Spillovers and Redistribution through Intra-Firm Networks: The Product Replacement Channel [*]

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Abstract

We study how regional shocks spill over across US local markets through intra-firm market networks and explore how such spillovers reshape household welfare across regions. We identify spillovers by linking data on barcode-region-level prices and quantities with producer-level information and by exploiting variation in firms' exposure to sudden differential drops in local house prices. We find that a firm's local sales decrease in response to a direct negative local demand shock and do so more strongly to indirect negative demand shocks originating in its other markets. The intra-firm cross-market spillover effects occur because (i) firms replace higher-value products—higher sales per product, unit price, and organic sales share—with lower-value products in response to negative demand shocks, and (ii) such product replacements are synchronized across markets within each firm. Counterfactual analysis using multiregion model with endogenous quality adjustment shows that our channel generates a novel and economically sizable regional redistribution effect during the Great Recession.

JEL Codes: E20, E32, F44, L11, L22, R32.

Keywords: Network, Spillover, Product Creation, Regional Redistribution, Regional Risk-Sharing, the Great Recession, House Prices.

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1 Introduction

How do regional shocks spill over and affect other regions in the economy? What distributional consequences do such spillovers have across regions? These longstanding questions in the macroeconomics and international economics literature have been extensively studied in an effort to understand the source of business cycle comovements and international risk-sharing. However, such questions have become equally relevant in within-country contexts, especially during and in the aftermath of the Great Recession. As the crisis involved a large *differential* collapse in local housing markets followed by wide disparities in regional economic activity within the United States, seminal papers, such as Mian et al. (2013) and Mian and Sufi (2014), established a large effect of changes in local housing market conditions on local consumption and non-tradable employment. The effect of such regional shocks, however, may not be restricted to local markets of origin, because the economy is highly connected across regions through various linkages; regional shocks could spill over and propagate and potentially reshape household welfare across regions. Given the importance of such spillovers, previous studies have identified numerous channels that could generate regional shock spillovers, such as trade, supply chains, and financial networks.

What is particularly not well understood in the literature is the role of spatial networks created by *multimarket firms*—producers selling their products in multiple counties and states that play an important role in US economic activities.[1] Because these firms could make their product supply decisions at the firm level, the appearance of a negative demand shock in one market can cause them to change their product supply decisions in another market. Three outcomes are possible. First, when firms face a negative demand shock and cannot sell their products in one market, they might sell their products in the other market to maintain their firm-level sales (e.g., Almunia et al. 2020). In this case, a decrease in demand and sales in one market leads to an increase in sales in the other market. Second, if firms that face a negative demand shock in one market have difficulty financing at the firm level due to the resulting low cash flow, the increase in financial costs might force these firms to decrease their supply of goods in the other market (e.g., Berman et al. 2015). Third, it is possible that firms make their decision entirely at the local level and do not spill over the regional shock, as standard international macro and trade models with constant marginal costs predict (e.g., Backus et al. 1992; Melitz 2003). In these models, exogenous foreign demand shocks that affect the export demand of an exporting company do not affect its domestic sales.

This paper fills this gap by investigating whether and how regional shocks spill over across regions through intra-firm spatial networks of multimarket firms and explores how the identified mechanism reshapes household welfare across local markets.

[1] Based on calculations from the ACNielsen Retail Scanner database, approximately 80% of consumer goods producers sell their products in multiple states, and these multistate firms accounted for more than 99% of total consumer goods expenditures in 2007 (Figure A.1 in Appendix B).

To identify the spillover effect, we construct detailed micro-level data that link barcode-region-level prices and quantities with producer-level information and exploit variation in firms' exposure to differential decrease in local house prices during the Great Recession. Our data combine barcode-region-level prices and quantities from the ACNielsen Retail Scanner database with various producer-level variables from the National Establishment Time-Series (NETS) database. Our combined dataset contains information on barcode-level product prices and quantities sold in each county produced by both public and private firms and their establishment-level information in the United States. For example, suppose that Coca-Cola generates sales in Manhattan (New York County) and Brooklyn (Kings County). In that case, we observe prices and quantities sold in Manhattan and Brooklyn separately for each barcode-level product (e.g., cherry-flavored 500 ml Diet Coke) produced by Coca-Cola and Coca-Cola's establishment location, primary industry code, and credit ratings. To generate the variation in local consumer demand conditions, we follow the seminal work of Mian et al. (2013) and rely on a sudden differential collapse in local house prices during the Great Recession. To do this, we supplement our dataset with the county- and state-level house prices from the Zillow database.

Armed with the detailed micro-level data and the corresponding identification strategy, we find that a firm's local sales decrease in response to not only the direct negative local demand shock but also the intra-firm indirect shock, which measures the average negative demand shock originating in the firm's other markets. Strikingly, a firm's county-level sales growth *decreases* by 3.5 percentage points when it faces a 10 percentage point average decline in house price growth in other counties connected through its market network, while it only decreases by 0.6 percentage point given the same percentage points decrease in direct county house price growth. The magnitude of the effect suggests that the non-local firm-level decision, which has been overlooked in previous studies of local consumption, is a crucial determinant of the decrease in the local firm sales during this period.[2] Since a typical firm in our sample sells to many markets, the local demand shock is relatively small for most firms and is unlikely to alter the firm-level decisions.[3] Consistent with this intuition, we find a larger spillover effect when firms initially generate larger sales from non-local markets than in the local market.

We conduct various robustness checks to confirm that the identified spillover effect is not driven by other mechanisms, such as common or geographically clustered regional shocks or establishment, retailer, or industry linkages across regions. Our placebo tests reveal that the spillover effects we

[2]Note that the magnitude we emphasize is the elasticity of the local firm sales with respect to the housing price growth, not the overall effect that accounts for the magnitude of the shock. Integrating the magnitude of the shocks still shows that the indirect demand effect is larger than the direct demand effect, but only slightly due to the relatively small variation in the indirect demand shock.

[3]For example, the median firm in our sample sells in 155 counties, and when examining the local sales growth for this particular firm, we measure the indirect demand shock by measuring the average demand shock that this firm faces in all 154 other markets.

identify are muted under the alternative network structures that could generate a similar sales correlation. We also confirm that our results cannot be explained by similar household demographics across locations, potentially differential effects on exporters, and the possibilities of certain firms' market selection into regions that experienced a larger decrease in housing prices. Moreover, our empirical results are largely robust to instrumenting for local housing price changes with house supply elasticity (Saiz 2010), house price sensitivity (Guren et al. 2020a), and a non-local mortgage lending shock (García 2018).

Behind the responses of local firm sales to direct and indirect demand shocks, the barcode-level data reveal a stark asymmetry: intra-firm cross-market spillover effects arise mainly from product replacement, whereas the direct local shock operates through the sales of continuing products.[4] We show that the identified spillover effects occur because firms replace products that have higher value—sales per product, unit price, and organic sales share—with lower-value products in response to negative demand shocks, and within each firm, such product replacements are *synchronized* across many markets, including by firms that did not face the direct demand shock. Therefore, a decline in firm sales occurs even in a local market that is not directly affected by the shock.

We formalize the spillover mechanism and discuss the aggregate implications by developing a stylized multimarket model with endogenous quality adjustments. Our model interprets the replacement of high-value products with low-value products as quality downgrading because (i) this replacement leads to a decrease in both sales and unit prices in the data, and (ii) at the barcode level, changes in product attributes and intrinsic qualities must involve product replacements.[5] In the model, firms that face a negative demand shock decrease their product quality due to both *scale effects* and *non-homothetic preferences*. The scale effect means that firms that experience depressed demand do not have sufficient sales to recover the high fixed cost of producing high-quality products. Non-homothetic preferences allow negatively affected consumers to prefer lower quality goods, and as a result, firms have the incentive to supply lower quality products. In their quality downgrading process, firms choose uniform product quality across markets, including markets that did not experience direct local demand shocks. This behavior of firms generates the intra-firm spillover effect, as observed in the empirical analysis.[6]

A counterfactual exercise with the model shows that the identified intra-firm cross-market

[4]When defining the product at a more aggregated level, we find that all the spillover effects operate through the sales of continuing products. Using barcode-level data is crucial in analyzing product entry and exit within firms.

[5]Based on the decrease in prices, one might imagine that firms reduce their price-cost markups through product replacement instead of lowering their product quality. However, if firms reduce their markups, they must do so to increase their sales, especially because the demand elasticities are generally larger than unity in the consumer packaged goods market (see, e.g., Broda and Weinstein (2010)).

[6]As an example, we observe that the Kraft company replaces their natural organic cheese with the processed non-organic cheese in both Pennsylvania and Maryland, where the state-level housing price changes massively differ (-5% and -23%, respectively). Their 10-K filing in 2009 states that "Consumers' willingness to purchase our products will depend upon our ability to offer products that appeal to consumers at the right price.", suggesting that the company lower their product quality to meet their overall demand condition.

spillover effect generates a novel interregional shock transmission, which leads to a quantitatively large consumption redistribution across states. With the intra-firm spillover, the model predicts a significantly smaller consumption dispersion across states relative to the counterfactual economy without the spillover. As identified in the data, when firms spill over the shock by choosing a uniform product quality across markets, regions that experience negative (positive) demand shocks face relatively higher (lower) product quality than when firms offer region-specific product quality and do not spill over the shock. Estimated to match the identified spillover effect and other broad features of the data, our model delivers the quality-adjusted real consumption distribution across states. Without the spillover, the standard deviations of the growth and level of real consumption are nearly 30% and 50% larger, respectively, than those of the benchmark model with the spillover effect. A back-of-the-envelop calculation shows that the real consumption growth corresponds to a one-time $400 per-household transfer (tax) in a state that experienced below-average (above-average) house price growth. This amount is economically meaningful and comparable to the tax rebate checks authorized by the US Congress in 2008 (Economic Stimulus Act of 2008), which were one-time payments that ranged from $300 to $1200 per qualifying household.

Literature Review

Our paper is related to several strands of literature in macro-, international, and financial economics. A rapidly growing literature in macroeconomics studies the network origins of macroeconomic fluctuations (e.g., Acemoglu et al. 2012), and correspondingly, these studies have explored different types of networks that can translate and propagate micro-level shocks. The most prominent network in this literature is a supply-chain network that translates sector- and firm-specific shocks (e.g., Acemoglu et al. 2016; Barrot and Sauvagnat 2016; Carvalho et al. 2016; Bigio and La'O 2017). Other studies emphasize the trade networks across regions that translate regional shocks (e.g., Adao et al. 2018; Caliendo et al. 2018; Stumpner 2019). In financial economics, several studies analyze the linkages created by interbank and intrabank networks (e.g., Cetorelli and Goldberg 2012; Gilje et al. 2016; Cortés and Strahan 2017; Baskaya et al. 2017; Mitchener and Richardson 2019) and social networks (Bailey et al. 2018). We complement these studies by identifying a novel regional network arising from multimarket, multiproduct firms, which translate a non-local shock across locations and substantially impact local consumption.

In a work closely related to the present article, Giroud and Mueller (2019) study how the intra-firm network created by multi-establishment firms translates regional demand shocks. They find that firms' local employment decreases in response to both a local demand shock and indirect demand shocks originating from its other *production facilities*. We complement their analysis by providing a new and much stronger intra-firm network created by firms that *sell* multiple products in multiple markets.[7] Specifically, Giroud and Mueller (2019) demonstrate that their intra-firm network is present in non-tradable sectors but not in tradable sectors. By providing a novel intra-firm product replacement mechanism that applies to tradable sectors, our evidence generalizes such intra-firm spillover effects—which our theory shows to be fundamental in understanding the regional welfare redistribution—to both tradable and non-tradable sectors. Similarly, for non-tradable sectors, Gilbert (2017) provides descriptive evidence that retailers' intra-firm networks synchronize consumption across regions through their product entry and exit decisions. Related to the study of retailers, DellaVigna and Gentzkow (2017) and Cavallo (2018) document uniform pricing behavior within retailers, which potentially spill over and smooths the local shock. On the other hand, the aime of our work is to establish a causal statement about shock spillovers through producers' intra-firm networks and product quality choices. In Appendix A, we show that both the establishment linkage and the retailer margin discussed in previous studies do not confound our identified multimarket intra-firm network.

At the international level, the importance of firm-level analyses in explaining international comovement is well documented in di Giovanni et al. (2018). Related to this study, Cravino and Levchenko (2017) shows how multinationals could explain positive international business cycle comovement across countries, and Boehm et al. (2019) shows that firm-level input-output network propagate shocks across countries. Although the direction of spillover through multinationals and the input-output network of firms is unambiguous in this literature, empirical evidence on how exporters react to local shocks is mixed; some papers find that exporters generate a positive shock spillover across countries (e.g., Berman et al. 2015; Erbahar 2019), whereas others find a negative shock spillover operating through exporters (e.g., Ahn and McQuoid 2017; Almunia et al. 2020). This literature tends to infer the exporter's cost of producing a given quantity through the spillover.[8] Unlike previous studies, our analysis emphasizes the fixed cost associated with product quality to understand the behavior of domestic multimarket firms within the United States, where detailed barcode-level data are available, and infers the real consumption inequality across states.[9]

Our theoretical predictions on consumption redistribution resembles those of previous studies that examine the role of the credit market (e.g., Asdrubali et al. 1996; Lustig and Nieuwerburgh

[7]The multi-establishment intra-firm network elasticity in Giroud and Mueller (2019) is approximately one-third of the direct elasticity, whereas the multimarket intra-firm network elasticity we identify is approximately six times larger than the direct elasticity. This difference likely arises because firms sell to many counties but have establishments in a relatively small number of counties.

[8]In a related study, Kim (2020) emphasizes the heterogeneous slope of marginal costs across industries in understanding the international business cycle.

[9]Given that our mechanism works through barcode-level product replacement, it is difficult for us to infer the direction of international spillovers across all countries, where common barcode-level products are rare. However, we expect our identified spillover effect to apply to sets of countries that share many of the same barcode-level products, such as the North American Free Trade Agreement (NAFTA) and European Union (EU). In the model, we are agnostic on the cost of production by assuming the conventional constant marginal cost; we allow a fixed cost that varies across the different quality of products, consistent with our empirical evidence and previous models (e.g., Faber and Fally 2020).

2005, 2010) and common policy instruments (Hurst et al. 2016) in risk-sharing across regions. Our paper complements this literature by identifying a quality-variety mechanism within the intra-firm network. The identified mechanism is closely related to a large literature that studies variety and quality adjustments, product turnover, and innovation by firms in the context of business cycles and economic inequality (e.g., Broda and Weinstein 2010; Bernard et al. 2010; Schmitt-Grohé and Uribe 2012; Nakamura and Steinsson 2012; Hottman et al. 2016; Anderson et al. 2017; Argente et al. 2018; Jaravel 2018; Anderson et al. 2018; Jaimovich et al. 2019). In particular, we allow the choice of quality by firms, as in Feenstra and Romalis (2014) and Faber and Fally (2020), and emphasize the economies of scale at the level of different product qualities, as in Dingel (2017). The firm-level product replacement mechanism arising from regional demand shocks resembles the international-level evidence with product variety changes in Mayer et al. (2014, 2016); we do not find supporting evidence for the variety channel in our study of domestic markets. Our identification strategy follows the literature analyzing the collapse in the housing market during the Great Recession. Previous studies document that a fall in house prices leads to a decline in local consumer spending (Mian et al. 2013; Kaplan et al. 2020; Guren et al. 2020a), price and price-cost markups (Stroebel and Vavra 2019), and employment (Mian and Sufi 2014; Giroud and Mueller 2017). We complement these studies by revealing the novel spillover effect arising from the decline in regional house prices.

The remainder of this paper is structured as follows. Section 2 describes the data and construction of variables, Section 3 presents the main intra-firm spillover results, and Section 4 provides empirical support for the underlying product replacement mechanism. Section 5 develops the multiregion model that matches the empirical findings and discusses the distributional implications. Section 6 concludes.

2 Data and Measurement of Variables

2.1 Data

Our dataset combines barcode-level prices and quantities sold in each county produced by public and private firms from the ACNielsen Retail Scanner database and various firm- and establishment-level variables obtained from the GS1 and NETS data. The combined data allow us to construct a firm's county-specific sales and its connection to other counties where the firm generates sales, together with various pieces of firm-level information including a firm's primary industry code, establishment location, and credit rating. We leverage the large differential collapse in local housing markets during the Great Recession and supplement our dataset with the county- and state-level house prices in 2007-2009 from the Zillow database to measure local demand shocks. Correspondingly, our sample period is 2007 to 2009. A detailed discussion of each dataset and merging procedure can be found in Online Appendix A.

The barcode-level price and quantity information in each county comes from the ACNielsen Retail Scanner database, which was made available by the Kilts Marketing Data Center at the University of Chicago Booth School of Business.[10] The data contain approximately 2.6 million barcode-level product prices and quantities recorded weekly from approximately 35,000 participating grocery, drug, mass merchandise, convenience, and liquor stores in all US markets. A barcode, a unique universal product code (UPC) assigned to each product, is used to scan and store product information. Participating retail stores use point-of-sale systems that record information whenever product barcodes are scanned during purchases. The data begin in 2006 and end in 2015, covering the Great Recession period and the housing market collapse. They mainly cover consumer packaged goods (CPGs), such as food, non-food grocery items, health and beauty aids, and general merchandise. According to Nielsen, the retail scanner covers more than half the total sales volume of US grocery and drug stores and more than 30 percent of all US mass merchandiser sales volume.

There are two notable advantages to using the ACNielsen Retail Scanner database when studying multimarket firm behavior. First, the database records product sales at the barcode level, which is likely to be the most granular scale at which the product can be defined. This feature allows us to decompose a firm's local sales growth into the intensive margin (arising from continuously existing products) and the extensive margin (arising from product creation and destruction). Using a broader product category classification as a product definition does not allow us to identify the extensive margin effect emphasized in this paper.[11] Second, the database has fewer measurement error problems. For example, unlike most firm-level international trade data that infer regional (domestic) sales by subtracting other regional (international) sales from total firm sales, Nielsen collects sales information independently in each region. This feature prevents the mechanical regional sales correlation problem raised in Berman et al. (2015). Compared to similar data that rely on consumer surveys, the Retail Scanner data directly record expenditures when consumers purchase and scan products at stores. Thus, our data do not suffer from household nonresponse and misreporting, which are common problems in survey data used in economic research (Einav et al. 2010; Meyer et al. 2015). One disadvantage of the Retail Scanner data is the sample selection, as it is likely to cover more large retailers. We confirm the robustness of our main intra-firm spillover results by leveraging the Homescan Panel data, which relies on household reporting but has a sample weight that can make the sample nationally representative, as shown in Table A.10 in Appendix A.

[10] Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (U.S.), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[11] As an alternative specification, we instead define products using the broader product group categories available in the ACNielsen data and decompose local sales growth into intensive and extensive margins. As shown in Table OA.3 in Online Appendix B, the spillover effect is entirely driven by the intensive margin and not the entry and exit of product group categories.

We integrate each product's prices and quantities with its producer information using the GS1 US Data Hub and the NETS. The GS1, a not-for-profit information standards organization, is the official source of barcodes for producers.[12] Their data record the company name and address for each barcode-level product, and we use this information to link barcode-level product information to producer-level information from the NETS data. NETS is the US establishment-level longitudinal database made available by Walls & Associates. The source of the data is Dun and Bradstreet (D&B) archival data, which are collected primarily for marketing and credit scoring. The data allow us to identify each firm's establishment location, primary industry code defined at the SIC 4-digit level, and D&B credit and payment rating during the 1990-2014 period. We use this information to compare firms that operate in the same primary industry to analyze heterogeneous treatment effects and in turn investigate the mechanism behind the spillover results and address concerns related to the supply-side effect or collateral channel.[13] Note that our sample excludes the participating retailers in the Retailer Scanner data, as their UPC codes are masked for confidentiality and cannot be combined with the GS1 data. Our baseline definition of a firm is based on the GS1 data, but using an alternative definition based on NETS data generates the same results.

We supplement our combined database with the county-level house price index from the Zillow database, the housing supply elasticity measure from Saiz (2010), the housing price sensitivity measure from Guren et al. (2020a), and the mortgage lending information from García (2018) for our identification strategy.[14] We further augment our data with the Rajan and Zingales (1998) industry-level external financial dependence index to explore the role played by financial frictions in spillovers. For the robustness check, we additionally use the NBER county distance database and the county-level variables used in Mian and Sufi (2014), such as household income and the debt-to-income ratio.

