance the applicability of knowledge to different products (e.g. standardization or codification of procedures). These practices also will make it easier for such knowledge to be used outside the firm. Alternatively, one could think of scalable expertise as innovation along dimensions that are fundamentally more attractive for other firms to learn.

To do this, we first construct a novel measure of diffusion across firms. This leverages the same attribute-level information from the Nielsen data. We start from the introduction of a new characteristic by a firm and then count the number of products by other firms that share that characteristic and were introduced after that date. This is a simple, *ex-post* measure of how broad-based a given characteristic becomes within the market after its introduction. Formally, for a characteristic c introduced by firm i, we define diffusion as follows:

$$\mathbb{D}_{c,m,i,t,\tau} = \frac{\text{Num. of products with } c \text{ introduced by firm } -i \text{ between } t \text{ and } t+\tau}{\text{Num. of products introduced by firm } -i \text{ between } t \text{ and } t+\tau}$$

where the numerator counts the number of times a characteristic c introduced by firm i in module m is observed in products introduced by other firms in the same module between time t and time $t+\tau$. The denominator counts the total amount of products introduced by other firms between n t and $t+\tau$. Clearly, $D_{c,m,i,t,\tau}$ is always between 0 and 1.

Our main empirical specification takes the form:

$$\mathbb{D}_{cmit\tau} = \alpha + \beta\, \mathcal{SI}_{amit-1} + \gamma\, n_{mit} + \lambda_{amt\tau} + \theta_{ami} + \epsilon_{amit\tau} \tag{19}$$

where c, a, m, i, and t denote the characteristic, attribute, product module, firm and time period, respectively. Thus, the dependent variable $\mathbb{D}_{cmit\tau}$ is the diffusion measure described above, while $\mathcal{SI}_{amit-1}$ is our Scalability Index measured for a given attribute a in firm i and module m in period $t-1$. Our coefficient of interest is β: in other words, we are interested in how the diffusion of a particular feature introduced by firm i over $(t, t+\tau)$ relates to the scalability of that firm in $t-1$. Lagging scalability is a way to deal with potential endogeneity concerns.

We estimate this relationships controlling for the total number of products of the firm in the same module, $N_{m,i,t}$, and under several specifications of fixed effects; the most saturated one has both attribute $\times$ module $\times$ time $\times$ age, $\lambda_{a,m,t,\tau}$, as well as firm $\times$ attribute $\times$ module effects, $\theta_{a,m,i}$. Our results, presented in columns (1)-(2) Table 7, show that the level of scalability is indeed positively associated with the level of diffusion. In particular, column (2) shows that the relationship is strong and significant after controlling for attribute $\times$ module $\times$ time $\times$ age effects.

Our strategy for measuring diffusion also points to an alternative way of defining scalability as a 'forward-looking' measure: specifically, by treating scalability as diffusion within a firm, we can construct an *ex-post* measure of how scalable a new feature turns out to be. Formally, this alternative Scalability Index for a characteristic c introduced by firm i is defined as:

$$\widetilde{\mathcal{SI}}_{cmit\tau} = \frac{\text{Num. of products with } c \text{ introduced by firm } i \text{ between } t \text{ and } t+\tau}{\text{Num. of products introduced by firm } i \text{ between } t \text{ and } t+\tau}$$

We repeat our earlier analysis with this alternative measure of scalability, i.e. estimate the following specification:

$$\mathbb{D}_{cmit\tau} = \alpha + \beta\, \widetilde{\mathcal{SI}}_{amit-1} + \gamma\, n_{mit} + \lambda_{amt\tau} + \theta_{ami} + \epsilon_{amit\tau} \tag{20}$$

where, as before, the scalability measure $\widetilde{\mathcal{SI}}$ is aggregated to the attribute level and lagged. Again, as before, we include the total number of products sold by the firm, $N_{m,i,t}$ and various fixed effects as controls. The results are shown in columns (3) and (4) in Table 7 and confirm that the strong positive relationship between diffusion and lagged scalability is robust to this alternative measure.

Table 7: **Diffusion and Scalability**

Diffusion	(1)	(2)	(3)	(4)
$\mathcal{SI}$	0.0599***	0.0097***		
	(0.000)	(0.001)		
$\widetilde{\mathcal{SI}}$			0.1326***	0.0282***
			(0.000)	(0.001)
n	-0.0292***	-0.0057***	-0.0013***	-0.0028***
	(0.000)	(0.000)	(0.000)	(0.001)
Observations	3,319,518	3,234,863	3,269,030	3,183,439
R-squared	0.808	0.914	0.812	0.913
Firm-Attribute-Module	N	Y	N	Y
Attribute-Module-Time-Age	Y	Y	Y	Y

Note: The table shows the results of estimating equation 19. The dependent variable is $\mathbb{S}_{c,m,i,t,\tau}$, the diffusion of characteristic c, launched in module m, by firm i between periods t and $t+\tau$. The independent variable in column (1) and (2) is the scalability $\mathcal{S}_{a,m,i,t-1}$ of a given attribute a in firm i and module m in period $t-1$. Details on the construction of these variables can be found in Section 4.1. The independent variable in column (3) and (4) is the scalability $\mathbb{S}_{a,m,i,t-1}$ of a given attribute a in firm i and module m in period $t-1$. All the specifications include a control for the total number of products sold by firm i in module m at time t.

Lastly, we use an instrumental variable approach to further demonstrate the connection between diffusion and scalability. In particular, we use the sectoral demand shocks as an instrument for scalability. In other words, we ask whether changes in scalability induced by demand shocks have an effect on the diffusion of new characteristics in that market. We test this hypothesis using a simple two-stage procedure. The first stage is given by equation (17), where we showed that scalability responds positively to exogenous changes in demand. The second stage is the following specification:

$$\Delta \ln \mathbb{D}_{ij\tau} = \alpha + \beta\, \Delta\widehat{s}_{ij\tau} + \gamma_1\, z_{ij\tau_0} + \gamma_2\, \Delta g_{j\tau} \times z_{ij\tau_0} + \Gamma_j + \epsilon_{ij\tau} \tag{21}$$

The dependent variable is the change in the (log of) our diffusion measure at the firm-level between 2006 and 2015. Table 8 presents the results. Column (1) shows the results of regression the change of diffusion on the change in scalability. In Column (2) we instrument the change in scalability using the fitted values from equation 17. It shows a strong positive association between the changes in scalability over this period and the changes in diffusion. Since we have previously shown in Table 6 that the changes in scalability are also related to the changes in scope and expertise over this period, in Column (3) we control for these effects and we include their interaction with the China penetration shock. In Column (4), we show the results of the instrumental variable approach including the controls and sector fixed effects, which is our preferred specification. Overall, we find a positive relation between scalability and diffusion implying that shocks increasing the diffusion of knowledge within the firm also increase the diffusion of knowledge outside the firm to the entire industry.