Table 1 provides the summary statistics of the final sample used in the empirical analyses. Our combined dataset consists of 4,171 firms and covers 991 US counties from 2007 to 2009.[15] Three features of the data are noteworthy. First, most of the firms in our sample sell many products in many counties. For example, the average firm in our sample sells 54 products across 513 counties. This feature of our sample, together with the large variation in county-level house price growth, allows us

[12] GS1 provides a business with up to 10 barcodes for a $250 initial membership fee and a $50 annual fee. Firms that purchase larger quantities of barcodes enjoy significant discounts on the cost per barcode (see http://www.gs1us.org/get-started/im-new-to-gs1-us).

[13] See, e.g., Neumark et al. (2011), Barnatchez et al. (2017), Rossi-Hansberg et al. (2018), and Asquith et al. (2019) for a more detailed discussion of the NETS data. According to Barnatchez et al. (2017), the NETS database is useful for studying cross-sectional business activities, but its information is limited in studying business dynamics. Thus, we only use the data for the pre-recession period and abstain from using the data's panel structure.

[14] We are grateful to the authors for sharing their estimates with us.

[15] As shown in Online Appendix A, our final combined sample covers approximately 40% of all sales in the Nielsen data. The 991 US counties cover approximately 75% of the total US population. We demonstrate the robustness of our results using the full Nielsen sample in Table OA.4 in Online Appendix B. Our results are also robust to using the state-level analyses, which cover all states except Hawaii.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
	Panel A: County-Firm variables					
$\tilde{\Delta}\mathrm{HP}_{rf,07-09}$ (other)	840,681	-.17	.04	-.21	-.17	-.12
$\tilde{\Delta}\mathrm{S}_{rf,07-09}$	840,681	-.04	.8	-1.18	.02	.94
$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf,07-09}$	840,681	-.06	.54	-.7	-.04	.53
$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf,07-09}$	840,681	.02	.53	-.53	0	.57
$\mathrm{S}_{rf,07}$	840,681	65.42	739.85	.11	2.35	70.29
$\mathrm{S}^{\mathrm{exist}}_{rf,07}$	840,681	56.52	631.47	.06	1.64	58.92
$\mathrm{S}^{\mathrm{exit}}_{rf,07}$	840,681	8.9	129.8	0	.2	8.68
$\mathrm{S}_{rf,09}$	840,681	68.07	768.49	.07	2.35	74.76
$\mathrm{S}^{\mathrm{exist}}_{rf,09}$	840,681	52.37	528.69	.04	1.47	56.33
$\mathrm{S}^{\mathrm{enter}}_{rf,09}$	840,681	15.69	283.81	0	.22	14.27
# of $\mathrm{UPCs}_{rf,07}$	840,681	34.18	106.99	1	9	70
	Panel B: Firm variables					
$\tilde{\Delta}\mathrm{HP}_{f,07-09}$	4,171	-.16	.09	-.27	-.16	-.07
$\mathrm{S}_{f,07}$	4,171	15.59	147.97	0	.28	14.68
# of $\mathrm{UPCs}_{f,07}$	4,171	54.24	231.78	2	12	110
# of $\mathrm{counties}_{f,07}$	4,171	513.24	669.99	10	155	1,655
# of $\mathrm{groups}_{f,07}$	4,171	2.7	3.42	1	2	6
	Panel C: County variables					
$\tilde{\Delta}\mathrm{HP}_{r,07-09}$	991	-.09	.14	-.26	-.08	.04
$\mathrm{S}_{r,07}$	991	55.5	131.94	.52	15.85	143.86
# of $\mathrm{UPCs}_{r,07}$	991	28,995.06	15,382.66	7,994	28,730	49,854
# of $\mathrm{firms}_{r,07}$	991	848.32	353.87	341	876	1,306

Note. r is county, f is firm, S is sale, HP is housing price, and $\tilde{\Delta}$ stands for the Davis et al. (1996) growth rate. $\tilde{\Delta}\mathrm{HP}_{r,07-09}$ is the county-level housing price change, $\tilde{\Delta}\mathrm{HP}_{f,07-09}$ is the firm-level housing price change, and $\tilde{\Delta}\mathrm{HP}_{rf,07-09}$ (other) is the indirect housing price change defined in Section 2.3. Sales growth ($\tilde{\Delta}\mathrm{Sale}_{rf,07-09}$) is exactly decomposed into the growth in continuing products ($\tilde{\Delta}\mathrm{Sale}^{\mathrm{C}}_{rf,07-09}$) and the growth due to the product replacement ($\tilde{\Delta}\mathrm{Sale}^{\mathrm{R}}_{rf,07-09}$), as shown in Section 2.2. Sales in 2007 ($\mathrm{Sale}_{f,07}$) are decomposed into sales of products that exist in 2009 ($\mathrm{S}^{\mathrm{exist}}_{rf,07}$) and that exit in 2009 ($\mathrm{S}^{\mathrm{exit}}_{rf,07}$). Similarly, sales in 2009 ($\mathrm{S}_{rf,09}$) are decomposed into sales of products that exist in 2007 ($\mathrm{S}^{\mathrm{exist}}_{rf,09}$) and that newly enter in 2009 ($\mathrm{S}^{\mathrm{enter}}_{rf,09}$). All county-firm-level sales variables are in thousands of US dollars, and the firm-level and county-level sales are in millions of US dollars.

to study spillover effects across counties through intra-firm networks: there is substantial variation across firms in their initial exposure to different counties, and local shocks differentially affect these counties. Given the relatively smaller variation in product groups within firms, we abstract the product group dimension in our primary analysis. However, the results are robust to comparing outcomes within product groups, as shown in Appendix A.

Second, each county has many firms that sell many products. On average, 848 firms sell their products in a county; even in a county in the 10th percentile of the distribution, 341 firms sell their products. Using the full Nielsen sample, the largest firm in a typical county has a sales share smaller than 5%. Given that each firm accounts for a small share of sales in a county, it is unlikely that an individual firm could affect the local economic conditions, ensuring the validity of the indirect demand shock. Finally, as documented in Hottman et al. (2016), there is extreme firm heterogeneity in the data. A firm in the 90th percentile of the distribution has approximately 3000 times more sales, produces approximately 55 times more products, and sells in approximately 160 times more counties than a firm in the 10th percentile of the distribution. We exploit this rich variation and confirm that the spillover effect is stronger for larger firms, consistent with the results in Argente et al. (2020).

2.2 Sales Growth and Decomposition

Our main dependent variable is region-firm sales. Let $\mathrm{S}_{rf,t}$ denote firm f's sales in region r at time t. We measure the region-firm-specific sales growth in 2007-2009 as

$$\tilde{\Delta}\mathrm{S}_{rf} \equiv \frac{\mathrm{S}_{rf,09} - \mathrm{S}_{rf,07}}{\overline{\mathrm{S}}_{rf}} \tag{2.1}$$

where $\overline{\mathrm{S}}_{rf} \equiv \frac{1}{2}(\mathrm{S}_{rf,07} + \mathrm{S}_{rf,09})$ is the simple average sales of firm f in region r in 2007 and 2009. This growth rate, which is a second-order approximation of the log difference growth rate around 0, follows previous papers that measure employment growth at the establishment level (e.g., Davis et al. 1996). This definition of the growth rate provides a symmetric measure around 0 and is bounded between -2 and 2. These features help limit the influence of outliers without arbitrarily winsorizing extreme observations. This growth rate can accommodate both the entry and exit of firms at the region level, and the main results are robust to such accommodations, as shown in Table A.12 in Appendix A.[16] Additionally, the qualitative results are robust to using the more conventional definition of sales growth in which the denominator equals 2007 sales; see Table OA.6 in Online Appendix B.

To understand the underlying mechanism behind the regional shock spillover, we investigate the role of the product creation and destruction by these firms in shock spillovers. Following Broda

[16] Given the relatively minor role of firm entry and exit in the intra-firm spillover effect, we do not integrate it in the theoretical analyses.

and Weinstein (2010), we decompose the sales growth defined in Equation (2.1) into two margins: the intensive margin associated with products that exist in both pre- and post-shock periods, and the extensive margin associated with product creation and destruction (i.e., net creation):

$$\tilde{\Delta}\mathrm{S}_{rf} = \tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf} + \tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf} \tag{2.2}$$

where $\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf} \equiv \frac{\mathrm{S}^{\mathrm{exist}}_{rf,09} - \mathrm{S}^{\mathrm{exist}}_{rf,07}}{\bar{\mathrm{S}}_{rf}}$ and $\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf} \equiv \frac{\mathrm{S}^{\mathrm{enter}}_{rf,09} - \mathrm{S}^{\mathrm{exit}}_{rf,07}}{\bar{\mathrm{S}}_{rf}}$. $\mathrm{S}^{\mathrm{exist}}_{rf,t}$ is the region-firm-time-specific sales from products that continuously existed in region r throughout the years 2007-2009, $\mathrm{S}^{\mathrm{exit}}_{rf,07}$ is the sales from products that existed in region r in 2007 but exited in 2009, and $\mathrm{S}^{\mathrm{enter}}_{rf,09}$ is the sales from products that did not exist in region r in 2007 but entered in 2009. Note that we use the following identity for the decomposition of sales growth: $\mathrm{S}_{rf,07} = \mathrm{S}^{\mathrm{exist}}_{rf,07} + \mathrm{S}^{\mathrm{exit}}_{rf,07}$ and $\mathrm{S}_{rf,09} = \mathrm{S}^{\mathrm{exist}}_{rf,09} + \mathrm{S}^{\mathrm{enter}}_{rf,09}$.

After establishing the positive spillover across regions within firms, we leverage the two decomposed margins of sales growth to quantify the source of the intra-firm regional spillover effect. Although Table 1 documents that the sales due to product entry or exit account for a small fraction of total sales, the results in Section 4 show that the extensive margin accounts for nearly the entire spillover effect.

We further decompose the extensive margin into two components by classifying products as firms' global and local products:

$$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf} = \tilde{\Delta}\mathrm{S}^{\mathrm{R,M}}_{rf} + \tilde{\Delta}\mathrm{S}^{\mathrm{R,L}}_{rf} \tag{2.3}$$

where $\tilde{\Delta}\mathrm{S}^{\mathrm{R,M}}_{rf}$ and $\tilde{\Delta}\mathrm{S}^{\mathrm{R,L}}_{rf}$ are the sales growth measures originating from the products that are replaced in multiple markets and the local market, respectively. As discussed in greater detail in Section 4, this distinction additionally clarifies how firms generate regional sales correlation by replacing their products.

2.3 The Indirect Demand Shock

Our main goal is to investigate whether a firm's local sales growth is affected by indirect demand shocks originating in the firm's other markets, conditional on the direct local change in demand. To this end, we define the region-firm-specific indirect demand shock as the average regional demand shock that a firm faces from its other markets, weighted by its initial sales share. The method of construction is similar to that proposed by Giroud and Mueller (2019).

In measuring the regional consumer demand shock, we exploit the sharp differential decline in local house prices during the Great Recession following the large literature studying the consequences of housing market disruptions.[17] It is well known that there was a dramatic decline in housing prices

[17] Our measure of house price changes using the Zillow data follows Giroud and Mueller (2017, 2019); Kaplan et al. (2020). Giroud and Mueller (2017) document that at the MSA level, this measure is highly correlated with both the

in this period following the massive increase in housing prices in previous years, and the magnitude of the fall in housing prices varied widely across regions. The regions that faced a larger decrease in local housing prices experienced a greater fall in local consumption relative to their counterparts because of the lower household wealth or worsened credit conditions arising from depressed collateral (housing) values (see, e.g., Mian et al. 2013; Kaplan et al. 2019). The resulting depressed local consumption, in turn, lowers wages and employment in the region and further reduces local consumption. (the local general equilibrium effect; see, e.g., Guren et al. 2020b).

Let $\mathrm{HP}_{r,t}$ denote the house price index in region r at time t. Consistent with the measure of sales growth, we define the region-specific house price growth in 2007-2009 as

$$\tilde{\Delta}\mathrm{HP}_r \equiv \frac{\mathrm{HP}_{r,09} - \mathrm{HP}_{r,07}}{\overline{\mathrm{HP}}_r} \tag{2.4}$$

where $\overline{\mathrm{HP}}_r$ is a simple average of the housing price index values in region r in 2007 and 2009, which is our baseline measure of the regional consumer demand shock. Given the region-specific house price growth, we take the weighted average of this growth measure across all regions r' within a firm f, excluding the particular region r, to measure the indirect demand shock that firm f faces in region r:

$$\tilde{\Delta}\mathrm{HP}_{rf}\ (\mathrm{other}) \equiv \sum_{r' \neq r} \omega_{r'f} \times \tilde{\Delta}\mathrm{HP}_{r'} \tag{2.5}$$

where $\omega_{r'f}$ is the initial sales share defined as $\frac{\mathrm{Sale}_{r'f,07}}{\sum_{r' \neq r} \mathrm{Sale}_{r'f,07}}$. The weight $\omega_{r'f}$ is firm f's initial sales share in region r', where shares are measured excluding region r. The weight measures the importance of each region to a firm, reflecting the idea that firms are more likely to be exposed to a consumer demand shock in region r' if they initially sold more in region r' than in other regions.

A primary concern in treating the local housing price as a shock is that a price is an equilibrium object that is jointly determined by housing demand and supply and associated with various confounding regional characteristics. The used of detailed county-firm data with a focus of the intra-firm spillover effects partially eases this concern. Our tightest specification allows region-sector fixed effects to absorb all regional and region-sector-specific characteristics potentially correlated with regional housing price changes. This specification, which compares firms within regions, aids the identification because the regional housing prices are likely to be exogenous to our sample of firms. The narrative evidence and previous studies suggest that the regional housing price changes in this period originated from factors outside of product markets, especially the CPG market that this study considers. The two leading explanations for the fall in housing prices are the household credit expansion in the pre-recession period (e.g., Mian and Sufi 2017) and a sudden change in household

"housing net worth shock" used in Mian et al. (2013); Mian and Sufi (2014) (86.3%) and the measure of house price changes from the Federal Housing Finance Agency (FHFA) data used in Adelino et al. (2015); Charles et al. (2018) (96.4%).

expectations (e.g., Adelino et al. 2018). We are not aware of any evidence that firms, particularly CPG firms, affect local housing prices by selling more or fewer products. Moreover, as discussed in Section 2, the firms' share in our sample is small in a county, and each firm would likely play no role in affecting local housing price changes.

Given that our sample of firms takes the housing price as given, another concern is the possibility that firms with certain characteristics that may affect their regional sales select into those regions that experience larger declines in house prices. Given the high persistence of regional market share in the CPG industry (see, e.g., Bronnenberg et al. (2009, 2012)), it is unlikely that firms selected into counties for reasons related to house price changes during the Great Recession. One of our placebo tests reveals that the effect is muted when we only consider those firms entering the local market of interest at the beginning of the recession. We also test this possibility by correlating the firms' initial observed characteristics with the average degree of housing price changes they face. As shown in Appendix Table A.1, we find that the firm size, scope, age, and financial stability, which are likely to affect firm local sales, are uncorrelated with the average regional demand shocks in our sample. Moreover, by utilizing the region and firm fixed effects in our regression specification, we test and confirm that firms are unlikely to select into regions based on their unobserved characteristics.

In addition to the regional change in housing prices, we supplement three other measures as instrumental variables (IVs) to confirm the findings: housing supply elasticity (Saiz 2010), housing price sensitivity (Guren et al. 2020a), and non-local mortgage lending shock (García 2018). The housing supply elasticity measures the degree of difficulty in building new houses for a metropolitan area by exploiting the variation in the land's topology. Given the concerns raised by Davidoff (2016) that this elasticity correlates with other regional factors, we utilize this instrument across firms within each county by allowing county fixed effects. This specification is similar to that of Guren et al. (2020a), who rely on the panel structure of the data to allow location fixed effects. We additionally include their estimates of housing price sensitivity in our analyses. Instead of utilizing land availability as in Saiz (2010), Guren et al. (2020a) infer the housing supply elasticity by exploiting the systematic differences in the sensitivity of local house prices to broader regional house price variation; a larger estimate corresponds to the less elastic housing supply.

The non-local mortgage lending shock exploits the variation in the change in mortgage lender health, which does not originate from the county of interest, to generate the exogenous variation in house prices in the local economy. Specifically, García (2018) utilize the rich region-lender mortgage credit information and separates the lender-specific credit change from the region-specific credit change by using a fixed effects methodology, similar to that employed in banking literature (see, e.g., Khwaja and Mian (2008), Chodorow-Reich (2014), and Amiti and Weinstein (2018)). He then takes a weighted average of the lender-specific credit changes across lenders within the county to construct a county-specific non-local mortgage lending shock, where the weight is the lagged market share of lenders.

With the three additional measures of local consumer demand shocks, we similarly construct the indirect demand shocks following Equation (2.5). To ease potential concerns related to the initial share, we use a one-year-lagged weight for all of our IVs, similar to the construction of the IVs in Autor et al. (2013). Table 2 reports the first-stage results. Housing supply elasticity, housing price sensitivity, and non-local mortgage lending shocks are highly correlated with indirect demand shocks.

Table 2: First-Stage Regression Results

	$\tilde{\Delta}\text{HP}_{\text{rf}}$ (other)					
	(1)	(2)	(3)	(4)	(5)	(6)
Housing supply elasticity$_{\text{rf}}$	0.098***	0.096***				
	(0.008)	(0.004)				
Housing price sensitivity$_{\text{rf}}$			-0.218***	-0.214***		
			(0.019)	(0.014)		
Non-local lending shock$_{\text{rf}}$					1.423***	1.383***
					(0.082)	(0.060)
Region-Firm Controls		✓		✓		✓
Sector x Region FE		✓		✓		✓
R^2	0.41	0.71	0.35	0.67	0.68	0.84
Observations	448,604	448,604	587,436	587,436	658,607	658,607

Note. The housing supply elasticity$_{\text{rf}}$, housing price sensitivity$_{\text{rf}}$, and the non-local lending shock$_{\text{rf}}$ are the leave-one-out lagged share-weighted average of the regional Saiz (2010) elasticity, Guren et al. (2020a) sensitivity estimates, and García (2018) non-local mortgage lending shock, respectively. Region is county, and sector is the 4-digit SIC code. Region-firm controls are the initial log of county-firm sales, firm sales, firm's number of markets, and firm's product groups. $\tilde{\Delta}\text{HP}_{\text{rf}}$ (other) is the indirect demand shock in Equation (2.5). The regression is weighted by initial county-firm sales; standard errors are two-way clustered by state and sector. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

3 The Intra-Firm Spillover Results

We use the following equation as the main specification throughout the empirical analyses:

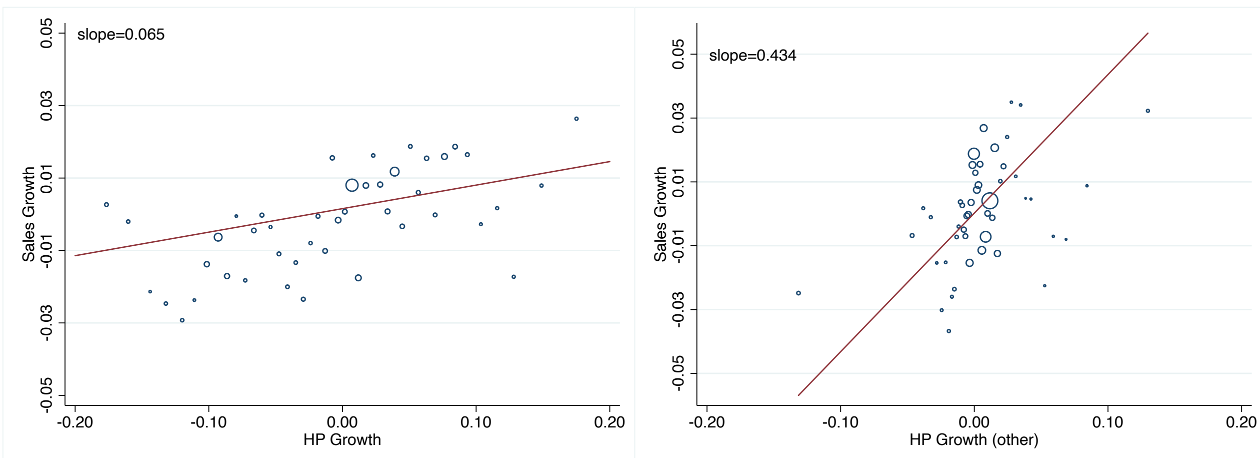
$$\tilde{\Delta}\text{S}_{rf} = \beta_0 + \beta_1 \tilde{\Delta}\text{HP}_r + \beta_2 \tilde{\Delta}\text{HP}_{rf} \text{ (other)} + \boldsymbol{X'_{rf}\beta_3} + \varepsilon_{rf} \tag{3.1}$$

where $\tilde{\Delta}\text{S}_{rf}$ is region-firm level sales growth defined in Section 2.2 and $\tilde{\Delta}\text{HP}_r$ and $\tilde{\Delta}\text{HP}_{rf}$ (other) are local consumer demand shock and the indirect demand shock defined in Section 2.3, respectively. $\boldsymbol{X'_{rf}}$ is a vector of control variables. All the regression analyses are weighted by initial region-firm sales, and the standard errors are two-way clustered by state and sector.[18]

[18] Although our indirect shock has a shift-share structure, it does not directly fall in the class of empirical models

Our central coefficient of interest is β_2. This coefficient measures the elasticity of the firm's local sales growth to the average regional demand shocks from the firm's other markets, conditional on the direct local demand shock. A priori, β_2 can have any sign; if the adverse regional demand shocks in other regions decrease (increase) the firm's local sales, then the sign of β_2 is positive (negative). β_2 is zero if firms make their decisions at the local level. On the other hand, β_1 measures the effect of direct regional housing price growth on a firm's local sales, which is similar to what is studied in Mian et al. (2013); Kaplan et al. (2020). Our empirical analyses focus on the differential decline in housing prices by absorbing any nationwide changes, such as the aggregate decline in housing prices or the aggregate productivity changes, with the intercept β_0.

Figure 1: The Direct and Indirect Effects of Regional Housing Market Disruptions



(a) Direct Effect

(b) Indirect Effect

Note. Figure 1a plots the correlation between $\tilde{\Delta}\mathrm{S}_{rf}$ and $\tilde{\Delta}\mathrm{HP}_r$, and Figure 1b plots the correlation between $\tilde{\Delta}\mathrm{S}_{rf}$ and $\tilde{\Delta}\mathrm{HP}_{rf}$ (other). For all variables, we use the Frisch-Waugh theorem and partial out controls used in column (1) of Table 3. We take a weighted average of each residualized variable by 50 equal-sized housing price growth bins to plot the graph. The reported slope coefficients are based on simple linear regressions using the 50 reported bins. The bins are weighted by initial sales, and the red lines represent a linear fit to the data. The bins with extreme values are excluded for visibility.

Figure 1 visualizes the direct and indirect spillover effects of regional demand changes by drawing binscatter plots based on Equation (3.1). As shown in Figure 1a, a firm's local sales growth decreases with respect to the decrease in local housing prices, confirming the results in Mian et al. (2013) and Kaplan et al. (2020) at the county-firm level. Figure 1b plots our main intra-firm spillover results. We find that firms reduce their regional sales when they face a negative demand shock originating from other markets ($\beta_2 > 0$).

studied recently in the context of trade literature (e.g., Adao et al. (2019) and Borusyak et al. (2018), among many others) because we consider regressions at the region-firm-level with the two-way clustering of standard errors by sector and state. Nevertheless, we estimate standard errors following Adao et al. (2019) by defining region-firm as a unit of analysis in Table OA.1 in Online Appendix B. Our results are robust to using the alternative standard errors.

Strikingly, Figure 1 reveals that the indirect demand elasticity arising from the intra-firm network on local firm sales is much larger than the direct demand elasticity; the slope of the linear line in Figure 1b is much steeper than the slope in Figure 1a. The relative importance of the indirect effect is intuitive because of the large number of markets in which each firm operates. For example, the median firm in our sample sells in 155 counties. For this firm, although the local demand changes are likely to affect local firm sales the most, at the firm level, the local shock would account for less than 1% of the firm-level shock (assuming that initial local sales are similarly distributed across locations). Given that local firm sales depend on firm-level decisions, it is plausible that the effect of the indirect demand changes originating from the other 154 markets is larger than the direct demand changes from one market.

Table 3: The Direct and Indirect Effects of the Regional Housing Market Disruptions

	$\tilde{\Delta}$ S_{rf}, 2007-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ordinary Least Squares				IV Estimation Using			
					elasticity	sensitivity	lending	all
$\tilde{\Delta}HP_r$	0.06**	0.06**						
	(0.03)	(0.03)						
$\tilde{\Delta}HP_{rf}$ (other)	0.35***		0.34***	0.40***	0.60***	0.72***	0.41**	0.44**
	(0.11)		(0.12)	(0.10)	(0.14)	(0.25)	(0.20)	(0.22)
Region-Firm Controls	✓		✓	✓	✓	✓	✓	✓
Region Controls		✓						
Firm FE		✓						
Sector FE	✓		✓					
Region FE			✓					
Sector x Region FE				✓	✓	✓	✓	✓
First-stage F statistics					541.20	231.20	540.50	254.70
Hansen's J-stat p-value								0.24
R^2	0.20	0.61	0.24	0.39				
Observations	840,681	840,681	840,681	840,681	448,604	587,436	658,607	417,869

Note. Region-firm controls are the initial log of the following variables: county-firm sales, firm sales, the firm's number of markets, and product groups. Region controls are pre-recession percentage white, median household income, percentage owner-occupied, the percentage with less than a high school diploma, percentage with only a high school diploma, unemployment rate, poverty rate, percentage urban, and employment share in a county for 2-digit industries. Region indicates county and sector is defined based on SIC 4-digit. The elasticity, sensitivity, and lending are the leave-one-out weighted average of the regional Saiz (2010) housing supply elasticity, Guren et al. (2020a) housing price sensitivity, and García (2018) non-local mortgage lending shock, respectively. The regression is weighted by initial county-firm sales; standard errors are two-way clustered by state and sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 column (1) confirms the positive and statistically significant direct and indirect effects of regional demand shocks on local consumption and that the indirect demand effect is stronger. The direct and indirect effects are 0.60 and 0.35, respectively.[19] A 10 percentage point decline in

[19]The magnitude of the estimated coefficient is smaller than the estimate reported in the previous study. For

local house price growth leads to a 0.6 percentage point decrease in the local firm sales growth, and the same decrease in the average of the other regional housing price growth reduces local firm sales growth by 3.5 percentage points. We include all regional control variables used in Mian et al. (2013) and detailed firm-level variables that proxy for firm size and scope.[20]

Columns (2)-(4) verify our empirical findings using the various fixed effects to test for and exclude unobserved confounding factors. Column (2) includes the firm fixed effects instead of the firm-level variables and the indirect demand shock, the variation of which mostly arises from the comparison across firms. The local demand shock's quantitative effect remains the same with and without the firm fixed effects, suggesting that there is no selection on unobserved firm characteristics into the regional housing price changes conditional on control variables. If unobserved firm characteristics make some firms more exposed to the regional demand shock, adding the firm fixed effects would correct the bias and change the coefficient.[21] Column (3) instead includes regional fixed effects that absorb all regional variation, including the local demand shock. The indirect effect is stable across columns (1) and (3), similar to the direct effect reported in columns (1) and (2), suggesting that there is no selection on unobserved regional characteristics into the indirect demand shock. Column (4) includes region times sector fixed effects that absorb all region-sector variation that might confound the results, such as the regional clustering of manufacturing sectors that could comove with the differential manufacturing sales across locations. The indirect intra-firm spillover effect remains stable in this specification. Columns (5)-(8) present the IV results and confirm the positive intra-firm spillover effects. As in previous literature studying the direct local effects, the IV estimates are larger than the OLS estimates, presumably due to the classical measurement errors that attenuate the coefficient size.[22] The first-stage F statistics are well above 10 in all specifications, and Hansen's J-statistics cannot reject the instruments' validity.

Among other concerns in identifying the indirect intra-firm spillover effects, one of the greatest threats is a common shock, which is often discussed in the international macroeconomics literature with more aggregate data (see, e.g., Kose et al. 2003). Although we rule out any common shocks to national, sector, or region-sector clusters, there may be other geographically clustered shocks within

example, using the Nielsen Retail Scanner data, Kaplan et al. (2020) show that the estimate is 0.207 at the county level, 0.239 at the MSA level, and 0.341 at the CBSA level. One key difference is the measure of the regional demand shock. If we use household net worth instead of housing prices as in Kaplan et al. (2020), our estimate of the local demand effect becomes 0.22.

[20]We do not include the variables from the NETS data, such as the measures of financial constraints and firm age, because they decrease the sample size and do not have statistically significant effects on firm local sales conditioning on firm size and scope. The effects of direct and indirect shocks are robust to including such controls.

[21]This analysis is similar to the test of unobserved characteristics implemented in the banking literature. See, e.g., Khwaja and Mian (2008); Chodorow-Reich (2014).

[22]The sample size does not make a substantial difference in the magnitude of the coefficients. The estimates with the elasticity and sensitivity instruments are larger than the estimate with the lending instrument. One explanation for this difference is how different instruments affect different subsamples based on the underlying channel. The elasticity and sensitivity instruments are likely to contain all the effects of housing prices on local consumption discussed in previous studies. In contrast, the lending instrument would affect households only through household mortgage borrowing.

broader regions, such as spatially correlated housing price changes. Such shocks could correlate with the indirect demand shocks and confound the results if the intra-firm initial networks are clustered in the same areas. Appendix A Tables A.2, A.3, and A.4 present various robustness exercises and rules out the possibility of a confounding effect of the clustered shocks. In measuring the indirect demand shocks, we exclude all counties near the local county of interest.[23] We also define a state as a region of analysis to exclude variations within the state, which could be more vulnerable to clustered shocks. Regardless of whether we use the different definitions of nearby counties or use the state as the unit of analysis, the indirect spillover effects remain strong.

We conduct placebo tests by varying the initial share weights when we measure the indirect demand shocks to inspect other common shocks or other general mechanisms. Within the markets in which firms operate, we consider weights of equal share, household population, household median income, and household debt-to-income ratio. We also use the initial share of entrants to explore firms' potential selection into the exposed regions and use the establishment network to understand the supply-side effect arising from land collateral or a productivity shock. Finally, we use a random weight; we randomize each firm's markets, measure the indirect shock, and run the regression. We perform this exercise one thousand times and report the average estimated coefficients and standard errors. The coefficient will not equal zero if there is any hidden structural correlation.

Table 4: Placebo Tests

	$\tilde{\Delta}$ S_{rf}, 2007-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alternative measures of $\tilde{\Delta}HP_{rf}$ (other) using						
	equal	pop.	inc.	debt	entry	plant	random
$\tilde{\Delta}HP_{rf}$ (other)	0.13	0.03	0.11	0.07	-0.03	-0.06	0.00
	(0.21)	(0.18)	(0.18)	(0.20)	(0.11)	(0.18)	(0.38)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓	✓	✓
Observations	840,681	840,681	840,681	835,778	833,290	704,809	840,681

Note. The regression specification is the same as that in Table 3 column (4). We consider seven alternative constructions of the indirect demand shock. We use different initial weights: equal is equal weight, pop. is population weight, inc. is household median income weight, and debt is the household debt-to-income weight. Entry is the weight that still uses 2007 sales but replaces the value with zero if the 2006 sales are nonzero, and the plant weight is based on the firms' establishment network. In the random specification, we randomly allocate markets to each firm, measure the indirect demand shock, and estimate the coefficient; we repeat the procedure 1000 times and report the average estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 shows that the intra-firm spillover effects we find are muted under the potential alternative explanations. Column (1) shows the results using the equal sales weight of firms across

[23] We consider radii of 50, 100, and 150 miles in measuring the indirect demand shocks that exclude nearby counties. We also calculate it by excluding all counties located within the same state of the county of the interest.

regions. The spillover effects are negligible, suggesting that a firm's initial exposure, not the general correlation structure across regions within firms, is essential for the spillover effects. Columns (2)-(4) consider weights formed on household characteristics, which are likely to make regional consumption more or less sensitive to regional housing price changes, and we again find no significant effects. If there is a mechanism—other than intra-firm behavior—that generates the correlation of sales across regions within firms, then household-characteristics-weighted housing price changes would affect the other region's sales through this mechanism. Our insignificant results rule out such a mechanism. Column (5) considers those firms that suffer from the indirect demand shock because they selected into the markets in 2007. The results are again negligible, suggesting that the initial share variation we use in our main analysis originates from the historical episodes. Column (6) considers the supply-side effects by using establishment-level employment information, and we do not find any effect.[24] Appendix A.4 further reports the robustness of our main results to the supply-side effects by using the indirect demand shock that excludes the regions where firms produce their products, similar to the identification strategy employed in Baker et al. (2020).[25] Finally, column (7) shows that using the random network does not generate any effect.

We conduct numerous additional robustness exercises to confirm our results, as shown in Appendix A. Our results are robust to retailer behavior (Table A.5), sales correlation of the granular product group across regions (Table A.6), controlling for the average household demographics firms face (clientele effect, Table A.8), and potentially differential changes in exporters' local sales (Table A.7). To address concerns about comparing firms with different characteristics, in addition to testing for the selection of firms based on observed (Table A.1) and unobserved characteristics (Table 3), we compare firms that share the same census division based on their largest markets; our results remain stable (Table A.9). We also confirm our intra-firm spillover results by using the ACNielsen Homescan Panel data, which has a more representative sample with online purchases, along with the analyses of pretrends (Tables A.10 and A.11).[26]

4 The Product Replacement Channel

Our reduced-form empirical results do not align with the predictions of the traditional models of international macroeconomics and trade, where firms make their decisions entirely at the market

[24] This result is consistent with those of Giroud and Mueller (2019), who show that there is no multi-establishment network effect for tradable industries.

[25] Specifically, we measure the region-firm-specific indirect shock by only including counties where (i) a firm sells its products and (ii) does not have establishments. We renormalize weights so that they sum to one. We find similar intra-firm spillover effects by using this measure.

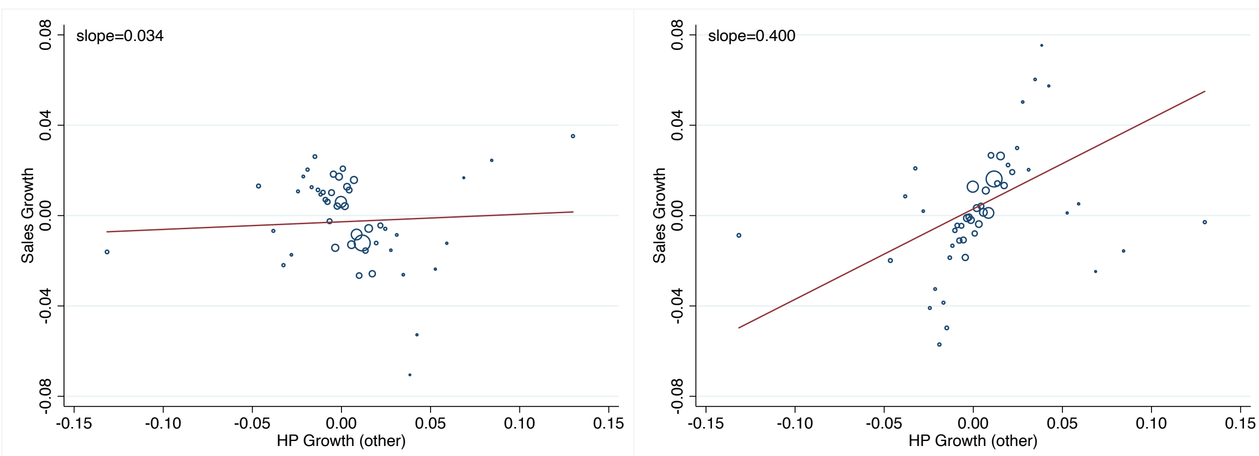
[26] In unpublished work, we also study the housing boom effect in 2004-2006 with the ACNielsen Homescan Panel data. We find very similar results for the intra-firm spillover effect but they are not statistically significant at the conventional level, potentially because of the larger measurement errors in the data's initial years. Also, we study the long-term consequence of the intra-firm spillover effect by considering the post-recession sales growth as a dependent variable. We find positive but statistically insignificant results at conventional levels.

level. The natural question is how firms spill over regional demand shocks across their markets.

This section presents strong empirical supports for the product replacement channel: The firms that face a negative demand shock replace their high-valued products with low-valued products, and they do so simultaneously in multiple markets and generate regional spillovers. In the empirical analyses, we find that all the intra-firm spillover effects arise from the products replaced in multiple markets. The newly introduced products have lower value—sales per product, unit price, and organic sales share—than the discontinued products. We formalize this channel with a stylized model in Section 5.

To empirically investigate the underlying mechanism, we use a simple regression framework to precisely decompose the spillover effect into the product replacement effect and continuing product effect. As described in Section 2, we decompose the local sales into two parts: intensive and extensive margins. The intensive margin is entirely conventional and refers to the local firm sales growth from the continuing products, which exist in both the initial and end periods. The extensive margin is the local firm sales growth that arises from product introduction and destruction in a given market. We regress each margin on the indirect demand shock to understand how firms that face a negative indirect demand shock change their local sales.

Figure 2: Decomposing the Intra-Firm Spillover Effect



(a) Continuing Product Effect **(b)** Product Replacement Effect

Note. Figure 2a and Figure 2b decompose the correlation between $\tilde{\Delta}\mathrm{S}_{rf}$ and $\tilde{\Delta}\mathrm{HP}_r$ (other) in Figure 1 into the correlation between $\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf}$ and $\tilde{\Delta}\mathrm{HP}_r$ (other) and the correlation between $\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf}$ and $\tilde{\Delta}\mathrm{HP}_{rf}$ (other), respectively. All variables are partialled out based on columns (2) and (3) of Table 5 and are weighted averaged by 50 equal-sized housing price growth bins. The bins are weighted by initial sales and the red lines represent a linear fit to the data.

Figure 2 visualizes the importance of product replacement in understanding the intra-firm spillover effect. Figure 2a plots the entirely conventional price and quantity effect of the intra-firm spillover, which arises from the continuing products. Surprisingly, there is a near-zero linear relationship between sales growth and the indirect demand shock. Depending on how one treats the observations subject to the extreme indirect demand shock, there is at most a *negative* relationship.[27] On the other hand, Figure 2b shows the intra-firm spillover effect through the extensive margin. The figure presents a strong positive relationship and closely replicates the overall spillover effect visualized in Figure 1b.