Table 8: Diffusion and Scalability - IV

	(1)	(2)	(3)	(4)
Δ Diffusion				
Δs	-0.018	0.201***	0.100***	0.100***
	(0.016)	(0.039)	(0.038)	(0.038)
Observations	8,453	8,433	8,433	8,432
R-squared	0.000	-0.024	-0.005	-0.004
Sector	N	N	N	Y
Controls	N	N	Y	Y
Shock	China	China	China	China
Estimator	OLS	IV	IV	IV

Note: The table presents the regressing the changes in diffusion on the changes in scalability. The dependent variable is the log change in diffusion of firm i in sector j in the period τ. The independent variable is the log change in scalability of firm i in sector j in the period τ. Column (1) shows the results of a simple OLS. Column (2) uses an instrumental variable approach, where the first stage is depicted in equation 17. Column (3) controls for the total revenue of the firm along with its interaction with the China penetration shock. Column (4) includes the same controls and sector effects.

5 Conclusion

The preceding sections develop and validate a rich model of firm size, based on the idea of firms as composite of multiple 'units'. Central to the forces at work is the concept of *scalability* of the firm's knowledge capital. The analysis delivers a simple, yet empirically relevant, insight: the effects of changes in the external environment can be heterogeneous, depending not so much on the overall size of the firm but on its scope and unit-level fundamentals.

There are many promising directions for future research. Our theoretical framework was kept intentionally simple and abstracts from many realistic elements (e.g. within-firm heterogeneity). We also abstracted from dynamics and stochastic fundamentals, both of which are no doubt essential to paint a complete picture of firm heterogeneity. Incorporating these elements and undertaking a full-fledged quantitative analysis is a natural, if ambitious, next step. Finally, exploring the aggregate implications of the link between scalability and diffusion (demonstrated in the previous section) is another interesting direction.

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A Proofs and derivations

B A Dynamic Model of Expertise as Precision

In this Appendix, we present a dynamic model, where expertise is micro-founded with an informational interpretation. We will describe the setup in discrete time and then take the continuous time limit. At time t, firm i operates a measure N_{it} of products (indexed by $s \in [0, N_{it}]$). The operating costs of a product are denoted F_t. [14] We suppress the sector subscript from the main text to lighten the notational burden.

Expertise Operating profits are determined by how precisely the firm is able to execute a series of tasks (production, distribution, marketing etc.), i.e. its *expertise*. We model this complicated, high-dimensional object using a tracking problem: the more closely the firm's operating decisions track an optimal or 'target' action, the higher are profits. Formally, at each t, a product line has a target action, denoted $\tilde{a}^*_{ist}$, which is the sum of two (mutually independent) components: a common (i.e. firm-wide) one, denoted $\tilde{a}^*_{it}$ and an idiosyncratic (i.e. product-specific) one $\tilde{a}^*_{ist}$:

$$\tilde{a}^*_{ist} = a^*_{it} + a^*_{ist} \quad , \tag{22}$$

where a^*_{ist} is iid across products.

For each product, the firm chooses a pair of actions $\{a_{it}, a_{ist}\}$. The operating profit from a product line are decreasing in the mean squared tracking error: specifically, they are proportional to the inverse of the expected squared deviations of the cumulative action $a_{it} + a_{ijt}$ from the target $a^*_{it} + a^*_{ijt}$:

$$\Pi_{ist} \quad = \quad \frac{G_t}{\mathbb{E}\left[\left((a_{it} + a_{ist}) - (a^*_{it} + a^*_{ist})\right)^2\right]} \tag{23}$$

where G_t is the general equilibrium constant (see main text). Exploiting the independence of firm-wide and product-specific components, we can express the profit as follows:

$$\Pi_{ijt} \quad = \quad \frac{G_t}{\mathbb{E}\left[(a_{it} - a^*_{it})^2\right] + \mathbb{E}\left[(a_{ist} - a^*_{ist})^2\right]} \quad = \quad G_t \quad Z(x_{it} \ , \ y_{ist}) \quad , \tag{24}$$

where

$$\boxed{Z(x_{it} \ , \ y_{ist}) \equiv \left(\frac{1}{x_{it}} + \frac{1}{y_{ist}}\right)^{-1}} \qquad x_{it} \equiv \frac{1}{\mathbb{E}\left[(a_{it} - a^*_{it})^2\right]} \qquad y_{ist} \equiv \frac{1}{\mathbb{E}\left[(a_{ist} - a^*_{ist})^2\right]} \quad .$$

We will refer to x_{it} (the precision with respect to firm-wide targets) as the *scalable* expertise of the firm and the set of and $\{y_{ist}\}$ (the precision associated with the product-specific components of target actions) as its *non-scalable* expertise.

We now turn to describing the stochastic processes for the target action as well as the firm's information.

[14] We allow this to be time-varying, which would be the case if it were denominated in labor units in an economy with rising wages.

We start with a discrete time specification and then take the continuous time limit. In the interest of brevity, we show the detailed derivations only for the firm-wide component a_i^* (the one for $\tilde{a}_{is}^*$ follows the same steps). Over a small interval dt, the process a_{it}^* evolves according to:

$$a_{it+dt}^* = a_{it}^* \left[1 + (\rho - 1)\, dt\right] + \varepsilon_{it+dt} \,, \qquad \varepsilon_{it+dt} \sim N\left(0, \sigma_\varepsilon^2 dt\right) \,,$$

where $\rho \leq 1$ indexes the persistence of the process.

Before choosing its actions at $t + dt$, the firm observes q_{it}^x signals (the choice of q_{it}^x is described later in this section), each of which is a noisy signal of the current target:

$$m_{it+dt}^k = a_{it+dt}^* + u_{it+dt}^k \,, \quad \text{with} \qquad u_{it+1}^k \sim N\left(0, \frac{1}{dt}\right) .$$

Finally, the firm also has access to an exogenous signal of the current innovation:[15]

$$s_{it+dt} = \varepsilon_{it+dt} + v_{it+dt}, \quad \text{where} \quad v_{it+dt} \sim N\left(0, \sigma_{st}^2\right) \quad \text{with} \quad \sigma_{st}^2 = \frac{\sigma_\varepsilon^2 dt}{x_{it} - 1} \,. \tag{25}$$

After observing the exogenous signal, the residual uncertainty about the innovation is given by:

$$\sigma_{\varepsilon,dt}^2 = \left(\frac{1}{\sigma_\varepsilon^2 dt} + \frac{x_{it} - 1}{\sigma_\varepsilon^2 dt}\right)^{-1} = \frac{\sigma_\varepsilon^2 dt}{x_{it}} \quad . \tag{26}$$

Then, given x_{it}, i.e. the precision over a_{it}^*, we have

$$\begin{aligned}
\text{Prior precision over } a_{it+dt}^* &= \left(\frac{\left(1 + (\rho - 1)\, dt\right)^2}{x_{it}} + \sigma_{\varepsilon,dt}^2\right)^{-1} = \left(\frac{\left(1 + (\rho - 1)\, dt\right)^2}{x_{it}} + \frac{\sigma_\varepsilon^2 dt}{x_{it}}\right)^{-1} \\
&= \frac{x_{it}}{\left(1 + (\rho - 1)\, dt\right)^2 + \sigma_\varepsilon^2 dt} \\
\text{Post. precision over } a_{it+dt}^* &= \frac{x_{it}}{\left(1 + (\rho - 1)\, dt\right)^2 + \sigma_{\varepsilon,dt}^2 x_{it}} + \sum_{k=1}^{q_{it}^x} dt \quad \equiv \quad x_{it+dt} \\
\Rightarrow \qquad x_{it+dt} - x_{it} &= \frac{x_{it}}{\left(1 + (\rho - 1)\, dt\right)^2 + \sigma_\varepsilon^2 dt} + q_{it}^x dt - x_{it} \\
&= x_{it} \left[\frac{-\left((\rho - 1)\, dt\right)^2 - 2\,(\rho - 1)\, dt - \sigma_\varepsilon^2 dt}{\left(1 + (\rho - 1)\, dt\right)^2 + \sigma_\varepsilon^2 dt}\right] + q_{it}^x dt \\
\Rightarrow \qquad \frac{x_{it+dt} - x_{it}}{dt} &= x_{it} \left[\frac{-\,(\rho - 1)^2 dt - 2\,(\rho - 1) - \sigma_\varepsilon^2}{\left(1 + (\rho - 1)\, dt\right)^2 + \sigma_\varepsilon^2 dt}\right] + q_{it}^x \\
\frac{dx_{it}}{dt} &= \lim_{dt \to 0} \frac{x_{it+1} - x_{it}}{dt} = x_{it} \left[-2\,(\rho - 1) - \sigma_\varepsilon^2\right] + q_{it}^x \\
&= -\delta^x x_{it} + q_{it}^x \quad .
\end{aligned}$$

[15] The scaling of the precision of this signal with x_{it} is not crucial and is made for analytical tractability.

Let $\dot{x}_{it} \equiv \lim_{dt \to 0} \frac{x_{it+dt} - x_{it}}{dt}$. Then, the law of motion for the firm's scalable expertise becomes:

$$\boxed{\dot{x}_{it} = -\delta^x x_{it} + q^x_{it}}, \qquad \text{where} \quad \delta^x \equiv \sigma^2_\varepsilon - 2\,(1-\rho) \tag{27}$$

is a composite parameter that reflects the effective depreciation rate of the firm's common expertise. It is increasing in the variability of innovations to the target action process (σ^2_ε) and decreasing in its persistence. The initial condition is given by $x_{is} = x_0$ where s is the time at which the firm is born and x_0 is the exogenous prior precision about the firm-wide component.

An analogous argument leads to the following evolution for product-specific expertise:

$$\boxed{\dot{y}_{ist} = -\delta^y y_{ist} + q^y_{ist}}\,. \tag{28}$$

Flow profits The firm's flow profit can be expressed as

$$\Pi_{it} \equiv \int_0^{n_{it}} (G_t Z_{ijt} - F_t) dj - C_i(q^x_{it}, \{q^y_{ijt}\};\; x_{it}, \{y_{ijt}\})\,, \tag{29}$$

As before, we adopt a partial equilibrium perspective and treat both G_t and F_t as exogenous.

Firm's problem The firm chooses time-paths for scope (i.e. the measure of active product lines, n_{it}) and expertise to maximize discounted profits, i.e. solves

$$\max_{n_{it}, x_{it}, \{y_{ijt}\}} \qquad \int_0^\infty e^{-rt}\; \Pi_{it}\; dt\,. \tag{30}$$

Next, we solve this dynamic problem when the cost of accumulating expertise takes the form of a capacity constraint, as in equation (7). We also impose additional parametric restrictions that considerably simplify the analysis but are not crucial for the insights. Formally, we impose the following assumptions:

Assumption 1. *The expertise cost function C_i is given by (7).*

Assumption 2. *Depreciation rates on scalable and non-scalable expertise are equal, $\delta^x = \delta^y = \delta$.*

Assumption 3. *Initial conditions are such that the firm's optimal choices of scope and expertise accumulation are always interior.*

Under these conditions, we can prove the following result:

Proposition 4. *Suppose Assumptions 1–3 hold. Then, the optimal policy of firm i is given by a process $(x^*_{it}, y^*_{it}, n^*_{it})$, which solves the following problem at each t:*

$$(x^*_{it}, y^*_{it}, n^*_{it}) \;=\; \arg\max_{n,x,y} \qquad n(G_t Z(x,y) - F_t) \quad , \tag{31}$$

$$\textit{subject to} \qquad \frac{x}{a^x_i} + \frac{ny}{a^y_i} \;\leq\; \frac{1 - e^{-\delta(t-\tau_i)}}{\delta} \;\;\equiv Q_{it}\,. \tag{32}$$

where τ_i is the time at which the firm was born.

Thus, Assumptions 1–3 effectively turn the dynamic problem in (30) into a sequence of static problems. At each t, the firm takes its cumulative capacity since birth, adjusted for depreciation – denoted Q_{it} – and allocates it to scope, scalable and non-scalable expertise. They (in particular, Assumption 3) also imply that all active products are operated at the same level of expertise.

C Data Appendix

C.1 Product Data

C.1.1 Datasets

The Nielsen Retail Measurement Services (RMS) consists of more than 100 billion unique observations at the UPC × store × week level that cover approximately \$2 trillion in sales. This volume represents about 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores. A key distinctive feature of this database is that the collection points include more than 40,000 distinct stores from around 90 retail chains in 371 MSAs and 2,500 counties. As a result, the data provide good coverage of the universe of products and of the full portfolio of firms in this sector.

Our baseline data set combines all sales at the national and quarterly level. For each firm f in quarter t, we define sales Y_{ft} as the total sales across all stores and weeks in the quarter. Likewise, quantity y_{ft} is defined as the total quantities sold across all stores and weeks in the quarter. We identify the state of the life cycle of a firm through information on its age. Scanner data sets do not directly measure the age of a firm. We infer the age by observing the timing of its initial transaction in the data set. More specifically, we define entry as the first quarter of sales of any of its products and exit as the quarter after we last observe any item being sold. We cannot determine entry and exit for some firm. For firm that are already active in the first two quarters of the sample (2006q1 and 2006q2), we classify them as left censored. These firms can include those created just before 2006 or very established firms. Likewise, we classify firms that have transactions in the last two quarters of the sample (2015q3 and 2015q4) as right censored. For those, we cannot determine exit and thus cannot measure how long they last in the market.