Table 5: Decomposing the intra-firm Spillover Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Ordinary Least Square, Decomposition						IV, Decomposition	
		$\tilde{\Delta}\mathrm{S}_{rf}$		$\tilde{\Delta}\mathrm{S}_{rf}$		$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf}$		$\tilde{\Delta}\mathrm{S}_{rf}$	
	$\tilde{\Delta}\mathrm{S}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R,M}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R,L}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{rf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R,M}}_{rf}$
$\tilde{\Delta}\mathrm{HP}_r$	0.06**	0.05***	0.01						
	(0.03)	(0.02)	(0.01)						
$\tilde{\Delta}\mathrm{HP}_{rf}$ (other)	0.35***	0.03	0.32***	-0.02	0.42***	0.42***	0.00	0.08	0.37**
	(0.11)	(0.06)	(0.09)	(0.05)	(0.10)	(0.10)	(0.00)	(0.08)	(0.17)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓						
Sector x Region FE				✓	✓	✓	✓	✓	✓
First-stage F statistics								254.70	254.70
Hansen's J-stat p-value								0.20	0.82
R^2	0.20	0.22	0.28	0.43	0.41	0.41	0.22		
Observations	840,681	840,681	840,681	840,681	840,681	840,681	840,681	417,869	417,869

Note. The regression specifications in columns (1)-(3), (4)-(7), and (8)-(9) are the same as those in Table 3 columns (1), (4), and (8), respectively. All the dependent variables are formally defined in Section 2. The coefficients in columns (2)-(3) decompose the coefficient in column (1), the coefficients in columns (4)-(5) decompose the coefficient in Table 3 column (4), the coefficients in columns (6)-(7) decompose the coefficient in column (5), and the coefficients in columns (8)-(9) decompose the coefficient in Table 3 column (8). Columns (8)-(9) report the results by using all three instrumental variables: the leave-one-out weighted average of the regional Saiz (2010) housing supply elasticity, Guren et al. (2020a) housing price sensitivity, and García (2018) non-local mortgage lending shock. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns (1)-(3) of Table 5 not only validate the visualization but also show a stark asymmetry: The direct demand effect works through the conventional intensive margin of price and quantity change, consistent with the price results in Stroebel and Vavra (2019), but the indirect demand effect works through product replacement. Column (1) replicates Table 3 column (1), and columns (2) and (3) exactly decompose the coefficients in column (1) into the continuing product effect and the product replacement effect. Approximately 83% (0.05/0.06) of the direct demand effect arises from

[27] For our baseline analyses, we seek to be agnostic on extreme values by including them but weight each observation by initial sales. Imagine that we were to trim our sample based on the indirect demand shock. In that case, the indirect demand shock would decrease the intensive margin of local firm sales growth, consistent with the international market results in Almunia et al. (2020). However, the indirect demand shock's overall effect is still positive in our analysis because there is a stronger positive intra-firm effect in the absence of extreme values, as shown in Figure 2b. This result is intuitive since many barcode-level products are shared across regions within the domestic markets, which generates the product replacement effect. In contrast, common products are rare at the international level.

continuing products, and approximately 92% (0.32/0.35) of the indirect demand effect occurs as a result of product replacement. This asymmetry of the direct and indirect effects ensures that the identified intra-firm spillover effect is unlikely to be confounded by the factors related to local housing price changes, which affect local firm sales through continuing products. Note that the barcode-level definition of products is important in this decomposition; if we instead define the product as the broader category of the product group, all the effects seem to arise from the continuing products, as shown in Online Appendix OA.3.

Columns (4) and (5) report that the intra-firm spillover effect remains robust after including region times sector fixed effects. When comparing the firms that sell in the same local market and operate in the same sector, we find that the firms that face a larger negative indirect demand shock decrease their local sales by replacing their products relative to their counterparts.

Columns (6) and (7) show that the intra-firm spillover effect results from the firms' synchronized product replacement decisions across multiple markets, not the firms' market-specific product replacement decisions. The coefficients reported in columns (6) and (7) further decompose the coefficient in column (5) by classifying products that are replaced in multiple markets and those replaced only in the local market. The local-market product replacement effect reported in column (7) is effectively zero, suggesting that the entire effect arises from products that are replaced in multiple markets simultaneously. This decomposition result is intuitive since almost all barcode-level products are sold in more than one market, and more than 80% of barcode-level products are replaced in multiple markets simultaneously in this period. The global product replacement result rules out the possibility that firms replace their products in each market separately when they face the indirect demand shock, potentially due to other firm-level costs.

Columns (8)-(9) further verify that the intra-firm spillover effects work through the global product replacement within firms. We rerun the decomposition analyses by using all three different IVs: the leave-one-out weighted average of the regional Saiz (2010) housing supply elasticity, Guren et al. (2020a) housing price sensitivity, and García (2018) non-local mortgage lending shock. Given that the local product replacement effects are close to zero in all specifications, these columns decompose the total spillover effects into the continuing product effects and the global product replacement effects. The global product replacement effects are both economically and statistically significant at conventional levels, but the continuing product effects are negligible.

Having established that firms replace their products and generate spillovers across regional sales, we investigate the associated changes in product values, characteristics, and varieties. We use the barcode-level sales, prices, and organic identifiers available in our data, aggregate them by county, firm, and entered and exited products, and construct the value differences between entered and exited products within county and firm as:

$$\tilde{\Delta} v_{rf} \equiv \frac{v_{rf,09}^{\text{enter}} - v_{rf,07}^{\text{exit}}}{\overline{v}_{rf}} \tag{4.1}$$

where $\overline{v}_{rf} \equiv \frac{1}{2}(v_{rf,07} + v_{rf,09})$. $v_{rf,09}$ is the county-firm-level measure of product values and characteristics and $v_{rf,09}^{\text{enter}}$ and $v_{rf,09}^{\text{exit}}$ measure $v_{rf,09}$ by using only those entered and exited products by county and firm, respectively. To investigate the role of product variety changes emphasized in previous studies (e.g., Mayer et al. (2014, 2016)), we similarly define the change in number of products by county and firm:

$$\tilde{\Delta} N_{rf} \equiv \frac{N_{rf,09} - N_{rf,07}}{\overline{N}_{rf}} \tag{4.2}$$

where N_{rf} is the total number of products in county r and firm f, and $\overline{N}_{rf} \equiv \frac{1}{2}(N_{rf,07} + N_{rf,09})$. We regress the change in product values, characteristics, and variety measured in Equations (4.1) and (4.2) on the indirect demand shock to investigate how firms spill over the regional shock by replacing their products.

Table 6: Changes in Product Value, Characteristics, and Variety

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\tilde{\Delta} v_{rf}$						$\tilde{\Delta} N_{rf}$	
v_{rf} is	S per UPC	Price			Organic			
		Simple	Weight	Weight, adj.	Sale	Number		
$\tilde{\Delta}\text{HP}_{rf}$ (other)	0.52**	0.73**	0.92**	0.70**	43.78**	12.78**	-0.04	-0.06
	(0.21)	(0.27)	(0.44)	(0.34)	(17.88)	(5.19)	(0.14)	(0.17)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓	✓	✓	✓
Sample Restriction								✓
R^2	0.40	0.51	0.41	0.42	0.38	0.36	0.35	0.40
Observations	464,423	461,672	461,672	461,672	27,930	27,907	840,681	464,423

Note. The regression specifications are the same as that in Table 3 column (4). S per UPC is defined as total sales per UPC. The simple and weighted price indexes in columns (2) and (3) are the simple and the sales-weighted geometric price across UPCs within the product group and firm. The simple index is the conventional price index component of the nested CES demand system in Hottman et al. (2016), and the weighted index is used to adjust for the importance of each UPC, as in the Cobb-Douglas utility function; all of them are sales-weighted averaged across groups. The weighted and adjusted price index in column (4) additionally subtracts the average group price following the quality index used in Argente et al. (2018). Columns (5) and (6) use the sales share and number of organic products, and columns (7) and (8) use the total number of products. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 shows that the products that are newly introduced in the local market by firms that face the negative indirect demand shock have lower values—sales per product, price, and organic share—than the products that are destroyed by the same firm in the same market. Columns (1)-(6)

consider different measures of values and characteristics by county, firm, and product entry and exit. Conditioning on the negative indirect demand shock, column (1) shows that the newly introduced products' sales are lower than those of destroyed products. Columns (2)-(4) use different weights and methods to construct the county-firm-level price index. Regardless of whether we fix the weight, vary the weight, or adjust for the product group mean, the new products have a lower price than the old products due to the negative indirect demand shock. Columns (5) and (6) consider the sales share and number of organic products. The negative indirect demand shock makes firms introduce fewer organic products and generate fewer sales from these new organic products in the local market. Columns (7) and (8) consider the effect on variety, but we do not find any effect on the number of products that firms sell in either the full sample or the restricted sample of counties in which firms replace their products.[28]

Our analyses suggest that the negative indirect demand shock makes firms adjust their product value and characteristics, not their price-cost markups or varieties. In the barcode-level data, for firms to change their product features, they must replace their products. It is difficult to interpret our findings with the markup adjustment through product replacement since those affected firms lower both prices and sales in our data. If firms lower prices and markups due to the indirect demand shock, as in the study of the variable markup (e.g., Alessandria et al. (2010)), they would generate more extensive sales and quantities conditioning on the direct demand change.[29] We rule out the variety adjustment channel because we do not find any supporting evidence, as shown in Table 6.[30]

To gain additional insights into the intra-firm spillover effect, we exploit the rich regional and firm heterogeneity in the data to estimate the heterogeneous treatment effect. We allow the intra-firm spillover effect to differ across initial and lagged exposure variables—local firm sales share, regional income and house prices, and firm sales and financial constraint measures—by interacting such variables with the indirect demand shock. We include them in the main regression Equation (3.1) along with the interacting variables.

Table 7 shows that the intra-firm spillover effect is more substantial for (i) firms that have smaller local market share, (ii) counties where household incomes or housing prices are high, (iii) large firms, and (iv) financially constrained firms. Columns (1) and (2) additionally clarify why the intra-firm spillover effect is stronger than the direct effect, as shown in Figure 1 and Table 3. When a

[28] As robustness checks, Table A.13 in Appendix A considers alternative definitions of price indexes, and Table A.14 in Appendix A conducts the analysis at the county-firm-product group level with the product group fixed effects.

[29] In unpublished work, we define the county-firm-level quantity and run the regression but do not find meaningful results.

[30] Although we report characteristics associated with intrinsic product values, firms may change the perceived product quality through national advertising or marketing; our analyses are consistent as long as these changes apply to the newly introduced products. Similarly, firms may resize and repackage products. As long as such changes decrease the value of products they sell and reduce their total local sales, the results are fully consistent with our intra-firm spillover effect. Section 5 formalizes product replacement as a quality change, and quality is broadly defined as what changes the market share conditional on product price.

Table 7: Heterogeneous Treatment Effect

	$\tilde{\Delta}$ S_{rf}, 2007-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
X_{rf} is	log share_{rf}	share_{rf} (D)	inc_r	HP_r	sales_f	paydex_f	RZ
$\tilde{\Delta}\text{HP}_{07-09}$ (other) x X_{rf}	-0.10***	-0.44***	0.39***	0.28***	0.28***	2.08*	3.75
	(0.03)	(0.11)	(0.08)	(0.08)	(0.05)	(1.22)	(2.33)
$\tilde{\Delta}\text{HP}_{rf,07-09}$ (other)	0.08	0.78***	-3.88***	-3.14***	-4.38***	-6.54	-0.10
	(0.13)	(0.09)	(0.98)	(1.11)	(0.80)	(3.94)	(0.33)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓	✓	✓
R^2	0.39	0.38	0.38	0.38	0.39	0.36	0.35
Observations	840,681	840,681	840,681	840,681	840,681	771,840	571,795

Note. The regression specification is the same as that in Table 3 column (4) except that we include the exposure variable X_{rf} and its interaction with the indirect demand shock $\tilde{\Delta}\text{HP}_{07-09}$ (other). We consider seven alternative measures of X_{rf}: The log share_{rf} is the log firm's initial local sales share, share_{rf} (D) is a dummy variable equal to 1 if the initial local sales share is larger than the median value of the total sample, inc_r is the initial household median income in region r, HP_r is the initial house price in the region r, sales_f denotes the initial log firm-level sales, Paydex_f is the 2002-2006 average numerical credit score given by Dun & Bradstreet, and RZ is the SIC 2-digit Rajan and Zingales (1998) external financial dependence index computed from Compustat data. The paydex_f is measured as ln(100-paydex) to facilitate interpretation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

firm's initial market share is small, the indirect demand shock closely proxies for the total firm-level shock, strengthening the intra-firm spillover effect. Columns (3) and (4) provide additional empirical support for the product replacement of high- to low-valued products presented in Table 6. Assume that wealthy households, which have a high income or live in counties where house prices are high, prefer high-valued or high-quality products (see, e.g., Handbury (2019)). Then there would be a larger decrease in firm sales in those counties where wealthy households dwell when firms provide low-valued (or low-quality) products. Column (5) indicates that the intra-firm effect is stronger for large firms, consistent with the direct effect results in Argente et al. (2020); it is likely easier for such firms to replace products because they (i) produce more standardized products (Holmes and Stevens 2014) or (ii) have a larger scope (Argente et al. 2020). Columns (6) and (7) show that the effect is marginally stronger for financially constrained firms, consistent with the multi-establishment network results in Giroud and Mueller (2019) and the international evidence in Berman et al. (2015). Such firms likely incur higher costs in keeping up with high-valued or high-quality products when facing the negative indirect demand shock, generating a larger spillover effect.[31]

[31] We also consider the indirect demand shock interaction with the distance from its origination, but we do not find any meaningful results conditioning on firm size.

5 The Model

Motivated by our empirical evidence, this section formalizes the spillover mechanism and discusses aggregate distributional implications by developing a stylized multimarket model with endogenous quality adjustments by firms. We simplify and extend the model environment in Melitz (2003) and Faber and Fally (2020) into a multiregion framework to match our empirical findings. The model reproduces the salient features we identified in our empirical analyses: (i) the elasticities associated with firms' local sales to direct and indirect shocks and (ii) the product replacement channel with product downgrading. Through a counterfactual analysis, we show that the identified intra-firm cross-market spillover effect generates a novel interregional shock transmission, which leads to a quantitatively large consumption redistribution across local markets.

This section presents the model's key elements. The full description of the model is in Online Appendix C, and the detailed derivations and proofs are in Online Appendix D.

Market Demand. Consider a static economy with R markets indexed by $r \in \mathcal{R} \equiv \{1, 2, ..., R\}$. Each market is populated by a continuum of mass L_r of individuals, each of whom is endowed with total income y_r, which is the sum of the exogenous income I_r and the dividends from the production sector D_r.[32] The regional demand shock is modeled as an exogenous change in individual income in market r. The economy consists of two broad sectors: the CPG sector, which is the focus of this paper, and an outside goods sector. Similar to Handbury (2019) and Faber and Fally (2020), we consider a two-tier constant elasticity of substitution (CES) utility where the upper-tier depends on the utility from CPG goods (U) and an outside good (z), which serves as a numeraire. The optimal consumption of CPG goods by an individual in market r (s_r) is the share of the income of the same individual (y_r), where the share depends on the regional CPG price index, the elasticity between CPG and outside goods, and the individual preference parameter on CPG goods over outside goods.

Each individual enjoys utility from both the quantity and quality of CPG product bundles produced by a continuum of firms. Individuals value product quality differently depending on their income due to the non-homothetic preferences. The utility from the CPG consumption is defined as:

$$U_r = \left[\int_{f \in G_r} (q_{rf} \zeta_{rf})^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}} \tag{5.1}$$

where f denotes a CPG firm, G_r is the set of firms selling in market r, q_{rf} is the quantity of product bundle produced by firm f and consumed by individuals in market r, ζ_{rf} refers to the perceived quality (or appeal, taste) of firm f's product bundle in market r, and σ refers to the elasticity of

[32] Since the wage rate equals one under the labor market structure described below, I_r can be interpreted as exogenous labor endowments as in Fajgelbaum et al. (2011). For simplicity, we assume that the dividends are distributed proportional to individuals' exogenous income.

substitution between the firms' product bundles.[33] We assume that the perceived quality depends on an intrinsic quality (i.e., product attribute) choice $\log\phi_f$ by firm f and a multiplicative term γ_r that governs the non-homothetic preferences:

$$\log\zeta_{rf} \equiv \gamma_r \log\phi_f \tag{5.2}$$

where γ is a function of individuals' income in market r and $\gamma_r \equiv \gamma(I_r)$; individuals living in a high-income market prefer high-quality products.[34]

There are two simplifying assumptions in this setup to reflect our empirical analyses. First, as we find no empirical evidence of product variety changes from the indirect demand shock, we do not explicitly model the multiproduct firms. Instead, we interpret the change in the quality of a product bundle, ϕ_f, as a product replacement within firms. Our empirical analyses of product values and organic shares suggest a change in product features that make it less desirable for consumers conditioning on product prices, which is precisely linked to the definition of product quality in this model. Second, firm f's choice of intrinsic product quality, ϕ_f, does not vary across markets. This assumption reflects our main empirical findings of synchronized product replacement across many markets presented in Section 4. In Appendix Figure A.1 and Table A.20, we additionally document that most of the products in the CPG industries are nationally sold, and there is a general synchronized product replacement pattern in these industries.[35]

Each individual in market r solves for their optimal CPG consumption bundle by maximizing equation (5.1) subject to his or her budget constraint, $\int_{f\in G_r} p_{rf}q_{rf}df \le s_r$, where p_{rf} is the price index of firm f's product bundle in market r. Defining the total expenditures in market r as $S_r \equiv s_r L_r$ and the total expenditures on firm f's product bundle in market r as $S_{rf} \equiv p_{rf}q_{rf}L_r$, the first-order condition is:

$$S_{rf} = (\zeta_{rf})^{\sigma-1}\left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} S_r \tag{5.3}$$

where the quality-adjusted regional CPG price index is given by

$$P_r \equiv \left[\int_{f\in G_r} (p_{rf})^{1-\sigma}(\zeta_{rf})^{\sigma-1}df\right]^{\frac{1}{1-\sigma}} \tag{5.4}$$

[33] As documented in Anderson et al. (1987), this utility function can be derived from the aggregation of discrete-choice preferences across many agents choosing only one firm's product bundle. See Online Appendix D.2 for the proof.

[34] Note that we allow non-homotheticity across quality (γ) but not across elasticity (σ) to make the model parsimonious. This specification is based on the previous analyses on the consumer packaged goods industry that integrates both types of non-homotheticity and find the dominant role of quality relative to the elasticity in explaining the heterogenous household consumption pattern. See, e.g., Handbury (2019); Faber and Fally (2020).

[35] Explicitly considering the choice of the market-specific quality in the model reveals that firms choose uniform product quality across markets when (i) their fixed costs of market-specific quality adjustment are high or (ii) they sell to many markets and find it less profitable to pay market-specific fixed costs. For the CPG goods, it would be very costly for firms to replace product county by county or state by state. See Online Appendix E for this extension.

CPG Production. There is a continuum measure of N firms that produce differentiated CPG bundles. Each firm simultaneously chooses optimal quality and prices subject to monopolistic competition. Since we consider sets of active firms in both pre- and post-shock periods in the empirical analyses, we abstract away from the firm's entry and exit decision and calibrate the model so that all firms enjoy the non-negative profit in the equilibrium. In this way, we directly map the firms used in the empirical analyses into the model.

There are variable and fixed costs of production measured in terms of the labor units, and producing high-quality products requires both costs. The marginal cost of production of firm f with productivity a_f is:

$$mc(\phi_f; a_f) \equiv \frac{\phi^{\xi}}{a_f} \tag{5.5}$$

where the parameter ξ is the elasticity of the cost to the level of product quality. Note that we assume the standard constant marginal costs of quantity production. This assumption reflects our empirical finding that there is no intra-firm spillover effect through continuing products within domestic markets. Assuming increasing or decreasing marginal costs of quantity would generate the spillover effect through continuing products because firms would sell different quantities in the local market when the change in marginal costs is induced by the demand shocks arising from their other markets.

The total fixed costs are given by $f(\phi_f) + f_0$, where $f(\phi_f)$ is the componenet of fixed costs that directly depends on quality. This component captures potential overhead costs such as design, marketing, or other contractual costs, which do not directly depend on the quantities being produced but affect product quality. Note that we are analyzing a relatively short period, 2007-2009, and any one-time costs that occur every two years are fixed cost in this setup. We assume a simple log-linear parameterization given by

$$f(\phi) = b\beta\phi^{\frac{1}{\beta}} \tag{5.6}$$

where β measures the responsiveness of fixed costs with respect to the supply of high product quality, and b is a constant parameter that rescales the quality component of the total fixed costs.

Firm f optimally chooses the intrinsic quality of product ϕ_f, which applies uniformly across its markets, and price p_{rf} by maximizing its profits

$$\pi_f = \sum_{r \in k_f} (p_{rf} - mc(\phi_f; a_f))\, q_{rf} L_f - f(\phi_f) - f_0 \tag{5.7}$$

subject to the market demand Equation (5.3). k_f is the set of markets in which firm f sells its products. We assume that each firm's markets are fixed, which reflects the historical persistence of the firms' markets as documented in previous studies (Bronnenberg et al. 2009, 2012) and as reflected in our empirical analyses. The optimal price and quality are given by

$$p_{rf} = \mu \left(\frac{\phi_f^{\xi}}{a_f} \right) \tag{5.8}$$

and

$$\phi_f = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta} \tag{5.9}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma-1}\right)$ indicates the price-cost markup. Product quality is higher when households prefer high-quality products (high γ) but lower when the variable costs increase too much given a small increase in quality (high ξ) or when households do not easily switch their products (low σ or high μ). Due to the fixed costs of producing high-quality products, the optimal quality increases with the size of market demand firms face (S_{rf}), and the magnitude of all such effects on quality depends on the responsiveness of fixed costs to product quality. The optimal price is a conventional markup over marginal cost.