Table A.I: Summary Statistics of Products by Censoring

	All	By Censoring Type			
		Complete	Right	Left	Right&Left
Total # of products	655,205	225,583	214,554	128,424	86,644
Duration (quarters)					
average	15	7.4	13	13	40
less than 4	33	52	29	31	0
less than 16	68	90	71	70	0
above 28	19	1.3	11	11	100
Revenue (quarterly, $1,000)					
mean	79	27	105	25	180
25th percentile	.5	.2	1	.1	2.2
median	3.8	1.9	7.7	1	13
75th percentile	29	13	54	7.7	89
90th percentile	147	56	233	42	407
95th percentile	342	122	482	107	833
Relative Price					
mean	-.02	-.082	.11	-.14	-.02
25th percentile	-.46	-.56	-.35	-.54	-.39
median	-.0031	-.043	.094	-.079	-.028
75th percentile	.45	.44	.56	.32	.35
90th percentile	.95	.97	1.1	.77	.78
95th percentile	1.3	1.3	1.4	1.1	1.1

Note: The table reports summary statistics for the products included in the baseline pooled sample for the period 2006q1-2015q4. For each product, we determine if it has sales in 2006q1 and in 2015q4 to determine if is left- and/or right- censored. Products that enter and are discontinued in the period under analysis are classified as "Complete", products for which we can determine entry but not exit are classified as "Right", products for which we do not observe entry but we observe exit are classified as "Left", and products for which both entry and exit cannot be determined are both right and left-censored ("Right&Left"). For each of these categories, we report the total number of observations, statistics on duration, and statistics on sales. The duration refers to the number of quarters for which we observe the products. Only for products products that enter and are discontinued in the period under analysis ("Complete") it can also be interpreted as the length of life the products. The statistics for the revenue are computed by determining the average quarterly sales (in thousands of dollars), deflated by the Consumer Price Index for All Urban Consumers. The table reports the average and distribution statistics of this variable.

Table A.II: Dispersion Across Sectors of Within-Sector (log) Sales Distribution

	Within-Sector Moments	Weighted Mean	Mean	Std. Dev.	IQ Range
All					
	Median	1.18	1.22	1.00	1.18
	IQ range	4.64	4.65	0.82	1.24
	90-10 percentile range	8.79	8.67	1.13	1.61
	95-5 percentile range	10.87	10.67	1.01	1.55
At entry					
	Median	1.71	1.40	1.35	1.61
	IQ range	4.44	4.18	0.87	1.05
	90-10 percentile range	8.11	7.65	1.20	1.25
	95-5 percentile range	10.02	9.49	1.31	1.25
At age 16					
	Median	1.62	1.44	1.10	1.59
	IQ range	5.01	4.72	1.13	1.58
	90-10 percentile range	8.83	8.44	1.29	1.93
	95-5 percentile range	10.74	10.23	1.24	1.55
At age 28					
	Median	1.84	1.48	1.38	1.88
	IQ range	4.93	4.60	1.23	1.36
	90-10 percentile range	8.74	8.13	1.58	1.86
	95-5 percentile range	10.62	9.99	1.50	1.80

Note: The table summarizes the within-sector moments of log sales across 92 product sectors. We identify product sectors according to their Nielsen classification of product group. Sales are computed by determining the average quarterly sales (in thousands of dollars), deflated by the Consumer Price Index for All Urban Consumers. For each sector, we compute the (log) sales moments across products. We use products included in the baseline pooled sample for the period 2006q1-2015q4. We provide results for all observations, and for sets of observations according to their age (new products, products with 16 quarters, and products with 28 quarters). Columns summarize the information across sectors in terms of the weighted mean (weighted by total number of products within the sector), mean, standard deviation, and inter-quartile range.

C.2 Sectoral Demand Shocks

C.2.1 House Price Shock

Table A.III: Instrumental Variables Regression - First Stage

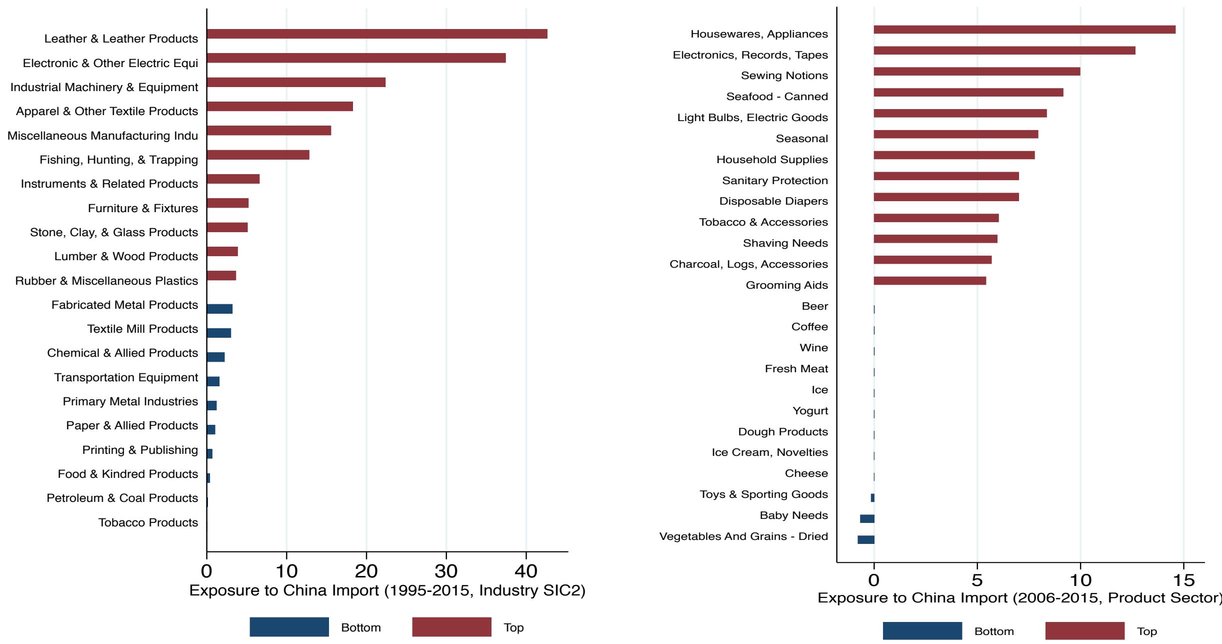
	(1)	(2)	(3)	(4)
Housing Supply Elasticity	-6.709***	-5.243***	7.260***	4.378***
	(0.838)	(0.825)	(0.980)	(0.947)
Observations	228	223	228	224
R-squared	0.221	0.371	0.195	0.418
Controls	N	Y	N	Y
Period	2001-2006	2001-2006	2006-2011	2006-2011

Note: Table shows results from the first-stage instrumental variable regression in equation 1. The unit of observation is an MSA, the dependent variable is house price growth over 2001-2006 in columns 1-2, and house price growth over 2007-2011 in columns 3-4. For the Saiz Elasticity Measure, higher values signal an MSA with more elastic housing supply. The control variables include the change in the number of retail establishments, the change in all establishments, the change in the construction share of employment, the change in the retail share of employment, and the change in the share of employment in the non-tradable sector.

C.2.2 China Import Penetration Shock

Figure A.1: China import penetration 2006–2015 by sector

(a) NETS (b) Nielsen



Note: The figure shows the average value of the baseline measure of China import penetration 2006–2015 $\Delta IP^1_{j,06-15}$ and the values of a selective group of sectors: the top and bottom 20 sectors.

C.3 Scalability

C.3.1 Illustrative Example

$$\mathcal{SI}_{mijt} \equiv 1 - \frac{\text{Unique}_{mijt}}{\text{N}_{mijt} \times \text{NumAttributes}_{mjt}}$$

An illustrative example: Firm A has the following set of products

Table A.IV: Measuring Scalability: An example (Lamps, incandescent)

		Attribute	
Firm	Product	Style	Use
General Electric	1	Clear	Nite Fixture
General Electric	2	Halogen	Appliance
General Electric	3	Clear	Bath & Vanity
General Electric	4	Clear	Ceiling Fan
General Electric	5	Frost	Chandelier

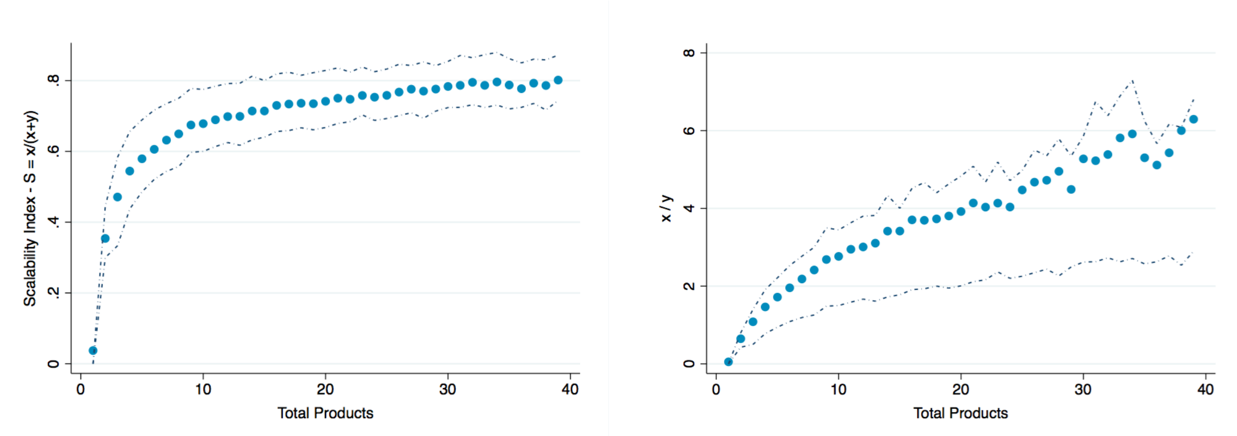
- Unique Characteristics: clear, halogen, nite fixture, etc.
- Attributes: style, use, etc.

$$\begin{aligned}
\text{Style:} \qquad S_{Style,GE} &\equiv 1 - \frac{\text{Unique Characteristics}}{\text{Number of Products}} = 1 - \frac{3}{5} = 0.4 \\
\text{Use:} \qquad S_{Use,GE} &\equiv 1 - \frac{\text{Unique Characteristics}}{\text{Number of Products}} = 1 - \frac{5}{5} = 0 \\
\text{Firm level:} \qquad S_{GE} &\equiv 1 - \frac{\text{Unique Characteristics}}{\text{Number of Products} \times \text{Number of Attributes}} = 1 - \frac{5+3}{5+5} = 0.2
\end{aligned}$$

C.3.2 Scalability and Scope

Panel (a) in Figure A.2 shows the Scalability Index as function of the total products of the firms. The figure shows that the index equals 0 for single-product firms and that, as firms grow, they are more likely to replicate the characteristics of their products across their portfolio. Panel (b) shows $S = \frac{\mathcal{S}}{1-\mathcal{S}}$, the ratio of common attributes to unique attributes, which is also increasing with the total number of products of the firm.

Figure A.2: Scalability Index - Total Number of Products



(a) Scalability Index ($\mathcal{S}$) (b) x/y ($\frac{\mathcal{S}}{1-\mathcal{S}}$).

Note: The figure shows the Scalability Index as a function of the total number of products of the firm. The index is computed using the entire portfolio of product of the firms using data from 2006 to 2015. The dashed lines indicated the 25th and 75th percentiles of the index.

We also test the correlation in a regression setting as follows

$$s_{ijt} = \log\left(\frac{\mathcal{S}_{ijt}}{1-\mathcal{S}_{ijt}}\right) = \alpha + \beta\, n_{ijt} + \Gamma_j + \epsilon_{ijt}$$

Table A.V: Scalability and Scope

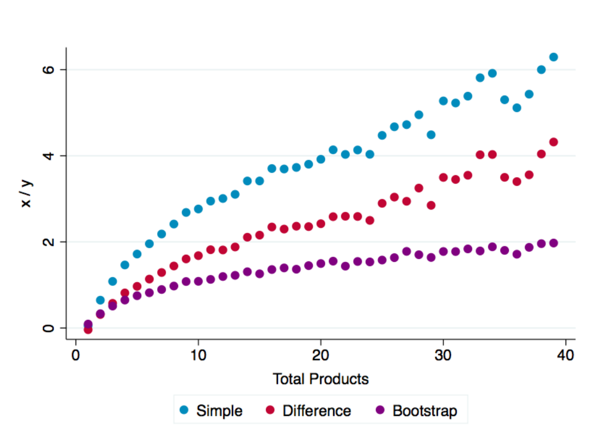
	(1)	(2)	(3)	(4)
Scalability				
n	0.6829***	0.7421***	0.6775***	0.7428***
	(0.019)	(0.020)	(0.016)	(0.018)
Constant	-0.9172***	-0.9996***	-0.9074***	-1.0009***
	(0.049)	(0.050)	(0.029)	(0.030)
Observations	49,461	47,656	49,461	47,656
Sector	N	N	Y	Y
Specification	All	Less than 100	All	Less than 100

Note: The dependent variable is the logarithm of scalability of a given firm i in sector j in period t. The independent variable is the logarithm of the total number of products of the firm. Columns 1 and 4 include all firms, columns 2 and 4 only those with less than 100 products. Columns 3-4 include sector fixed effects.

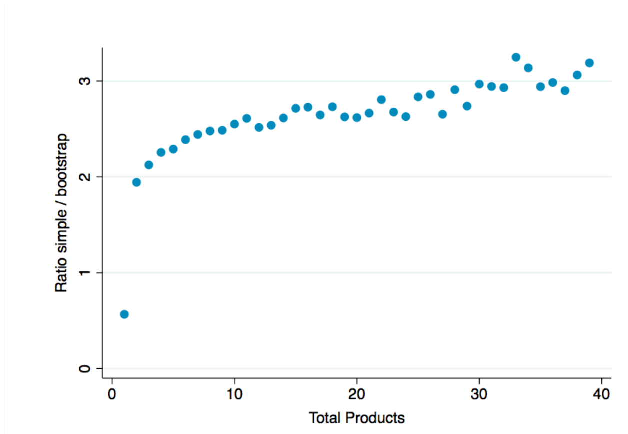
C.3.3 Bootstrap

A potential concern is that S mechanically increases as firms introduce more products. In order to minimize this concern, we construct an alternative index where we randomize products, within a module, and assign them to firm of different sizes. Then, we compute an alternative (bootstrapped) scalability index that we use as reference. Panel (a) in Figure A.3 shows our measure of S for both the original index and the bootstrapped version. The purple dots show that part of the positive relationship between S and the total number of products comes from the fact that, as firms grow, they are more likely to have products sharing common attributes. Nonetheless, our measure captures a size-dependent relationship that goes beyond that established by chance. The red dots show the difference between the original measure and the bootstrapped version. As shown in the graph, the difference is also increasing with size. Panel (b) shows the ratio between the original and the bootstrapped version. It shows that the ration increases as firms add products to the portfolio indicating that larger firms replicate characteristics across their products.