Combining the local firm product demand (5.3), the definition of product quality (5.2), and the equilibrium firm local price (5.8), we derive the following local firm sales equation:

$$S_{rf} = \phi_f^{(\sigma-1)(\gamma_r - \xi)} \left[\frac{a_f}{\mu} P_r \right]^{\sigma-1} S_r \tag{5.10}$$

Local firm sale, which is the primary outcome variable in the empirical analyses, depends on intrinsic product quality in this framework. Holding everything else constant, an increase in firm product quality leads to an increase in local firm sales, and the responsiveness depends on the demand elasticity (σ), individuals' preference on product quality (γ), and the elasticity of the marginal cost with respect to product quality (ξ). When the demand elasticity is large, individuals easily switch products, and the increase in product quality leads to a more considerable increase in sales. If individuals initially prefer high-quality products, the increase in product quality leads to higher market share. However, if there is a larger marginal cost associated with the increase in product quality, then the firm's output price increases by more, decreasing sales further. Productivity and markup affect local firm sales through output prices, and responsiveness depends on the demand elasticity, as in conventional models.

With sufficiently small β, the equilibrium price and quality are unique and the equilibrium firm product quality ϕ_f, local sales S_{rf}, and profit π_f increase monotonically with firm productivity a_f.

See Online Appendices D.3 and D.4 for the proof.

5.1 From Theory to Empiric

By replacing the equilibrium firm quality in Equation (5.10) with the optimal quality (5.9) and taking the log difference of the combined equation, we derive the local firms sales growth equation that clarifies the underlying mechanism behind our empirical analyses:

$$\hat{S}_{rf} = \Upsilon_r \sum_{r \in k_f} \omega_{rf} \left[\hat{S}_{rf} + \hat{\psi}_r \right] + (\sigma - 1)\hat{a}_f + (\log X_f)\Upsilon_r \hat{\psi}_r + \hat{A}_r \tag{5.11}$$

where $\hat{x} \equiv \log x'/x$ is the growth rate of any variable x, $\Upsilon_r \equiv \beta(\sigma - 1)(\gamma_r - \xi)$, $\psi_r \equiv (\gamma_r - \xi)$, $\omega_{rf} \equiv \frac{S_{rf}\psi_r}{\sum_{r' \in k_f} S_{r'f}\psi_r}$, $X_f \equiv \sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\psi_r}{\mu} \right)$, and $A_r \equiv (P_r)^{\sigma-1} S_r$.

The first part on the right-hand side of Equation (5.11) presents and decomposes the interdependency of markets through the multimarket firms' internal networks, which is linked to our empirical analyses. The interdependency works through the firms' uniform product quality decision across their markets, which makes their local sales respond to both their overall sales growth ($\sum_{r \in k_f} \omega_{rf} \hat{S}_{rf}$) and the change in the overall household preference on quality ($\sum_{r \in k_f} \omega_{rf} \hat{\psi}_r$). Firm sales affect its local sales because of the scale effect: firms downgrade their product quality when they lack sufficient revenue to recover the high fixed cost of producing high-quality products. The overall change in household preferences affects local firm sales through the non-homothetic preferences: as households prefer low-quality products, firms lower their product quality to meet their demand and to save the associated costs. The initial weight, ω_{rf}, reflects the importance of each market to the firm with respect to sales (S_{rf}) and the net benefit of the high-quality products (ψ_r). The overall shock firms face $\left(\sum_{r \in k_f} \omega_{rf} \left[\hat{S}_{rf} + \hat{\psi}_r \right] \right)$ mirrors the indirect demand shock in the empirical analyses. As emphasized in Section 3, CPG firms sell in many markets, approximately 513 counties on average. The local market share is negligible at the firm level, and almost all the variation of the global firm-level shock arises from the indirect demand shock. Consistent with this notion in the indirect demand shock, the intra-firm spillover effect we identified is stronger because the indirect demand shock better proxies for the global firm-level shock, as shown in Table 7.

The responsiveness of local firm sales to both overall sales growth and the preference change is Υ_r, which consists of the inverse elasticity of the fixed cost (β) and the elasticity of market share ($(\sigma - 1)(\gamma_r - \xi)$) with respect to quality. As the indirect demand shock closely proxies for the overall firm-level shock, the structural parameters in Υ_r effectively control the strength of the intra-firm spillover effect we identified in the data.[36] From the cost side, if a firm can raise its product quality by paying a small amount of fixed costs (high β), it would raise quality and local sales more than its

[36] By fixing γ across counties, it is straightforward to recover the empirical Equation (3.1) by replacing the housing price growth in the indirect demand shock with sales growth.

counterpart conditional on the same firm sales growth. From the demand side, if firms can acquire considerable market share by raising their product quality (high $(\sigma-1)(\gamma_r-\xi)$), firms that face overall sales growth would increase their quality and local sales more than their counterparts. As described in Equation (5.10), the effect of quality on market share depends on the substitutability of products (σ), individual preferences (γ), and the marginal cost of quality that passes through to output price (ξ). Consistent with the prediction on γ_r, the spillover effect is larger for high-income regions as reported in Table 7.

We leverage our model to analytically solve for the direct effect and the indirect intra-firm spillover effect that we identified in the data. Proposition 1 characterizes the direct effect.

Proposition 1. *Suppose that (i) β is sufficiently small and (ii) P_r and D_r are fixed. Then, $\frac{\partial \log \phi_f}{\partial \log y_r} > 0$ and $\frac{\partial \log S_{rf}}{\partial \log y_r} > 0$ for $r \in k_f$.*

Proof. See Online Appendix D.5. □

As in our empirical analyses, the negative regional demand shock decreases local firm sales and product quality. The effect on both local firm sales and product quality holds when we allow P_r to vary with y_r, as long as the variation is relatively small. Note that a sufficiently small β guarantees the unique equilibrium in the model.

Because a negative regional demand shock decreases product quality, Proposition 2 indicates that such a decrease in product quality can generate the intra-firm spillover effect.

Proposition 2. *Suppose that (i) y_r is fixed and (ii) P_r is fixed. Then, $\frac{\partial \log S_{rf}}{\partial \log \phi_f} > 0$ for $r \in k_f$.*

Proof. See Online Appendix D.5. □

Conditional on the direct demand shock, decreasing product quality lowers local firm sales. This prediction is consistent with the intra-firm spillover effect we identified in the data. Tables 5 and 6 provide empirical support that firms' uniform product replacement of high-value products with low-value products—arising from the indirect demand shock—lowers their local firm sales.

5.2 Regional Redistribution

Analytical Results. How do regional sales, prices, and welfare change through the multimarket firm network when holding the direct regional demand shock constant? Although our detailed micro-level empirical analyses provide clean results on market-firm-level outcomes with minimal assumptions, they do not directly speak to regional or aggregate changes. We leverage our model to understand the welfare redistribution across markets through the multimarket firms' internal networks. We first analytically characterize the regional indirect demand shock's partial equilibrium effect on the local market in Proposition 3.

Proposition 3. *Suppose y_r is fixed. Then,* $\frac{\partial \log P_r}{\partial \log \phi_f} < 0$, $\frac{\partial \log S_r}{\partial \log \phi_f} > 0$, $\frac{\partial \log U_r}{\partial \log \phi_f} > 0$ *for* $r \in k_f$

Proof. See Online Appendix D.5. □

Proposition 3 shows the risk-sharing of quality-adjusted consumption across regions through multimarket firm behavior. When conditioning on the regional demand shock, decreasing firm-level product quality increases the regional quality-adjusted price index and decreases local sales and quality-adjusted CPG consumption.[37] Thus, our model predicts that a market that did not experience any negative regional shock could experience welfare loss through the quality downgrading of multimarket firms. However, market r', which faces the direct negative demand shock, benefits from the other market r, which did not face the negative demand shock. Since market r faces a nonnegative demand shock, the quality downgrading in market r' is alleviated. Thus, market r and market r' share the burden of the negative demand shock that affects market r'.

Quantification. Armed with the economic intuition in Proposition 3, we numerically solve for the full general equilibrium effect of the intra-firm network on the consumption redistribution across states.[38] We include both single-market firms and multimarket firms in our analyses, which yields a total of 5,186 firms that see in at most 49 states. We compare our baseline economy with the counterfactual economy, which shuts down the intra-firm network channel by assuming the firm's market-specific quality choice. As stated in Proposition 6 in Appendix D, this economy features no spillover through an intra-firm network, as in conventional models of international economics. See Appendix D for the full description of the counterfactual economy.

Appendix E presents the full description of the calibration and estimation of parameters. We leverage Equation (5.11) by using the indirect demand shock from empirical analyses as an IV to estimate the key parameter Υ. We rely on the relationship between housing prices and consumption identified in Berger et al. (2018) to feed the 2007-2009 state-level housing price growth into the model. The calibration and estimation of other parameters mostly follow the previous literature, and a summary of the resulting parameter values is reported in Appendix Table A.21. We check the validity of the model and parameters by feeding the state-level housing price growth into the model, generate data from the model, and estimate Equation (3.1). As shown in Appendix Table A.17, the estimated model replicates the elasticity of local firm sales growth concerning both the direct and the indirect demand shocks.

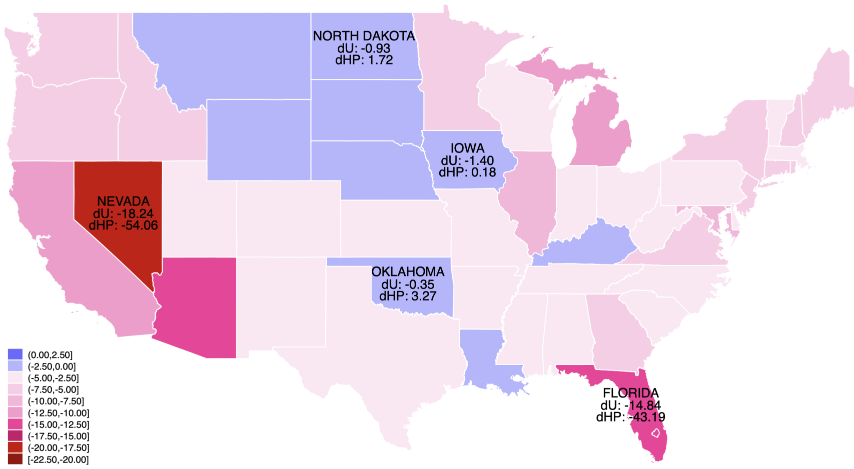
Figure 3 shows that the intra-firm spillover effect we identified in the data substantially reduced the real CPG consumption inequality across states. We plot both the baseline and counterfactual model-generated quality-adjusted CPG consumption per capita across states in Figures 3a and 3b,

[37] Total consumption, which includes both CPG consumption and outside goods, also decreases due to the decrease in product quality adjustment in CPG industries.

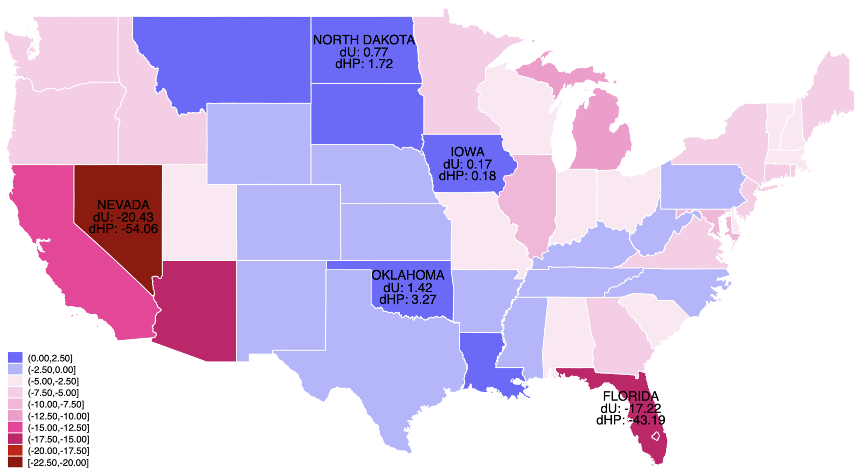
[38] Our reduced-form empirical results are robust to defining the market as a state, as shown in Appendix Table A.4.

Figure 3: Regional Redistribution across US States

(a) Benchmark Economy



(b) Counterfactual Economy



Note. dU is the state-level CPG consumption growth, mapped with different colors across states, and dHP is the state-level housing price growth. The benchmark economy in Figure 3a plots the CPG utility growth by assuming the same product quality choice of firms across multiple markets as in our empirical analyses. The counterfactual economy in Figure 3a plots the CPG utility growth by assuming the market-specific quality choice of firms, as in Appendix D. Table A.19 reports a full description of the utility and housing price growth.

respectively; Figure 3a includes the intra-firm spillover effect, whereas Figure 3b shuts down this effect. Despite the same level of housing price changes across the two different economies, the counterfactual economy features a substantially larger variance of CPG consumption sales growth per capita across states than the baseline economy. In the counterfactual economy, the standard deviation of the CPG consumption growth per capita is 5.21, approximately 29% larger than the standard deviation of 4.03 in the benchmark economy. When using total consumption, we obtain the same qualitative results. Appendix Figures A.2 and A.3 additionally compare the cross-sectional dispersion of the *level* of

CPG and total consumption, and we find that the standard deviation increases by approximately 50% in the counterfactual economy.

The underlying mechanism behind the consumption redistribution is the intra-firm product quality decision across markets. Firms supply the same product quality to both negatively and positively affected states in the benchmark economy, but in the counterfactual economy, firms offer lower product quality to more negatively affected areas. For example, Oklahoma experienced a modest increase in housing prices in this period (dHP=3.27). Nevertheless, with the intra-firm spillover effect, the state's real consumption growth is negative (dU=-0.35) as it is offered low-quality products. If firms had supplied market-specific product quality, Oklahoma would have experienced positive CPG consumption growth (dU=1.42). On the other hand, Florida experienced a large decrease in housing price growth (dHP=-43.19), resulting in a decrease in real consumption by 14.84 percent. If firms had provided low-quality products in Florida, its real consumption would have fallen by 17.32 percent. The results are similar for total consumption.[39]

A simple back-of-the-envelope calculation reveals that the intra-firm spillover effects correspond to a one-time \$400 per-household transfer (tax) to negatively (positively) affects states, an amount comparable to that of transfer policies. In the counterfactual economy, we reduce the dispersion of regional shocks to the extent that the standard deviation of total consumption growth across states equals that of the benchmark. On average, this reduction requires a 0.58 percentage point change in income growth in the corresponding states. Since the initial cross-state average of the median household income was approximately \$69,000, the dollar transfer would be $\$400 \approx \$69000 \times 0.0058$. This amount is comparable to the tax rebate checks authorized by the US Congress in 2008 (Economic Stimulus Act of 2008), which were one-time payments ranging from \$300 to \$1200 per qualifying household.

6 Conclusion

This paper uses detailed barcode-level data to study whether and how multimarket firms spill over regional shocks across US local markets through their intra-firm network. We find that a firm's local sales decrease in response to the direct negative local demand shock and do so more strongly to indirect adverse local demand shocks, which affect its other markets. We observe a stark asymmetry

[39] Note that the scale effects and the non-homothetic preference effect generate different regional consumption distributive effects. With homothetic preferences, uniform quality adjustments mitigate quality-adjusted regional consumption inequality because regions with higher demand face lower product quality than the counterfactual economy, while areas with lower demand enjoy relatively higher product quality. However, under non-homothetic preferences, both high-income and low-income markets can experience decreases in real consumption because both regions face the same unfavorable product quality. High-income markets prefer higher product quality, while low-income markets prefer lower product quality at low prices because they are poor. Thus, both types of markets experience additional level effects that reduce consumption, and the resulting regional inequality is unclear. In our analyses, we find that the effect of non-homotheticity on regional consumption inequality is limited. Our estimation result assigns a dominant role to the scale effects compared to non-homothetic preferences.

in this finding: the direct effect operates through continuing products, but the intra-firm spillover effect is mostly attributable to product creation and destruction. To explain the intra-firm spillover effect, we propose the product replacement mechanism: firms that face a negative regional demand shock replace their high-valued products with low-valued products, and they do so in multiple markets and spill over the shock. We provide empirical support and formalize the mechanism with a stylized model. Counterfactual analyses reveal that the identified intra-firm spillover serves as a redistributive mechanism and substantially mitigates regional consumption inequality.

Our work underscores the importance of multimarket, multiproduct firm behavior in understanding regional consumption inequality. Integrating the importance of such firms would deepen the understanding of the regional welfare distribution.

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Appendix A Additional Tables

Table A.1: Balance Checks

	Firm-level Avg. $\tilde{\Delta}$HP		
Variable	Coefficient	Std. Error	P-Value
Log of Firm Sales	-1.101	1.531	0.472
Log of Num. Market	-0.581	0.917	0.527
Log of Num. Prod.Group	1.404	0.971	0.148
Log of Local Sales (Avg.)	-0.520	1.169	0.656
Log of Local Sales-per-UPC (Avg.)	0.513	0.852	0.547
Log of (100-Paydex)	-0.177	0.147	0.229
Log of Num. Establishments	1.477	2.168	0.496

Note. This table reports coefficients from regressing firm-level initial characteristics on the firm-level average $\tilde{\Delta}$HP (averaged across counties) and sector fixed effects (at the SIC 4-digit level). The sample includes 4,171 firm-level observations.