Figure A.3: S - Original vs Bootstrap



(a) S



(b) Bootstrap

Note: Panel (a) shows S as a function of the total number of products of the firm. The blue dots show the estimates using the original measure. The purple dots are the estimates of S when the sample of products is randomized within modules and across firms. The red dots are the difference between the original measure and the bootstrapped version. Panel (b) shows the ratio the estimates of S of the original and the bootstrapped version. S is computed using the entire portfolio of product of the firms using data from 2006 to 2015.

D Testable Implications using the China Shock

D.1 Construction of China Shock

In this section we describe the data sources used to update the China Shock measure by Autor et al. (2013). The U.S. value of shipments ($Y_{j,06}$) at the 4-digit 1987 SIC industry level from NBER-CES.[16] We obtain gross output ($YO_{j,06}$) at the 4-digit ISIC rev.3 industry level for several European countries from UNIDO. We pick the five largest European economies: Germany, France, UK, Italy and Spain following Bai and Stumpner (2019). These countries have the largest coverage at the 4-digit ISIC rev.3 industry level in the UNIDO data set. We use the trade flows ($M_{j,06}$,$E_{j,06}$) for both U.S. and European countries from UN Comtrade at the HS 6-digit level, obtained from CEPII-BACI (Gaulier and Zignago (2010)).[17] This data set is slightly different from the trade flows data used in Acemoglu et al. (2016) since their data on trade flows is directly from UN Comtrade. The data provided by CEPII-BACI is a harmonized version of UN Comtrade that reconcile the declarations of the exporter and the importer. This harmonization procedure extends considerably the number of countries (150 countries in CEPII_BACI) for which trade data are available, as compared to the original data set. Lastly, we use the PCE deflator provided by the BEA-NIPA for the US and the PCE deflator provided by Eurostat for the five European countries we consider.

D.2 Robustness Specifications

We use the following specifications:

1. Long changes in dependent variables and long changes in shock

$$\Delta \ln Y_{ij,06-15} = \alpha \Delta IP_{j,06-15} + \beta \Delta IP_{j,06-15} \times \ln X_{ij,06} + \gamma \ln X_{ij,06} + \sigma_j + \epsilon_{ij,06-15} \tag{33}$$

$$\begin{aligned}
\Delta IP^1_{j,06-15} &= \frac{M^{UC}_{j,15} - M^{UC}_{j,06}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100 \\
\Delta IP^2_{j,06-15} &= \frac{M^{OC}_{j,15} - M^{OC}_{j,06}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100
\end{aligned}$$

2. Semi-long changes in dependent variables and semi-long (contemporaneous) changes in shock

$$\Delta \ln Y_{ij,\tau} = \alpha \Delta IP_{j,\tau} + \beta \Delta IP_{j,\tau} \times \ln X_{ij,\tau} + \gamma \ln X_{ij,\tau} + \sigma_{jt} + \epsilon_{ij,\tau} \tag{34}$$

$$\begin{aligned}
\Delta IP^1_{j,\tau} &= \frac{\Delta M^{UC}_{j,\tau}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100 \\
\Delta IP^2_{j,\tau} &= \frac{\Delta M^{OC}_{j,\tau}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100
\end{aligned}$$

[16] http://www.nber.org/nberces

[17] http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=1

In the following regressions we use data for the following time periods: 2006–2009, 2009–2012, 2012–2015.

3. Annual changes in dependent variables and long changes in shock

$$\Delta \ln Y_{ij,t} = \alpha \Delta IP_{j,06-15} + \beta \Delta IP_{j,06-15} \times \ln X_{ij,t-1} + \gamma \ln X_{ij,t-1} + \sigma_{jt} + \epsilon_{ij,t} \quad (35)$$

$$\Delta IP^1_{j,06-15} = \frac{M^{UC}_{j,15} - M^{UC}_{j,06}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

$$\Delta IP^2_{j,06-15} = \frac{M^{OC}_{j,15} - M^{OC}_{j,06}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

4. Annual changes in dependent variables and (lagged) annual shock

$$\Delta \ln Y_{ij,t} = \alpha \Delta IP_{j,t-1} + \beta \Delta IP_{j,t-1} \times \ln X_{ij,t-1} + \gamma \ln X_{ij,t-1} + \sigma_{jt} + \epsilon_{ij,t} \quad (36)$$

$$\Delta IP^1_{j,t} = \frac{M^{UC}_{j,t} - M^{UC}_{j,t-1}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

$$\Delta IP^2_{j,t} = \frac{M^{OC}_{j,t} - M^{OC}_{j,t-1}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

5. Annual changes in dependent variables and (contemporaneous) annual shock

$$\Delta \ln Y_{ij,t} = \alpha \Delta IP_{j,t} + \beta \Delta IP_{j,t} \times \ln X_{ij,t-1} + \gamma \ln X_{ij,t-1} + \sigma_{jt} + \epsilon_{ij,t} \quad (37)$$

$$\Delta IP^1_{j,t-1} = \frac{M^{UC}_{j,t-1} - M^{UC}_{j,t-2}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

$$\Delta IP^2_{j,t-1} = \frac{M^{OC}_{j,t-1} - M^{OC}_{j,t-2}}{Y_{j,06} + M_{j,06} - E_{j,06}} \times 100$$

In what follows we use lower case letters to refer to variables in logs (e.g. $\ln(X) = x$) and we refer to the demand shocks (e.g. China import penetration shock ΔIP) as Δg.

D.2.1 Heterogeneous Response to Demand Shocks: Robustness

Table A.VI: Heterogeneous Response to Demand Shocks - Size (Sales)

	(1)	(2)	(3)
Δzn			
$\Delta g \times zn$	0.054***	0.061***	0.201***
	(0.001)	(0.001)	(0.062)
Observations	538,199	514,314	34,574
R-squared	0.077	0.089	0.115
Sector	Y	Y	Y
Shock	Housing	Housing	China
Period	2001-2006	2007-2011	2006-2015
Data	NETS	NETS	NETS

Note: The table reports the results of estimating equation 14. The dependent variable is the log change in the total sales of firm i in sector j in the period τ. The reported coefficient is the effect of changes in exposure to demand shocks by firm size. The first three columns use the NETS data and the last two the Nielsen data. Column 1 uses as demand shock the housing price shock from 2001-2006, Columns 2 and 4 the housing price shock from 2006-2011, and Column 3 and 5 the China import penetration shock. All the specifications include sector effects.

Table A.VII: Heterogeneous Response to Demand Shocks - Extensive and Intensive Margins (Sales)

	(1) Δz	(2) Δn	(3) Δz	(4) Δn	(5) Δz	(6) Δn
$\Delta g \times zn$	0.019***	0.036***	0.029***	0.032***	0.144**	0.057**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.056)	(0.025)
Observations	538,199	538,694	514,314	515,328	34,574	34,581
R-squared	0.051	0.060	0.058	0.065	0.095	0.046
Sector	Y	Y	Y	Y	Y	Y
Shock	Housing	Housing	Housing	Housing	China	China
Period	2001-2006	2001-2006	2007-2011	2007-2011	2006-2015	2006-2015
Data	NETS	NETS	NETS	NETS	NETS	NETS

Note: The table reports the results of estimating equation 14. The dependent variables are the change in the number of plants/products of firm i in sector j in period τ ($\Delta \log N_{ij,\tau}$) or the change in the sales per plant/product ($\Delta \log Z_{ij,\tau}$). The reported coefficient is the effect of changes in exposure to demand shocks by firm size. The first six columns use the NETS data and the last three the Nielsen data. Column 1 an 2 use as demand shock the housing price shock from 2001-2006, Columns 3,4,7, and 8 the housing price shock from 2006-2011, and Column 6 and 9 the China import penetration shock. All the specifications include sector effects.

Table A.VIII: Elasticity of Scope to Aggregate Demand Shocks (Sales)

	(1)	(2)	(3)
Δn			
$\Delta g \times n$	0.021***	0.018***	0.057***
	(0.000)	(0.000)	(0.012)
$\Delta g \times z$	0.006***	0.006***	-0.000
	(0.000)	(0.001)	(0.029)
Observations	538,694	515,328	34,575
R-squared	0.127	0.121	0.127
Sector	Y	Y	Y
Shock	Housing	Housing	China
Period	2001-2006	2007-2011	2006-2015
Data	NETS	NETS	NETS

Note: The table reports the results of estimating equation 14. The dependent variable is the change in the scope of firm i in sector j between τ_0 and τ ($\Delta n_{ij,\tau}$). The reported coefficients are the effects of changes in exposure to demand shocks by the level of scope of the firms or their level of expertise at the initial period. The first three columns use the NETS data and the last two the Nielsen data. Column 1 uses as demand shock the housing price shock from 2001-2006, Columns 2 and 4 the housing price shock from 2006-2011, and Column 3 and 5 the China import penetration shock. All the specifications include sector effects.

D.2.2 Long changes in dependent variables and long changes in shock

Table A.IX: The Scope Effect of Chinese Import Penetration

Δn	(1)	(2)	(3)	(4)
Δg	-3.75***		-6.23***	
	(0.689)		(1.484)	
$\Delta g \times z$	1.51**	1.12*	5.40***	5.44***
	(0.689)	(0.640)	(1.032)	(0.797)
Observations	21,320	21,320	21,320	21,320
R-squared	0.009	0.040	0.073	0.141
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in number of products of firm i in Sector j between 2006 and 2015, $\Delta n_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^{1}_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

Table A.X: The Scope Effect of Chinese Import Penetration: Alternative measure of China Imports Exposure

Δn	(1)	(2)	(3)	(4)
Δg	-3.68***		-7.54**	
	(1.219)		(3.005)	
$\Delta g \times z$	1.94*	1.21	6.80***	6.60***
	(1.068)	(1.077)	(2.574)	(2.154)
Observations	21,320	21,320	21,320	21,320
R-squared	0.004	0.040	0.065	0.134
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in number of products of firm i in Sector j between 2006 and 2015, $\Delta n_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^2_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XI: The Expertise Effect of Chinese Import Penetration

Δz	(1)	(2)	(3)	(4)
Δg	-14.24***		-14.95***	
	(2.761)		(3.289)	
$\Delta g \times z$	-4.86*	-6.40***	4.42*	3.70*
	(2.709)	(2.366)	(2.251)	(2.187)
Observations	21,320	21,320	21,320	21,320
R-squared	0.101	0.164	0.038	0.094
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in number of products of firm i in Sector j between 2006 and 2015, $\Delta n_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^1_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XII: The Expertise Effect of Chinese Import Penetration: Alternative measure of China Imports Exposure

Δz	(1)	(2)	(3)	(4)
Δg	-19.37***		-13.10*	
	(5.294)		(7.241)	
$\Delta g \times z$	-6.28	-10.29***	1.77	0.78
	(4.769)	(3.632)	(5.247)	(2.901)
Observations	21,320	21,320	21,320	21,320
R-squared	0.096	0.164	0.012	0.092
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in number of products of firm i in Sector j between 2006 and 2015, $\Delta n_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^2_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XIII: The Scalability Effect of Chinese Import Penetration

Δs	(1)	(2)	(3)	(4)
Δg	-2.45***		-4.56***	
	(0.593)		(0.678)	
$\Delta g \times z$	1.23	0.81	2.71***	2.42***
	(0.852)	(0.729)	(0.687)	(0.549)
Observations	16,077	16,076	16,077	16,076
R-squared	0.005	0.031	0.042	0.085
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in baseline scalability of firm i in Sector j between 2006 and 2015, $\Delta s_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^1_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XIV: The Scalability Effect of Chinese Import Penetration: Alternative measure of China Imports Exposure

Δs	(1)	(2)	(3)	(4)
Δg	-2.92***		-3.88**	
	(0.883)		(1.854)	
$\Delta g \times z$	1.95*	1.22	3.23**	3.01**
	(1.087)	(1.109)	(1.612)	(1.467)
Observations	16,077	16,076	16,077	16,076
R-squared	0.004	0.031	0.025	0.083
Sector	N	Y	N	Y
Weights	N	N	Y	Y

Note: The dependent variable is 100 times the log change in baseline scalability of firm i in Sector j between 2006 and 2015, $\Delta s_{ij,06-15}$. The import penetration measure in all regressions is the change in Chinese imports between 2006 and 2015, $\Delta g^2_{j,06-15}$, as defined above. Δz refers to standardized (log) total sales divided by total products in 2006. Each regression controls for the variable Δz and different sets of fixed-effects. The results are estimated by OLS for a balanced sample of firms that are active every year between 2006 and 2015. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (2) and (4) do not report the coefficient on Δg because the shock varies with product category and it becomes collinear with the product category fixed-effects. Robust standard errors in parenthesis are clustered at the product category level.

D.2.3 Semi-long changes in dependent variables and semi-long changes in shock

Consider an alternative estimation strategy consists of running equations of the following type

$$\Delta y_{ij,\tau} \quad = \quad \alpha \Delta g_{j,\tau} + \beta \Delta g_{j,\tau} \times x_{ij,\tau} + \gamma x_{ij,\tau} + \sigma_j + \delta_t + \epsilon_{ij,\tau} \tag{38}$$

where $\Delta y_{ij,t}$ is 100 times the log change in the outcome of firm i in Sector j over the period τ; $\Delta g_{j,\tau}$ is a measure of change in Chinese import penetration in product category over the period τ; $x_{ij,\tau}$ is log of revenue per product in the beginning of the period τ(standardized); σ_j and δ_t are product category and period fixed-effects; and $\epsilon_{ij,t}$ in the error term. In the following regressions we use data for the following time periods: 2006–2009, 2009–2012, 2012–2015.