Table A.2: Excluding Nearby Regions

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, out-of-state)	0.335^{***}			
	(0.090)			
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, $\geq$50mi)		0.400^{***}		
		(0.087)		
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, $\geq$100mi)			0.396^{***}	
			(0.087)	
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, $\geq$150mi)				0.359^{***}
				(0.082)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.393	0.394	0.395	0.395
Observations	838812	840235	839548	838641

Note. The regression specification is the same as that in Table 3 column (4). $\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, out-of-state) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, where we exclude "other counties" that are located in the same state (by assigning zero weights to them and renormalizing the remaining weights to one), $\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other, $\geq$"N"mi) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, where we exclude "other counties" within "N" mile radius around the county (by assigning zero weights to them and renormalizing the remaining weights to one). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: State-level: Decomposition of Sales Growth

	(1)	(2)	(3)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.303**	0.376***	-0.074
	(0.113)	(0.085)	(0.067)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.357	0.449	0.426
Observations	83610	83610	83610

Note. The regression specification is the same as that in Table 3 column (4), where we define the local market at the state instead of the county level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.4: State-level: Extensive Margin Decomposition

	(1)	(2)	(3)
	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R,M}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R,L}}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.376***	0.389***	-0.013
	(0.085)	(0.078)	(0.011)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.449	0.450	0.144
Observations	83610	83610	83610

Note. The regression specification is the same as that in Table 3 column (4), where we define the local market at the state instead of the county-level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.5: Allowing Retailer Dimension: County-Firm (Producer)-Retailer Level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (firm, other)	0.533***	0.520***	0.537***	-0.017
	(0.025)	(0.030)	(0.048)	(0.046)
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (firm-retailer, other)		0.071	0.055	0.016
		(0.141)	(0.145)	(0.082)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region x Retailer FE	✓	✓	✓	✓
R^2	0.506	0.506	0.451	0.515
Observations	1691268	1691268	1691268	1691268

Note. $\tilde{\Delta}\mathrm{S}_{(07-09)}$ is county-firm-retailer-specific sales growth between 2007 and 2009, $\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$ is county-firm-retailer-specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$ is the county-firm-retailer-specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, and $\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (firm-retailer, other) is the initial county-firm-retailer-specific sales-weighted house price growth between 2007 and 2009 in the other counties where retailer generates sales by selling the firm's products. Sectors are defined based on the SIC 4-digit classification. Region-firm controls include the log of initial county-firm-retailer-specific sales, log of initial firm-level sales, log of firm's initial number of local markets, and log of firm's initial number of product groups. All regressions are weighted by county-firm-retailer-specific initial sales. Standard errors (in parentheses) are three-way clustered at the state, sector, and retailer level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: County-Firm-Product Group-Level Regression with County-Firm-Level Indirect Shock

	(1)	(2)	(3)
	$\tilde{\Delta}\text{S}_{(07-09)}$	$\tilde{\Delta}\text{S}^{\text{R}}_{(07-09)}$	$\tilde{\Delta}\text{S}^{\text{C}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, firm)	0.173**	0.306***	-0.133
	(0.070)	(0.049)	(0.099)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Prod.Group x Region FE	✓	✓	✓
R^2	0.420	0.485	0.475
Observations	1592287	1592287	1592287

Note. $\tilde{\Delta}\text{S}_{(07-09)}$ is the county-firm-product group-specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{S}^{\text{R}}_{(07-09)}$ is the county-firm-product group-specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{S}^{\text{C}}_{(07-09)}$ is the county-firm-product group-specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, firm) is the initial county-firm-specific sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales (i.e., same shock as in the main county-firm-level analyses). Sectors are defined based on SIC 4-digit industries. Region-firm controls include the log of initial county-firm-product group-specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm-product group-specific initial sales. Standard errors (in parentheses) are clustered at the state and sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Exclude Exporters or Include Exporter Dummy

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.519***	0.384***	0.134	0.397***
	(0.165)	(0.037)	(0.107)	(0.102)
I(Export)				-0.015
				(0.029)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.439	0.466	0.506	0.392
Observations	481946	481946	481946	840681

Note. The regression specification is the same as that in Table 3 column (4). By using the exporter definition in the NETS data, we either exclude exporter or allow exporter fixed effect to control for the international exposure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Control Firms' Customer Types

	(1)	(2)	(3)
	$\tilde{\Delta}\text{S}_{(07-09)}$	$\tilde{\Delta}\text{S}^{\text{R}}_{(07-09)}$	$\tilde{\Delta}\text{S}^{\text{C}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.637**	0.598***	0.039
	(0.261)	(0.150)	(0.245)
Income (other)	-0.004	0.002	-0.006*
	(0.003)	(0.002)	(0.003)
Educ (other)	-0.016***	-0.001	-0.015***
	(0.005)	(0.004)	(0.002)
White (other)	-0.003	0.003	-0.006
	(0.006)	(0.003)	(0.003)
Owner (other)	0.005	-0.007**	0.012**
	(0.004)	(0.003)	(0.005)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.395	0.409	0.429
Observations	840681	840681	840681

Note. The regression specification is the same as that in Table 3 column (4), where we include additional demographic controls constructed in a similar way as in $\tilde{\Delta}\text{HP}_{(07-09)}$ (other). These include pre-recession median household income, percentage with high school diploma or less, percentage white, and percentage owner-occupied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Control Largest Market

	(1)	(2)	(3)
	$\tilde{\Delta}S_{(07-09)}$	$\tilde{\Delta}S^{R}_{(07-09)}$	$\tilde{\Delta}S^{C}_{(07-09)}$
$\tilde{\Delta}HP_{(07-09)}$ (other)	0.423***	0.349***	0.073
	(0.121)	(0.072)	(0.172)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Sector x Largest.Mkt FE	✓	✓	✓
R^2	0.502	0.521	0.500
Observations	840681	840681	840681

Note. The regression specification is the same as that in Table 3 column (4), where we add sector-by-largest-market fixed effects. We define a firm's largest market as the census division that has largest within-firm sales share. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.10: Homescan Panel: Controlling for Lagged Dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.325*	0.246**	0.079	0.311*	0.238**	0.080
	(0.188)	(0.110)	(0.168)	(0.173)	(0.105)	(0.169)
$\tilde{\Delta}\mathrm{S}_{(04-06)}$				0.086***		
				(0.009)		
$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(04-06)}$					0.100***	
					(0.010)	
$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(04-06)}$						-0.007
						(0.011)
Region-Firm Controls	✓	✓	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓	✓
R^2	0.427	0.419	0.389	0.432	0.426	0.389
Observations	161537	161537	161537	161537	161537	161537

Note. We constructed state-firm level observations using the ACNielsen Homescan Panel database. To make the sample representative, we use the state-level variation. $\tilde{\Delta}\mathrm{S}_{(07-09)}$ is the state-firm-specific sales growth between 2007 and 2009, $\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$ is the state-firm-specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from continuing products. $\tilde{\Delta}\mathrm{S}_{04-06}$, $\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{04-06}$, and $\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{04-06}$ are corresponding growth rates between 2004 and 2006. $\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other) is the lagged sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. The weights are constructed using 2004 state-firm-specific sales. We group companies by their three largest product groups and classify those operating in the same sector. Region-firm controls include the log of 2004 state-firm-specific sales, log of 2004 firm-level sales, log of the 2004 number of local markets a firm has, and log of the 2004 number of product groups a firm has. All regressions are weighted by state-firm-specific initial sales. Standard errors (in parentheses) are two-way clustered at the state and sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Homescan Panel: Pre-trend Regression

	(1)	(2)	(3)
	$\tilde{\Delta}\mathrm{S}_{(04-06)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(04-06)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(04-06)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.171	0.082	0.089
	(0.287)	(0.150)	(0.170)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.449	0.421	0.428
Observations	161537	161537	161537

Note. The regression specification is the same as that in Table A.10 except the dependent variable. We use the 2004-2006 sales growth as a dependent variable to check for the pre-trend. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Accommodating Firms' Local Market Entry/Exit

	(1)	(2)	(3)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	0.446^{***}	0.486^{***}	-0.040
	(0.113)	(0.124)	(0.080)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.434	0.434	0.442
Observations	1455914	1455914	1455914

Note. The regression specification is the same as that in Table 3 column (4). While constructing each growth rate, we accommodate firms' local market entry and exit by assigning 2 (entry) and -2 (exit), respectively. All regressions are weighted by county-firm-specific average sales (across 2007 and 2009) to avoid assigning zero weight to a newly entered local market in 2009. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Replacement from High- to Low-Value Products: Alternative Price Measures

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Price}_{(07-09)}$		$\tilde{\Delta}\text{Price (Avg. Adj.)}_{(07-09)}$	
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.310**	0.456**	0.344*	0.481**
	(0.122)	(0.189)	(0.195)	(0.209)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
Index	Equal Weight	Sales Weight	Equal Weight	Sales Weight
R^2	0.417	0.397	0.428	0.419
Observations	461672	461672	461672	461672

Note. The regression specification is the same as that in Table 3 column (4). The measure of value (price) change, $\tilde{\Delta}v_{rf}$, is defined as $\tilde{\Delta}v_{rf} \equiv \frac{v_{rf,09}^{\text{enter}} - v_{rf,07}^{\text{exit}}}{\overline{v}_{rf}^{R}}$ (instead of $\overline{v}_{rf}$ in the denominator) where $\overline{v}_{rf}^{R} \equiv \frac{1}{2}(v_{rf,07}^{\text{exit}} + v_{rf,09}^{\text{enter}})$. In the left panel, $\tilde{\Delta}\text{Price}_{(07-09)}$ is the county-firm-specific price growth at the replacement margin between 2007 and 2009. The simple and weighted price indexes in columns (1) and (2) are the simple and the sales-weighted geometric price across UPCs within the product module and firm. The simple index is the conventional price index component of the nested CES demand system in Hottman et al. (2016), and the weighted index is used to adjust for the importance of each UPC, as in the Cobb-Douglas utility function. In the right panel, the price index additionally subtracts the average module price similar to the quality index used in Argente et al. (2018). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.14: County-Firm-Product Group-Level Regression:
Replacement from High- to Low-Value Products

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Price}_{(07-09)}$		$\tilde{\Delta}\text{Price (Avg. Adj.)}_{(07-09)}$	
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	1.483***	1.510***	0.857***	0.838***
	(0.222)	(0.513)	(0.107)	(0.214)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
Prod.Group x Region FE	✓	✓	✓	✓
Index	Equal Weight	Sales Weight	Equal Weight	Sales Weight
R^2	0.575	0.553	0.573	0.609
Observations	704750	704750	704750	704750

Note. The regression specification is the same as that in Table A.6. The measure of value (price) change, $\tilde{\Delta}v_{rf}$, is defined as in (4.1). In the left panel, $\tilde{\Delta}\text{Price}_{(07-09)}$ is the county-firm-product group-specific price growth at the replacement margin between 2007 and 2009. The simple and weighted price indexes in columns (1) and (2) are the simple and the sales-weighted geometric price across UPCs within the product module and firm. The simple index is the conventional price index component of the nested CES demand system in Hottman et al. (2016), and the weighted index is used to adjust for the importance of each UPC, as in the Cobb-Douglas utility function. In the right panel, price index additionally subtracts the average module price similar to the quality index used in Argente et al. (2018). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.15: Relationship between γ_{rt} and Log of State Income Level

	(1)	(2)	(3)	(4)	(5)	(6)
	ln γ_{rt}	ln γ_{rt}	ln γ_{rt}	ln γ_{rt}	ln γ_{rt}	ln γ_{rt}
ln(Income$_{rt}$)	0.166***	0.202***	0.147**			
	(0.033)	(0.045)	(0.058)			
ln(HP$_{rt}$)				0.033**	0.089***	0.012
				(0.013)	(0.022)	(0.013)
Year Dummy (2009)	0.002	0.002	0.002	0.007	0.016	0.003
	(0.012)	(0.011)	(0.002)	(0.013)	(0.011)	(0.003)
Constant	-1.825***	-2.222***	-1.610**	-0.381**	-1.067***	-0.114
	(0.373)	(0.500)	(0.650)	(0.159)	(0.269)	(0.156)
Census Division FE	-	✓	-	-	✓	-
State FE	-	-	✓	-	-	✓
R^2	0.153	0.561	0.994	0.053	0.540	0.993
Observations	98	98	98	98	98	98

Note. ln(Income$_{rt}$) is the log of state-level average income in year t, and ln(HP$_{rt}$) is the log of the state-level house price in year t. The regression pools 2007 and 2009 observations with year dummy (Year FE) and either census division fixed effects or state fixed effects. All regressions are weighted by market size measured by state-level sales. Robust standard errors are reported in parentheses. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

Table A.16: Regression of the Structural Equation: State-Firm level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{S}_{(07-09)}$	$\tilde{\Delta}\text{S}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$
$(\tilde{\Delta}\text{S}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)})$ (avg)	0.996***	0.618***	0.144***	0.317**
	(0.007)	(0.096)	(0.020)	(0.152)
IV	-	✓	-	✓
First-stage F stat	-	22.1	-	22.1
State-Firm Controls	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
R^2	0.707	0.544	0.327	-0.009
Observations	83550	83550	83550	83550

Note. The regression specification is the same as that in Table 3 column (4), where we define the local market at the state instead of the county level. $\tilde{\Delta}\text{S}_{(07-09)}$ is the state-firm-specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Price}_{(07-09)}$ is the state-firm-specific price growth between 2007 and 2009, and $(\tilde{\Delta}\text{S}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)}$ (avg) is the measure of $\sum_{r' \in k_f} \left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$. In Column (2) and Column (4), we instrument $(\tilde{\Delta}\text{S}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)}$ (avg) using $\Delta\text{HP}_{(07-09)}$ (other). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.17: Goodness of Fit: State-Firm-Level Regression, Data vs. Model

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$	0.159***	0.150***		
	(0.051)	(0.004)		
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.203*	0.191***	0.238***	0.236***
	(0.103)	(0.021)	(0.085)	(0.020)
Region-Firm Controls	✓	✓	✓	✓
Region FE	-	-	✓	✓
Source	Data	Model	Data	Model
Observations	83610	83610	83610	83610

Note. Column (1) and Column (3) use the actual data, and Column (2) and Column (4) use the model-generated variables by feeding in the observed house price growth as the state-level exogenous shock in the model. The regression specification is the same as that in Table 3 column (4), where we define local market at the state instead of the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.18: Regression of the Structural Equation under Homogeneous Utility Function across Regions with Homothetic Preferences: State-Firm Level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{S}_{(07-09)}$	$\tilde{\Delta}\mathrm{Price}_{(07-09)}$	$\tilde{\Delta}\mathrm{Price}_{(07-09)}$
$(\tilde{\Delta}\mathrm{S}_{(07-09)})$ (avg)	0.997***	0.646***	0.144***	0.331**
	(0.006)	(0.096)	(0.020)	(0.161)
IV	-	✓	-	✓
First-stage F stat	-	20.3	-	20.3
State-Firm Controls	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
R^2	0.707	0.556	0.327	-0.016
Observations	83550	83550	83550	83550

Note. The regression specification is the same as that in Table 3 column (4), where we define the local market at the state instead of the county level. $\tilde{\Delta}\mathrm{S}_{(07-09)}$ is the state-firm-specific sales growth between 2007 and 2009, $\tilde{\Delta}\mathrm{Price}_{(07-09)}$ is the state-firm-specific price growth between 2007 and 2009, and $(\tilde{\Delta}\mathrm{S}_{(07-09)})$ (avg) is the measure of $\left(\sum_{r' \in k_f} \omega_{r'f,0} \hat{S}_{r'f}\right)$ where $\omega_{rf,0}$ is the initial sales weight. In Column (2) and Column (4), we instrument $(\tilde{\Delta}\mathrm{S}_{(07-09)})$ (avg) using $\Delta\mathrm{HP}_{(07-09)}$ (other). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.19: Regional Redistribution across States

State	$\hat{HP}_r(\%)$	$\hat{I}_r(\%)$	$\hat{U}_r(\%)$ Benchmark	$\hat{U}_r(\%)$ Counterfactual	$\hat{U}_r(\%)$ Abs. Diff.	$\hat{V}_r(\%)$ Benchmark	$\hat{V}_r(\%)$ Counterfactual	$\hat{V}_r(\%)$ Abs. Diff.	Weight (%)
AL	-7.88	-1.81	-4.10	-3.16	0.94	-2.22	-2.03	0.19	1.54
AZ	-38.13	-8.77	-13.67	-15.40	1.72	-9.73	-10.09	0.36	2.12
AR	-4.68	-1.08	-2.90	-1.75	1.15	-1.39	-1.16	0.23	0.95
CA	-33.11	-7.61	-11.70	-13.40	1.71	-8.40	-8.76	0.36	12.20
CO	-5.53	-1.27	-3.17	-2.10	1.07	-1.60	-1.39	0.22	1.62
CT	-13.04	-3.00	-5.76	-5.23	0.53	-3.51	-3.40	0.11	1.17
DE	-8.14	-1.87	-4.06	-3.03	1.03	-2.26	-2.05	0.21	0.29
DC	-11.91	-2.74	-5.25	-4.46	0.79	-3.20	-3.03	0.16	0.20
FL	-43.19	-9.93	-14.84	-17.22	2.38	-10.89	-11.40	0.51	6.09
GA	-17.11	-3.93	-6.76	-6.76	0.00	-4.46	-4.46	0.00	3.19
ID	-14.74	-3.39	-6.27	-5.75	0.52	-3.92	-3.82	0.11	0.50
IL	-20.33	-4.68	-7.75	-8.10	0.35	-5.25	-5.32	0.07	4.29
IN	-8.76	-2.02	-4.33	-3.52	0.81	-2.43	-2.27	0.17	2.12
IA	0.18	0.04	-1.40	0.17	1.57	-0.20	0.12	0.32	1.00
KS	-3.59	-0.83	-2.60	-1.33	1.26	-1.13	-0.88	0.26	0.93
KY	-2.36	-0.54	-2.24	-0.86	1.38	-0.83	-0.55	0.28	1.42
LA	1.28	0.30	-1.10	0.63	1.73	0.07	0.42	0.35	1.43
ME	-14.07	-3.24	-5.87	-5.28	0.58	-3.72	-3.60	0.12	0.44
MD	-22.93	-5.27	-8.74	-9.14	0.40	-5.93	-6.01	0.08	1.87
MA	-10.19	-2.34	-4.66	-3.99	0.67	-2.76	-2.62	0.14	2.15
MI	-29.68	-6.83	-10.69	-11.75	1.06	-7.57	-7.79	0.22	3.36
MN	-16.95	-3.90	-6.80	-6.67	0.12	-4.44	-4.41	0.03	1.73
MS	-4.51	-1.04	-2.88	-1.70	1.18	-1.36	-1.12	0.24	0.97
MO	-6.47	-1.49	-3.49	-2.51	0.98	-1.84	-1.64	0.20	1.96
MT	0.06	0.01	-1.47	0.12	1.59	-0.23	0.09	0.32	0.32
NE	-1.67	-0.38	-2.08	-0.57	1.51	-0.67	-0.37	0.31	0.59
NV	-54.06	-12.43	-18.24	-20.43	2.19	-13.59	-14.06	0.47	0.86
NH	-13.11	-3.02	-5.59	-4.93	0.65	-3.49	-3.35	0.13	0.44
NJ	-17.26	-3.97	-7.14	-7.13	0.01	-4.56	-4.56	0.00	2.90
NM	-5.18	-1.19	-3.06	-1.92	1.14	-1.52	-1.29	0.23	0.66
NY	-15.23	-3.50	-6.33	-6.28	0.05	-4.03	-4.02	0.01	6.44
NC	-6.23	-1.43	-3.35	-2.41	0.95	-1.77	-1.58	0.19	3.02
ND	1.72	0.39	-0.93	0.77	1.70	0.18	0.52	0.34	0.21
OH	-9.11	-2.10	-4.37	-3.67	0.70	-2.50	-2.36	0.14	3.83
OK	3.27	0.75	-0.35	1.42	1.77	0.58	0.94	0.36	1.21
OR	-15.86	-3.65	-6.46	-6.14	0.33	-4.17	-4.10	0.07	1.25
PA	-4.56	-1.05	-2.82	-1.75	1.06	-1.35	-1.14	0.22	4.15
RI	-18.61	-4.28	-7.44	-7.15	0.29	-4.87	-4.81	0.06	0.35
SC	-8.37	-1.92	-4.03	-3.20	0.83	-2.30	-2.13	0.17	1.47
SD	0.72	0.16	-1.26	0.38	1.64	-0.07	0.26	0.33	0.27
TN	-5.76	-1.33	-3.16	-2.17	0.98	-1.64	-1.44	0.20	2.05
TX	-5.93	-1.36	-3.30	-2.38	0.93	-1.70	-1.52	0.19	7.98
UT	-10.82	-2.49	-4.77	-4.07	0.70	-2.90	-2.76	0.14	0.88
VT	-7.40	-1.70	-3.84	-2.74	1.10	-2.08	-1.86	0.22	0.21
VA	-15.83	-3.64	-6.24	-6.08	0.16	-4.12	-4.09	0.03	2.57
WA	-17.97	-4.13	-7.39	-7.35	0.04	-4.75	-4.74	0.01	2.16
WV	-4.02	-0.92	-2.66	-1.45	1.21	-1.22	-0.98	0.24	0.60
WI	-7.07	-1.63	-3.64	-2.72	0.92	-1.98	-1.80	0.19	1.87
WY	-1.32	-0.30	-2.02	-0.42	1.60	-0.60	-0.27	0.32	0.17
Mean	-16.60	-3.82	-6.65	-6.61	0.97	-4.34	-4.34	0.20	Sum: 100
Std	12.97	2.98	4.03	5.21		3.20	3.44		

Note. $\hat{HP}_r(\%)$ is the state-level house price growth. $\hat{I}_r(\%)$ is the exogenous regional income growth which is calculated as $\hat{HP}_r(\%) \times 0.23$. Benchmark indicates the model with uniform quality choice in Section 5, and counterfactual indicates the model with market-specific quality choice in Appendix D. $\hat{U}_r(\%)$ is the welfare growth from CPG expenditures ("CPG welfare"), and $\hat{V}_r(\%)$ is the welfare growth from both CPG and outside good expenditures ("overall welfare"). Summary statistics are weighted by population.

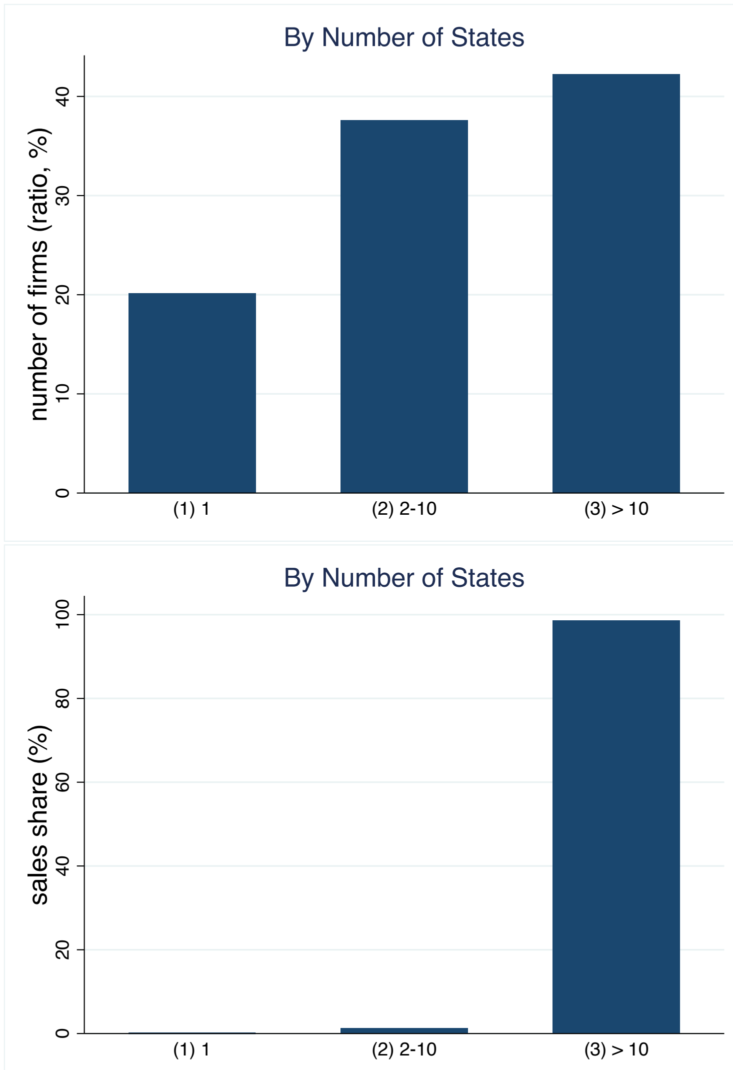
Table A.20: Product Creation and Destruction Patterns

(A) Product Destruction	Exits (>50%) of Mkt	Exits (>90%) of Mkt
	0.87	0.56
(B) Product Creation	Enters (>50%) of Mkt	Enters (>90%) of Mkt
	0.90	0.82

Note. Panel (A) calculates the share of value lost by the destruction of products that is attributed to the products that exited more than 50% (90%) of the markets in which they were initially sold in 2007. Panel (B) calculates the share of value generated by the creation of products that is attributed to the products that entered more than 50% (90%) of the firm's total markets in 2009. Consistent with our model, we define local markets at the state level.

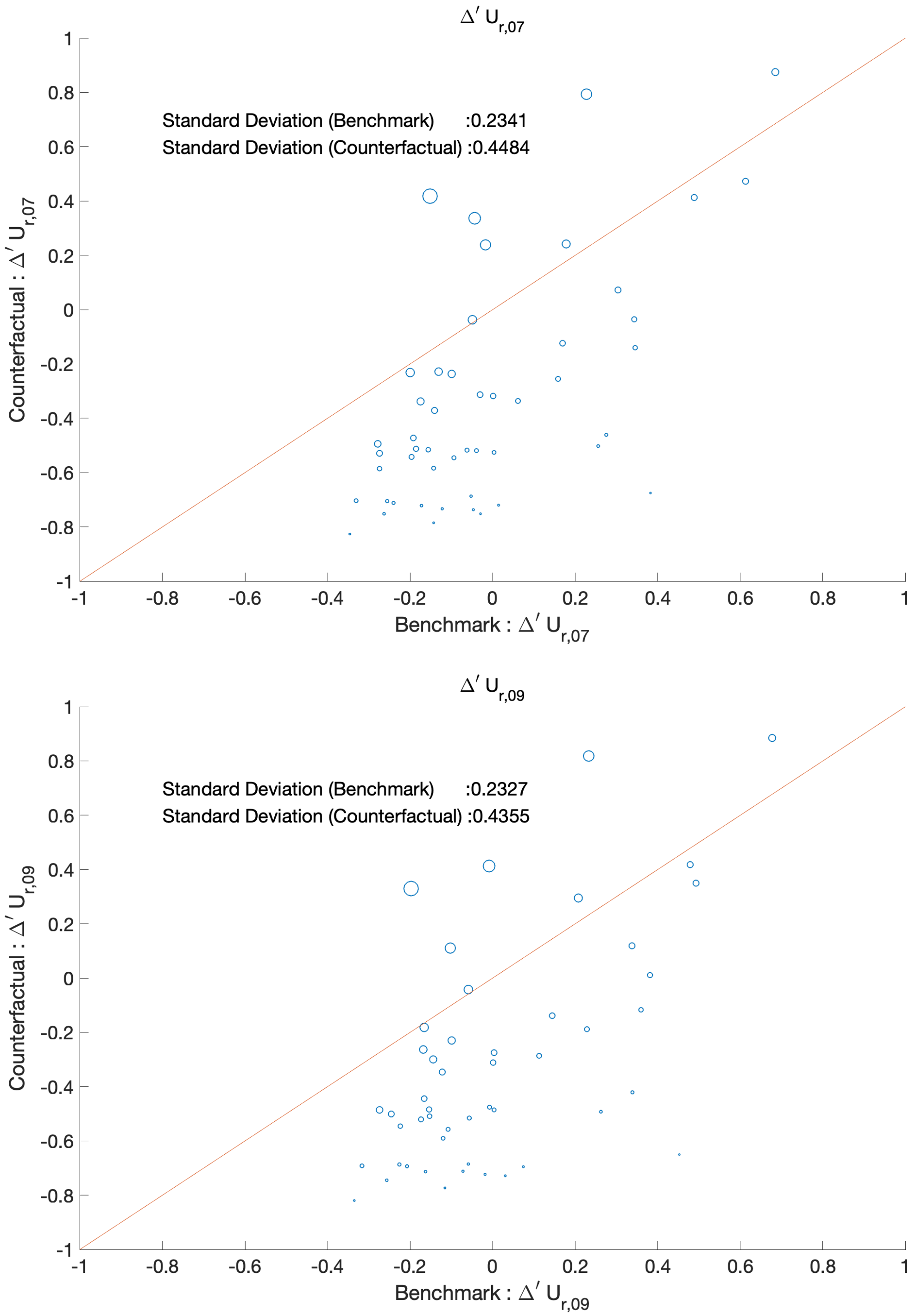
Appendix B Additional Figures

Figure A.1: Share of Consumer Goods Producers by the Number of States in which They Sell: The Number and Sales Share of Firms



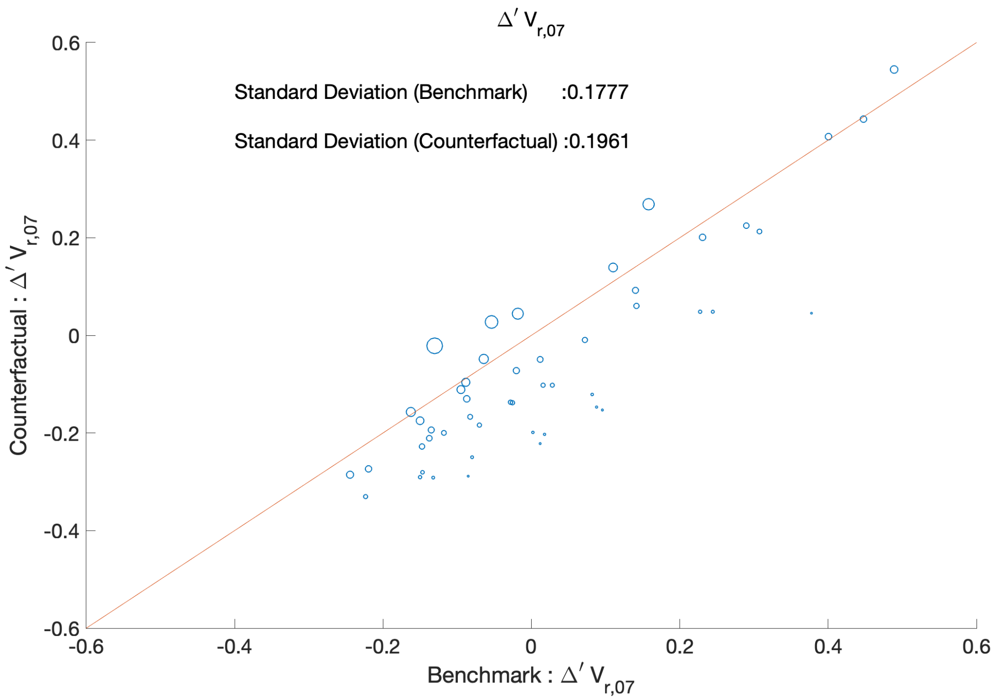
Note. The calculation is based on the ACNielsen Retailer Scanner database combined with the GS1 database. The first figure presents the percentage of firms that sell to one state, two to ten states, and more than ten states. The second figure presents the percentage of sales share of firms that sell to one state, two to ten states, and more than ten states.

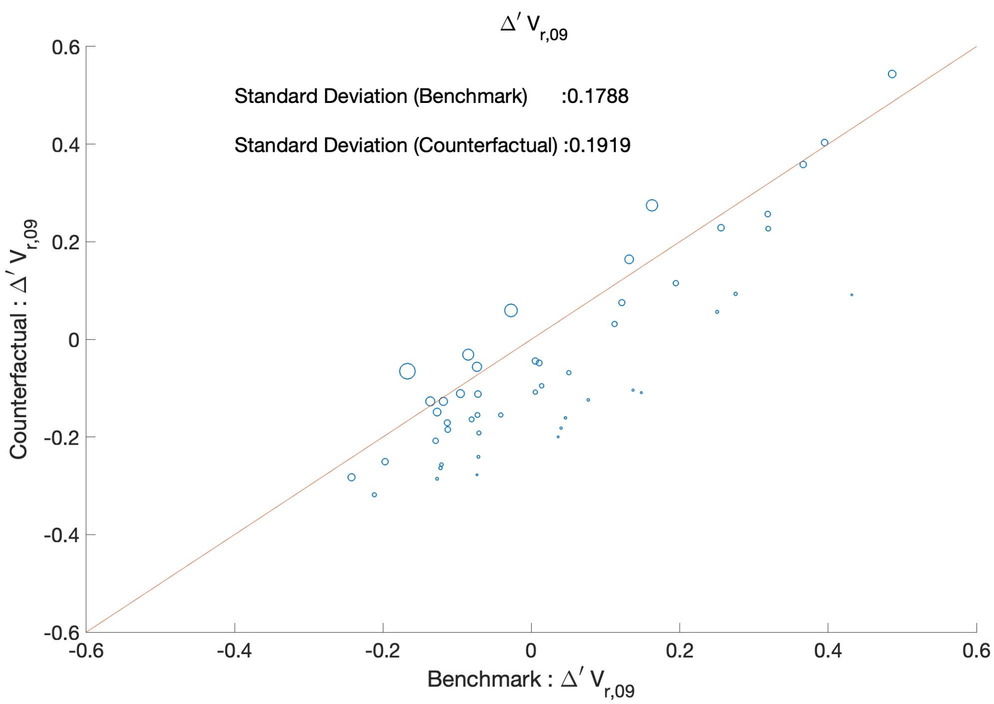
Figure A.2: Cross-Sectional Dispersion of Regional CPG Welfare



Note. $\Delta' U_{r,t} \equiv (U_{r,t} - \text{Avg.}U_{r,t})/\text{Avg.}U_{r,t}$ measures the cross-sectional dispersion of CPG welfare at time t. The sizes of the circles reflect population weights. The mean, Avg.$U_{r,t}$, and the reported standard deviations are weighted by state-level population. The red line is a 45 degree line; the steeper scatter plot shows the larger dispersion of CPG welfare in the counterfactual economy than the one in the baseline economy.

Figure A.3: Cross-Sectional Dispersion of Regional Overall Welfare





Note. $\Delta' V_{r,t} \equiv (V_{r,t} - \text{Avg.}V_{r,t})/\text{Avg.}V_{r,t}$ measures the cross-sectional dispersion of regional overall welfare at time t. The sizes of the circles reflect population weights. The mean, Avg.$V_{r,t}$, and the reported standard deviations are weighted by state-level population. The red line is a 45 degree line; the steeper scatter plot shows the larger dispersion of total welfare in the counterfactual economy than the one in the baseline economy.

Appendix C Derivation of Optimal Prices and Quality

From the profit function (5.7), we have

$$\pi_f = \sum_{r \in k_f} \left(S_{rf} - \frac{c(\phi_f)}{a_f} Q_{rf} \right) - f(\phi_f) - f_0$$

where $S_{rf} = {\phi_f}^{(\sigma-1)\gamma_r} {p_{rf}}^{1-\sigma} A_r$ and $Q_{rf} = (\phi_f)^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r$ with $A_r \equiv {P_r}^{\sigma-1} S_r$ indicating a regional aggregate term.

To obtain the first-order conditions with respect to p_{rf} and ϕ_f, we first calculate $\frac{\partial S_{rf}}{\partial p_{rf}}$, $\frac{\partial Q_{rf}}{\partial p_{rf}}$, $\frac{\partial S_{rf}}{\partial \phi_f}$, $\frac{\partial Q_{rf}}{\partial \phi_f}$, $\frac{\partial c(\phi_f)}{\partial \phi_f}$, and $\frac{\partial f(\phi_f)}{\partial \phi_f}$:

$$\begin{aligned}
\frac{\partial S_{rf}}{\partial p_{rf}} &= (1-\sigma){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r \ , & \frac{\partial Q_{rf}}{\partial p_{rf}} &= -\sigma {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma-1} A_r \\
\frac{\partial S_{rf}}{\partial \phi_f} &= (\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r - 1} p_{rf}^{1-\sigma} A_r \ , & \frac{\partial Q_{rf}}{\partial \phi_f} &= (\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r - 1} p_{rf}^{-\sigma} A_r \\
\frac{\partial c(\phi_f)}{\partial \phi_f} &= \xi (\phi_f)^{\xi-1} \ , & \frac{\partial f(\phi_f)}{\partial \phi_f} &= b(\phi_f)^{\frac{1}{\beta}-1}
\end{aligned}$$

We derive the first-order conditions for prices and quality below. The proof of uniqueness (i.e., second-order conditions) can be found in Online Appendix D.3.

C.1 First-Order Conditions in Prices

The first-order condition with respect to p_{rf} is given as follows.

$$0 = \frac{\partial \pi_f}{\partial p_{rf}} = \frac{\partial S_{rf}}{\partial p_{rf}} - \frac{c(\phi_f)}{a_f} \frac{\partial Q_{rf}}{\partial p_{rf}}$$

By plugging in the corresponding derivatives, the above equation can be written as

$$\begin{aligned}
0 = \frac{\partial \pi_f}{\partial p_{rf}} =& (1-\sigma){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r + \frac{c(\phi_f)}{a_f} \sigma {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma-1} A_r \\
=& \left[(1-\sigma) + \frac{c(\phi_f)}{a_f} \frac{\sigma}{p_{rf}} \right] {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r
\end{aligned} \tag{C.1}$$

This implies an optimal price

$$p_{rf} = \frac{c(\phi_f)}{a_f} \left(\frac{\sigma}{\sigma-1} \right)$$

where the markup is given by $\mu \equiv \frac{\sigma}{\sigma-1}$.

C.2 First-Order Condition in Quality

The first-order condition with respect to $\phi^s(a^s)$ is given as follows.

$$\begin{aligned}
0 = \frac{\partial \pi_f}{\partial \phi_f} &= \sum_{r \in k_f} \frac{\partial S_{rf}}{\partial \phi_f} - \frac{1}{a_f}\frac{\partial c(\phi_f)}{\partial \phi_f}\sum_{r \in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r \in k_f}\frac{\partial Q_{rf}}{\partial \phi_f} - \frac{\partial f(\phi_f)}{\partial \phi_f} \\
&= \sum_{r \in k_f} (\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r - 1} p_{rf}^{1-\sigma} A_r - \frac{1}{a_f}\xi(\phi_f)^{\xi-1}\sum_{r \in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r \in k_f}(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&= \sum_{r \in k_f}\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{1-\sigma} A_r - \sum_{r \in k_f}\xi\left(\frac{\phi_f^{\xi-1}}{a_f}\frac{1}{p_{rf}}\right){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&=(\phi_f)^{-1}\left[\sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\xi\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \\
&=(\phi_f)^{-1}\left[\sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)(\gamma_r - \xi)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \qquad \text{(C.2)}
\end{aligned}$$

where in the last equality we used the relationship $\frac{\sigma-1}{\sigma} = \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}$ $(\Leftrightarrow \left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right) = \left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1))$ from the first-order condition w.r.t. price.

By multiplying ϕ_f on both sides of the equation, we obtain

$$\begin{aligned}
0 &= \sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \xi\left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}} \\
&= \sum_{r \in k_f}\left(\frac{\sigma-1}{\sigma}\right)(\gamma_r - \xi)S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \\
&= \sum_{r \in k_f}\left(\frac{\gamma_r - \xi}{\mu}\right)S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \qquad \text{(C.3)}
\end{aligned}$$

By rearranging terms, we obtain the optimal quality choice

$$\phi_f = \left[\sum_{r \in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r - \xi}{\mu}\right)\right]^{\beta}$$

C.3 Structural Equation of Market Interdependency – Derivation

We start with equation (5.10). Define $\Upsilon_r \equiv \beta(\sigma-1)(\gamma_r-\xi)$, $B(a_f) \equiv \left[\frac{\mu}{a_f}\right]^{1-\sigma}$, $X_f \equiv \left[\sum_{r\in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r-\xi}{\mu}\right)\right]$, and $A_r \equiv (P_r)^{\sigma-1}S_r$. Denote a firm's initial local sales as $S_{rf,0}$.

Take the logarithm on both sides of (5.10):

$$\log S_{rf} = \Upsilon_r \log X_f + \log B_r(a_f) + \log A_r$$

By defining $\hat{y} \equiv \log y/y_0$, we have

$$\hat{S}_{rf} = (\Upsilon_{r,0}e^{\hat{\Upsilon}_r})\hat{X}_f + \Upsilon_{r,0}(e^{\hat{\Upsilon}_r}-1)\log X_{f,0} + (\sigma-1)\hat{a}_f + \hat{A}_r$$

Linearization with respect to the hat variables implies

$$\hat{S}_{rf} = \Upsilon_{r,0}\hat{X}_f + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r + (\sigma-1)\hat{a}_f$$

Now, let us derive $\hat{X}_f$. Denote the initial state as

$$X_{f,0} \equiv \sum_{r\in k_f} S_{rf,0}\left(\frac{1}{b}\frac{\gamma_{r,0}-\xi}{\mu}\right)$$

By defining $\psi_{r,0} \equiv \gamma_{r,0}-\xi$ and using $x = x_0 e^{\hat{x}}$, we obtain

$$\hat{X}_f \equiv \sum_{r\in k_f} \omega_{rf,0}\left[\hat{S}_{rf} + \hat{\psi}_r\right]$$

where $\omega_{rf,0} \equiv \frac{S_{rf,0}(\gamma_{0,r}-\xi)}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$ with $\sum_{r\in k_f}\omega_{rf,0} = 1$. Note that if $\gamma_r = \gamma$ for all $r \in \mathcal{R}$, $\omega_{rf,0} = \frac{S_{rf,0}}{\sum_{r'\in k_f} S_{r'f,0}}$ becomes the initial sales weight.

Thus, we obtain

$$\hat{S}_{rf} = \Upsilon_{r,0}\sum_{r\in k_f}\omega_{rf,0}\left[\hat{S}_{rf} + \hat{\psi}_r\right] + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r + (\sigma-1)\hat{a}_f \tag{C.4}$$

The following alternative expression for (C.4) is also useful for estimation:

$$\hat{S}_{rf} = \Upsilon_{r,0}\sum_{r\in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r + (\sigma-1)\hat{a}_f \tag{C.5}$$

where $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$. Here, we performed linearization with respect to $\hat{\gamma}_r$ instead of $\hat{\psi}_r$.