Table A.XV: The Scope Effect of Chinese Import Penetration: Semi-long

Δn	(1)	(2)	(3)	(4)	(5)	(6)
Δg	-0.57		-0.64		-2.50*	
	(0.599)		(1.117)		(1.373)	
$\Delta g \times z$	1.04***	1.00***	1.78***	1.91***	1.69***	1.38***
	(0.320)	(0.309)	(0.424)	(0.349)	(0.566)	(0.481)
Observations	95,548	95,548	95,548	95,548	63,927	63,927
R-squared	0.017	0.025	0.079	0.103	0.024	0.069
Product Category	Y	N	Y	N	Y	N
Period x Product Category	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in number of products of firm i in the period τ, $\Delta \ln N_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^1_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XVI: The Scope Effect of Chinese Import Penetration: Semi-long, Alternative Measure of China Imports Exposure

Δn	(1)	(2)	(3)	(4)	(5)	(6)
Δg	-0.13		-0.46		1.74	
	(0.820)		(0.891)		(1.541)	
$\Delta g \times z$	1.55***	1.61***	2.26**	2.40**	0.70	0.77
	(0.546)	(0.471)	(0.999)	(0.959)	(0.768)	(0.494)
Observations	95,548	95,548	95,548	95,548	63,927	63,927
R-squared	0.017	0.025	0.079	0.103	0.020	0.068
Product Category	Y	N	Y	N	Y	N
Period x Product Category	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in number of products of firm i in the period τ, $\Delta \ln N_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^2_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XVII: The Expertise Effect of Chinese Import Penetration: Semi-long

Δz	(1)	(2)	(3)	(4)	(5)	(6)
Δg	2.74**		0.27		-2.55	
	(1.089)		(1.962)		(1.699)	
$\Delta g \times z$	-2.83***	-2.37***	1.20	2.23	-0.79	-1.01
	(0.797)	(0.811)	(1.602)	(1.475)	(1.088)	(1.089)
Observations	95,464	95,464	95,464	95,464	63,919	63,919
R-squared	0.088	0.092	0.030	0.039	0.068	0.082
Sector	Y	N	Y	N	Y	N
Period x Sector	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in revenue per profit of firm i in Sector j in the period τ, $\Delta z_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^1_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XVIII: The Expertise Effect of Chinese Import Penetration: Semi-long, Alternative Measure of China Imports Exposure

Δz	(1)	(2)	(3)	(4)	(5)	(6)
Δg	1.73		-3.19**		5.26	
	(1.949)		(1.579)		(3.217)	
$\Delta g \times z$	-5.98***	-5.95***	3.20**	3.34**	-5.92**	-6.25**
	(1.824)	(1.839)	(1.558)	(1.672)	(2.584)	(2.687)
Observations	95,464	95,464	95,464	95,464	63,919	63,919
R-squared	0.088	0.092	0.030	0.039	0.069	0.083
Product Category	Y	N	Y	N	Y	N
Period x Product Category	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in revenue per profit of firm i in Sector j in the period τ, $\Delta z_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^2_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XIX: The Scalability Effect of Chinese Import Penetration: Semi-long

Δs	(1)	(2)	(3)	(4)	(5)	(6)
Δg	-0.73		-0.51		-1.58	
	(0.653)		(1.297)		(1.109)	
$\Delta g \times z$	1.04***	0.99**	1.33***	1.22***	1.16**	0.89*
	(0.397)	(0.381)	(0.353)	(0.347)	(0.531)	(0.490)
Observations	69,215	69,212	69,215	69,212	51,268	51,265
R-squared	0.013	0.020	0.044	0.072	0.013	0.034
Product Category	Y	N	Y	N	Y	N
Period x Product Category	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in our baseline scalability firm i in Sector j in the period τ, $\Delta s_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^1_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

Table A.XX: The Scalability Effect of Chinese Import Penetration: Semi-long, Alternative measure of Chinese Import Penetration

Δs	(1)	(2)	(3)	(4)	(5)	(6)
Δg	0.02		1.54		1.38	
	(1.298)		(1.481)		(1.933)	
$\Delta g \times z$	1.81**	2.04***	1.18	1.36	1.06	1.44**
	(0.762)	(0.608)	(0.942)	(0.838)	(0.854)	(0.557)
Observations	69,215	69,212	69,215	69,212	51,268	51,265
R-squared	0.013	0.020	0.046	0.071	0.012	0.034
Product Category	Y	N	Y	N	Y	N
Period x Product Category	N	Y	N	Y	N	Y
Weights	N	N	Y	Y	N	N

Note: The dependent variable is 100 times the log change in our baseline scalability firm i in Sector j in the period τ, $\Delta s_{ij,\tau}$. The import penetration measure in all regressions is the change in Chinese imports in the period τ, $\Delta g^2_{j,\tau}$, as defined above. Δz refers to standardized (log) total sales divided by total products in the beginning of period τ. Each regression controls for the variable Δz and different sets of fixed-effects. Columns (1) and (2) presents the results of OLS for all observations. Columns (3) and (4) presents the results for weighted OLS, where the weights are the total number of products of each firm. Columns (5) and (6) presents the results of OLS for a balanced sample of firms that are active every year between 2006 and 2015. We use data for the following time periods: 2006–2009, 2009–2012, 2012–2015. Robust standard errors in parenthesis are clustered at the product category level.

E Diffusion

$$\mathbb{D}_{cmit\tau} = \alpha + \beta\, s_{amit-1} + \gamma\, n_{mit} + \lambda_{amt\tau} + \theta_{ami} + \epsilon_{amit\tau} \tag{39}$$

Table A.XXI: Diffusion and Scalability S

	(1)	(2)	(3)	(4)
Diffusion				
$\mathcal{SI}$	0.0184***	0.0047***		
	(0.000)	(0.000)		
$\widetilde{\mathcal{SI}}$			0.0151***	0.0083***
			(0.000)	(0.000)
n	-0.0337***	-0.0082***	-0.0020***	-0.0039***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2,617,434	2,571,827	2,088,205	2,082,748
R-squared	0.805	0.901	0.516	0.636
Firm-Attribute-Module	N	Y	N	Y
Attribute-Module-Time-Age	N	Y	N	Y

Note: The table presents the results of estimating equation 39 to analyze the relationship between scalability and diffusion. The dependent variable is $D_{cmit\tau}$, the diffusion of characteristic c, launched in module m, by firm i between periods t and $t+\tau$. Details on the construction of this variable can be found in Section 4.1. The independent variable in columns (1) and (2) is the logarithm of scalability $S_{amit-1} = \mathcal{SI}_{amit-1}/(1 - \mathcal{SI}_{amit-1})$ of a given attribute a in firm i and module m in period $t-1$. The independent variable of column (3) and (4) is the logarithm of scalability $\widetilde{\mathcal{SI}}_{amit-1}/(1 - \widetilde{\mathcal{SI}}_{amit-1})$ of a given attribute a in firm i and module m in period $t-1$. All the specifications include a control for the total number of products sold by firm i in module m at time t.