Appendix D Counterfactual: Market-Specific Quality Choice

In this section, we describe the counterfactual economy where all firms choose market-specific quality as well as market-specific prices.

D.1 Price and Quality Choice

We denote the market-specific choice of quality by ϕ_{rf}. To distinguish optimal prices under market-specific quality from those under uniform quality, we denote the optimal price under market-specific quality by p^m_{rf}. We denote the corresponding quantity, sales, and profit by Q^m_{rf}, S^m_{rf}, and π^m_f. The market-level aggregates are denoted by Q^m_r and S^m_r.

We allow potentially different fixed cost structures between uniform quality and market-specific quality. If a firm chooses market-specific quality, the firm potentially supplies different levels of quality across its markets, thereby incurring market-specific fixed costs. We assume that to supply a quality ϕ_r for the product bundle in market r, the firm pays fixed costs of $f^m(\phi_{rf}) + f^m_{0r}$. We let the term f^m_{0r} capture both market-specific and firm-wise fixed costs that do not depend on the choice of quality. The superscript m is used to indicate the cost associated with the market-specific quality strategy. We parametrize $f^m(\phi_{rf})$ as

$$f^m(\phi_{rf}) \equiv b_m \beta_m (\phi_{rf})^{\frac{1}{\beta_m}} \tag{D.1}$$

where we allow the fixed cost parameters b_m and β_m under market-specific quality to have different values from corresponding parameters b and β under uniform quality.[40]

The price and quality choice problem of firm a^k under market-specific quality is formally written as follows:

$$\max_{\{\phi_{rf}, p^m_{rf}\}_{r\in k_f}} \pi^m_f = \sum_{r\in k_f} \left[\left(p^m_{rf} - mc(\phi_{rf}; a_f)\right) Q^m_{rf} - f^m(\phi_{rf}) - f^m_{0r}\right] \tag{D.2}$$

subject to demand condition

$$Q^m_{rf} = \phi_{rf}^{(\sigma-1)\gamma_r} (p^m_{rf})^{-\sigma} (P^m_r)^{\sigma-1} S^m_r \tag{D.3}$$

We can show that the optimal price is

$$p^m_{rf} = mc(\phi_{rf}; a_f) \times \mu \tag{D.4}$$

[40] Only for the cases of b_m and β_m do we use a subscript instead of a superscript m to avoid notational confusion with raising the power of b and β.

and the optimal quality for market $r \in k_f$ is given by

$$\phi_{rf} = \left[S^m_{rf} \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m} \tag{D.5}$$

where

$$S^m_{rf} = (\phi_{rf})^{(\sigma-1)\gamma_r} \left(\frac{p^m_{rf}}{P^m_r} \right)^{1-\sigma} S^m_r \tag{D.6}$$

The profit under market-specific quality can be rearranged as

$$\pi^m_f = \sum_{r \in k_f} \left[\left(1 - \mu^{-1}\right) S^m_{rf} - f^m(\phi_{rf}) - f^m_{0r} \right]$$

By plugging (D.5) into (D.1), we obtain the expression for the equilibrium fixed cost for quality adjustments as $f^m(\phi_{rf}) = \beta_m(\mu^{-1}) S^m_{rf}(\gamma_r - \xi)$. By combining these two equations, we obtain

$$\pi^m_f = \sum_{r \in k_f} \left[\frac{1}{\sigma} \left[1 - \beta_m(\sigma - 1)(\gamma_r - \xi)\right] S^m_{rf} - f^m_{0r} \right] \tag{D.7}$$

The expression for the sales of firm f in market r, S^m_{rf}, is derived using (D.4), (D.5), and (D.6) as

$$S^m_{rf} = \left[S^m_{rf} \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m(\sigma-1)(\gamma_r-\xi)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} (P^m_r)^{\sigma-1} S^m_r \tag{D.8}$$

This implies

$$S^m_{rf} = \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right)^{\frac{\beta_m(\sigma-1)(\gamma_r-\xi)}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \left[\frac{\mu}{a_f} \right]^{\frac{1-\sigma}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \left[(P^m_r)^{\sigma-1} S^m_r \right]^{\frac{1}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \tag{D.9}$$

where we assume that $\beta_m > 0$ is sufficiently small that $\beta_m(\sigma - 1)(\gamma_r - \xi) < 1$.

The optimal price of a firm with a^k in market r is

$$p^m_{rf} = \left[S^m_{rf} \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m \xi} \left[\frac{\mu}{a_f} \right] \tag{D.10}$$

Note that from (D.9), $S^m_{rf} = S^m_{rf'}$ if $a_f = a_{f'}$. Additionally, it is clear from (D.9) that $\frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0$ as long as $\beta_m(\sigma - 1)(\gamma_r - \xi) < 1$. Additionally, from (D.5) and (D.10), we have that if $a_f = a_{f'}$, then $\phi_{rf} = \phi_{rf'}$ and $p^m_{rf} = p^m_{rf'}$. These results imply that regardless of the market network a firm has, each firm's optimal quality and price in market r only depends on local market conditions and the productivity a_f under the market-specific quality strategy. We summarize these results below.

Proposition 4. *(Productivity, Quality and Sales under Market-Specific Quality Choice)*

Under market-specific quality choice, we have $S^m_{rf} = S^m_{rf'}$, $\phi_{rf} = \phi_{rf'}$, and $p^m_{rf} = p^m_{rf'}$ if $a_f = a_{f'}$. Additionally, if $\beta_m > 0$ is sufficiently small that $\beta_m(\sigma-1)(\gamma_r - \xi) < 1$, we have

$$\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0 \tag{D.11}$$

$$\frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0 \tag{D.12}$$

Proof. We only need to prove that $\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0$. We know that $\frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0$ under $\beta_m(\sigma-1)(\gamma_r - \xi) < 1$. Note that (D.5) implies $\frac{\partial \log \phi_{rf}}{\partial \log S^m_{rf}} > 0$. Thus, we have $\frac{\partial \log \phi_{rf}}{\partial \log a_f} = \frac{\partial \log \phi_{rf}}{\partial \log S^m_{rf}} \frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0$. □

Corollary 5. *Under the conditions in Proposition 4, the equilibrium profit π^m_f under market-specific quality strictly monotonically increases with firm productivity a_f.*

Proof. It is immediate from equation (*D.7*) and $\frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0$. □

D.2 Market Independence under Market-Specific Quality

In contrast to the case under a uniform quality choice, we can show that (firm-level) market independence arises under the market-specific quality strategy.

Proposition 6. *(Independence across Markets under Market-specific Quality Choice)*

Consider a firm under market-specific quality. Let $r, r' \in k$ and $r \neq r'$. Suppose that we shut down general equilibrium adjustments by fixing P^m_r and D^m_r (and thus treat y_r as exogenous). Then, $\frac{\partial \log S^m_{rf}}{\partial \log y_{r'}} = 0$, $\frac{\partial \log \phi_{rf}}{\partial \log y_{r'}} = 0$, and $\frac{\partial \log p^m_{rf}}{\partial \log y_{r'}} = 0$.

Proof. $\frac{\partial \log S^m_{rf}}{\partial \log y_{r'}} = 0$ is immediate from (D.9) and the fact that $\frac{\partial \log P^m_r}{\partial \log y_{r'}} = \frac{\partial \log S^m_r}{\partial \log y_{r'}} = 0$ since we shut down the general equilibrium effect through P^m_r. $\frac{\partial \log \phi_{rf}}{\partial \log y_{r'}} = \frac{\partial \log p_{rf}}{\partial \log y_{r'}} = 0$ follows from (D.4) and (D.5) and $\frac{\partial \log S^m_{rf}}{\partial \log y_{r'}} = 0$. □

Appendix E Parameter Calibration and Estimation

Table A.21: Parameter Values

Parameter	Value	Description	Source
$\bar{\Upsilon}$	0.62	Elasticity of Local Sales wrt $(\tilde{\Delta} Sale + \tilde{\Delta}\gamma)$	Own Estimation
$\beta \times \xi$	0.32	Elasticity of Local Price wrt $(\tilde{\Delta} Sale + \tilde{\Delta}\gamma)$	Own Estimation
σ	2.20	EoS across Firm's Product Bundle	Faber & Fally (2017)
ξ	0.39	Elasticity of Marginal Cost wrt Quality	Derived from Own Estimation
β	0.81	Elasticity of Fixed Cost wrt Quality	Derived from Own Estimation
$\bar{\gamma}$	1.03	Elasticity of Perceived Quality wrt Quality	Own Estimation
δ_2	0.17	Elasticity of γ wrt Income	Own Estimation
$b^{\text{benchmark}}$	1	Fixed Cost Parameter	Normalize
$b^{\text{counterfactual}}$	0.04	Fixed Cost Parameter	Mean Quality = Benchmark Value
η	1	EoS across CPG and Outside Goods	Cobb-Douglas
α	0.20	CPG Share Parameter	CPG share = 0.20 given η

E.1 Calibration

Since our empirical results are robust to using state-firm-level variation, as shown in Appendix Table A.4, we define the state as the market for the numerical analyses. The state-level analyses substantially reduce computational burden in matching the firm-level spatial network. We include both single-market firms and multimarket firms in our analysis, which yields a total of 5186 firms that sell in at most 49 states.

We match I_r and L_r in the model using the 2007 state-level average income obtained from the American Community Survey data and state population. Each firm's market network k_f is directly obtained from the data. For the exogenous local demand shock, $\hat{I}_r$, we use state-level house price growth multiplied by 0.23, which is the consumption elasticity with respect to the house price shock estimated in Berger et al. (2018).[41] Although we utilize house price growth to be consistent with the empirical analyses, using the change in state-level average income does not change the main implications of the model. In this exercise, we abstract away the productivity heterogeneity (i.e., $a_f = \bar{a}$) since it plays a minor role for the set of balanced firms we consider. Nevertheless, for each

[41] Berger et al. (2018) report the aggregate consumption elasticity, which might differ from the regional elasticity. However, this number plays a minor role in our analyses because we use this elasticity to rescale house price growth into income growth, which translates into expenditure growth in the model.

firm, we match the sales distribution across states by using the sales per firm in each state.[42]

For the elasticity of substitution parameter η in the upper-tier utility, we impose the limiting case $\eta \to 1$ which implies the Cobb-Douglas upper-tier utility function.[43] Using a larger η only strengthens the implication that we find (i.e., it generates stronger mitigation of regional consumption and welfare inequality). We bring in the elasticity of substitution σ from Faber and Fally (2020), which is $\sigma = 2.2$. Since the estimate is based on the pooled estimation of the within-module cross-firm elasticity of substitution, σ is interpreted as a proxy for the average within-module elasticity of substitution across firms.[44]

E.2 Estimation

The remaining key parameters we need to recover are β, ξ, and $\gamma_r = \gamma(I_r)$.

(1) Estimation of γ_r and $\hat{\gamma}_r$

By replacing the definition of product quality (5.2) in state-firm-level sales (5.3) and taking the log of the combined equation, we have

$$\log S_{rft} = (1-\sigma)\log p_{rft} + (\sigma-1)\gamma_{rt}\log\phi_{ft} + (1-\sigma)\log P_{rt} + \log S_{rt} \tag{E.1}$$

where subscript t denotes year. We filter out state-time-specific components by calculating the difference between the reference firm F, which we define to be the largest firm in the sample, and other firms f: $\Delta'\log S_{rft} = (1-\sigma)\Delta'\log p_{rft} + (\sigma-1)\gamma_{rt}\Delta'\log\phi_{ft}$, where $\Delta' x_{rft} \equiv x_{rFt} - x_{rft}$. By rearranging terms, we arrive at

$$\Xi_{rft} = \gamma_{rt}\Delta'\log\phi_{ft}$$

where $\Xi_{rft} \equiv \frac{1}{(\sigma-1)}\left[\Delta'\log S_{rft} - (1-\sigma)\Delta'\log p_{rft}\right]$. Note that the model predicts that the larger the firm size is, the greater the product quality, implying that $\gamma_{rt}\Delta'\log\phi_{ft} > 0$. This holds without

[42] In the model, the state-level CPG expenditure S_r is equal to the aggregate state-level CPG producers' sales, $S_r = \sum_{f\in G_r} S_{rf}$. Additionally, note that $S_r \equiv s_r L_r = \Theta_r y_r L_r = \Theta_r I_r \left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right) L_r$, where Θ_r is the share of CPG goods as described in Online Appendix C. Thus, we have $I_r L_r = \sum_{f\in G_r} S_{rf}\left[\Theta_r\left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right)\right]^{-1}$. Because we use the Cobb-Douglas upper-tier utility in the numerical exercise, $\Theta_r = \alpha$, we have $(I_r L_r) = \sum_{f\in G_r} S_{rf} \times \left[\alpha\left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right)\right]^{-1}$. Under our choice of the initial I_r (using the state-level average income from ACS data), $(I_r L_r)$ and S_r are highly correlated with a correlation coefficient 0.93. Thus, given $(I_r L_r) \propto S_r = \sum_{f\in G_r} S_{rf}$ and that we are directly bringing information $(I_r L_r)$ and N_r (number of firms in market r) using the data, we are matching the pooled distribution of the "average state-firm-level sales" (averaged across firms within a state). More formally, we match the distribution of $\frac{\sum_{f\in G_r} S_{rf}}{N_r}$ across markets.

[43] We set the CPG expenditure share parameter α to 0.20, which is close to the United States counterpart. This number is calculated based on the BLS report—*Consumer Expenditures in 2007*. We categorize the following major categories as CPG expenditures: Food, Alcoholic beverages, Apparel and services, Personal care products and services, and Tobacco products and smoking supplies.

[44] The product module is a granular categorization of each barcode (product) provided by ACNielsen. There are approximately 1,000 product modules. An example of a product module is "Multi-Vitamins".

estimated values.

Under the calibration of $\sigma = 2.2$, we directly measure Ξ_{rft}. By taking the log of the expression, we obtain

$$\log \Xi_{rft} = \log \gamma_{rt} + \log\left(\Delta' \log \phi_{ft}\right) \tag{E.2}$$

We pool 2007 and 2009 observations and regress $\log \Xi_{rft}$ on state-year and firm-year fixed effects, where the former absorbs $\log \gamma_{rt}$ and the latter absorbs $\log\left(\Delta' \log \phi_{ft}\right)$.

For $\gamma_{rt} = \gamma(I_{rt})$, we impose a simple log-linear functional form:

$$\log \gamma_{rt} \equiv \delta_1 + \delta_2 \log I_{rt} \tag{E.3}$$

where δ_2 governs the strength of the non-homotheticity. It measures the responsiveness of the quality demanded to a change in individuals' income in the market r. With the measured $\log \gamma_{rt}$, we obtain the predicted $\log \gamma_{rt}$, which we denote as $\log \gamma_{rt}^{predict}$, by regressing $\log \gamma_{rt}$ on $\log I_{rt}$ to estimate δ_1 and δ_2 in Equation (E.3) and calculating $\log \gamma_{rt}^{predict} = \hat{\delta}_1 + \hat{\delta}_2 \log I_r$.

Table A.15 in Appendix A summarizes the estimation result. We use either the log average income or the log house price as a measure of $\log I_{rt}$. Broadly, we find a strong positive association between $\log \gamma_{rt}$ and $\log I_{rt}$ across different specifications, although directly measuring $\log I_{rt}$ using the average income yields a clearer association. We use the simplest specification in column (1) as our benchmark, which is a pooled regression across state and year with the inclusion of year fixed effects. The $\log \gamma_{rt}^{predict}$ obtained from column (1) serves as our measure of $\log \gamma_{rt}$, implying that $\delta_2 = 0.166$.[45]

(2) Estimation of β and ξ

With the measures of γ_r and $\hat{\gamma}_r$, we recover the average Υ_r, $\bar{\Upsilon}$, by estimating the structural equation (5.11), which is the model counterpart of our reduced-form regression equation (3.1). We estimate the structural equation by instrumenting $\sum_{r \in k_f}\left[\omega_{r'f}\hat{S}_{rf} + \theta_{rf}\hat{\gamma}_r\right]$ with the indirect demand shock along with the state and industry fixed effects and other various state-firm level controls. Table A.16 in Appendix A presents the result. Column (1) uses OLS with the state and sector fixed effects. We obtain a coefficient of 0.996, indicating that local sales growth is highly correlated across regions within a firm. Column (2) uses the indirect demand shock as an instrument, and the estimated coefficient is $\bar{\Upsilon} = 0.618$, which is our baseline measure.

[45]Note that in the counterfactual analysis, we use $0.23 \times \tilde{\Delta} HP_r$ as a proxy for the exogenous demand shock ($\hat{I}_r$), while the predicted $\log \gamma_{rt}^{predict}$ is calculated by regressing $\log \gamma_{rt}$ on the log of state-level average income (instead of the log of the state-level house price). This discrepancy does not pose a problem in our estimation of the structural parameters (e.g., β and ξ) because we instrument $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ using the indirect shock $\tilde{\Delta} HP_{rf}(\text{other})$, which is constructed by using the house price growth.

To recover other parameters, we utilize the equilibrium local price of a firm f:

$$p_{rf} = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta\xi} \left[\frac{\mu}{a_f} \right] \tag{E.4}$$

which is derived from the equilibrium firm local price (5.8) and quality (5.9). Taking the log difference, we obtain

$$\hat{p}_{rf} = \beta\xi \sum_{r \in k_f} \left[\omega_{rf} \hat{S}_{rf} + \theta_{rf} \hat{\gamma}_r \right] - \hat{a}_f \tag{E.5}$$

which allows us to estimate $\beta\xi$ by using the indirect demand shock as an IV, similar to the estimation of the average Υ. Column (3) of Table A.16 reports an OLS estimate of $\beta\xi$, and Column (4) reports the IV estimate of $\beta\xi = 0.317$, which is our baseline measure.[46]

Once we obtain consistent estimates of $\bar{\Upsilon} \equiv \beta(\sigma - 1)(\bar{\gamma} - \xi)$ and $\beta\xi$, we recover ξ using the relationship

$$\xi = \frac{\sigma - 1}{\kappa + \sigma - 1} \bar{\gamma} \tag{E.6}$$

obtained by rearranging $\kappa \equiv \frac{\bar{\Upsilon}}{\beta\xi} = \frac{\beta(\sigma-1)(\bar{\gamma}-\xi)}{\beta\xi}$. Since we have values for κ, σ and $\bar{\gamma}$ (which is the average γ_r across states), we can recover ξ. β is recovered using $\beta = \frac{\beta\xi}{\xi}$.[47]

[46] In Table A.18 in Appendix A, we show the estimation result under the assumption that $\gamma_{rt} = \gamma$ for all r and t. This implies a homogeneous utility function across regions with homothetic preferences. Under this assumption, (5.11) and (E.5) become $\hat{S}_{rf} = \Upsilon \left(\sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right) + (\sigma - 1)\hat{a}_f + \hat{A}_r$ and $\hat{p}_{rf} = \beta\xi \left(\sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right) - \hat{a}_f$, respectively, where $\Upsilon \equiv \beta(\sigma - 1)(\gamma - \xi)$ and $\omega_{rf} \equiv \frac{S_{rf}}{\sum_{r' \in S_{r'f}}}$ is the initial sales weight. The point estimates of Υ and $\beta\xi$ (as well as the precision) are very similar to those in Table A.16 reflecting small variations in $\left(\sum_{r \in k_f} \theta_{rf} \hat{\gamma}_r \right)$ relative to $\left(\sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right)$ (i.e., the ratio of standard deviations of these variables across firms is .5:100, which partially reflects the fact that $\hat{\gamma}_r$ does not vary across firms while $\hat{S}_{rf}$ varies across firms). This implies that non-homotheticity plays a limited role in our estimation.

[47] Note that the calculation of the independent variable $\sum_{r' \in k_f} \left[\omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'} \right]$ requires knowledge of ξ because of $\theta_{rf} \equiv \frac{S_{rf}\gamma_r}{\sum_{r' \in k_f} S_{r'f}(\gamma_{r'} - \xi)}$. Thus, in practice, we start with a guessed value of ξ, measure $\sum_{r' \in k_f} \left[\omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'} \right]$ and run the regression, and then check whether (E.6) returns the same value of ξ.