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

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Abstract

This paper studies how regional shocks spillover across U.S. local markets through intra-firm market networks and explores how such spillovers reshape household welfare across regions. We identify the spillover 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 not only to a direct negative local demand shock but also more strongly to indirect negative demand shocks originating in its other markets. The intra-firm cross-market spillover effects arise from product replacements, whereas the direct local shock operates through the sales of continuing products. Spillover effects occur because (i) firms replace products that have higher value—sales per product, unit price, and organic sales share—with lower-value ones in response to negative demand shocks, and (ii) such product replacements are synchronized across many markets within each firm. Counterfactual analysis using an estimated multi-region model with endogenous quality adjustment shows that our channel generates a novel inter-regional shock transmission, which leads to an economically sizable regional consumption redistribution 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 spillover and affect other regions in the economy? What are the distributional consequences across regions of such a spillover? These long-standing questions in the macroeconomics and international economic literature have been extensively studied in an effort to understand the source of business cycle co-movements. Yet, 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 change in local housing market conditions on local consumption and non-tradable employment in those periods exploiting regional variation in the housing net worth changes. The effect of such regional shocks, however, may not be restricted to local markets of origin, given that the economy is highly connected across regions through various linkages. Regional shocks could spillover and propagate through various regional linkages 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 chain, and financial networks.

What is particularly not well understood in the literature is the role of spatial networks created by *multi-market 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 decision 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 keep up their firm-level sales. 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 trouble financing at the firm-level due to the low cash flow, the increase in financial cost might force these firms to decrease their supply of goods in the other market. 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 export demand of an exporting company do not affect its domestic sales.

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

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

In order to identify the spillover effect, we construct a detailed micro-level data that links barcode-region-level prices and quantities with producer-level information and exploit variation in firms' exposure to differential drops in local house prices during the Great Recession. Our data combines barcode-region-level prices and quantities from the ACNielsen Retail Scanner database with various producer-level information 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, if Coca-Cola generates sales in Manhattan (New York County) and Brooklyn (Kings County), we observe prices and quantities sold in Manhattan and Brooklyn separately for each barcode level product (e.g., cherry-flavored 500ml diet coke) produced by Coca-Cola as well as Coca-Cola's establishment location, primary industry code, and their 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 *spillover shock*, which measures the average indirect negative demand shock originating in the firm's other markets. Strikingly, a firm's county-level sales growth *decreases* by 3.5%p when it faces a 10%p average decline in house price growth in other counties connected through its market network, while it only decreases by 0.6%p due to the same percentage points drop of 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 the local consumption, is a crucial determinant of the drop in the local firm sales in this period. This result is intuitive since a typical firm in our sample sells to a large number of markets, and correspondingly, the measure of spillover shock is close to the average demand shock a firm faces from all markets.[2] Consistent with the intuition, we find a larger spillover effect when firms initially generate larger sales from non-local markets compared to the local market.

We conduct numerous robustness checks and placebo tests to confirm that the identified spillover effect is not driven by other mechanisms, such as common or geographically clustered regional shocks and the establishment or retailer linkages. Also, our empirical results are largely robust to instrumenting the local housing price changes with the house supply elasticity (Saiz 2010) and the local mortgage credit supply shock (García 2018), addressing the concerns on potentially endogenous change in house prices in this period.

[2]For example, the median firm in our sample sells in 155 counties, and in looking at the local sales growth for this particular firm, we measure the spillover shock by measuring the average demand shock this firm faces in all other 154 markets.

Behind responses of local firm sales to direct and spillover shocks, the barcode-level data reveals a stark asymmetry: intra-firm cross-market spillover effects arise mainly from product replacement, whereas direct local shock operates through the sales of continuing products.[3] 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 ones in response to negative demand shocks, and within each firm, such product replacements are *synchronized* across many markets including those that did not face a direct shock. Therefore, a decline in firm sales occurs even in a local market that is not directly affected by the shocks.

We formalize the spillover mechanism and discuss aggregate implications by developing a stylized multi-region model with firms' endogenous quality adjustments. Our model interprets the replacement of high-value products with low-valued 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.[4] In the model, firms that face a negative demand shock decrease their product quality due to both the *scale effects* and the *non-homothetic preferences*. The scale effect reflects that firms experiencing depressed demand do not have enough sales to recover the high fixed cost to produce high-quality products. The non-homothetic preference allows negatively affected consumers to prefer lower quality goods, and as a result, firms have the incentive to supply lower quality of products. In their quality downgrading process, firms choose the 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 in the empirical analysis.

A counterfactual exercise with the model shows that the identified intra-firm cross-market spillover effect generates a novel inter-regional shock transmission mechanism, 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 spillover the shock by choosing a uniform product quality across markets, regions that experience a negative (positive) demand shocks face relatively higher (lower) product quality compared to the case 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

[3] Defining the product at more aggregated-level, we find that all the spillover effects work through the sales of continuing products. This analysis highlights the importance of using barcode-level data in analyzing the product entry and exit within firms.

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

real consumption are nearly 30% and 50% larger than those of the benchmark model with the spillover effect, respectively. A back-of-the-envelop calculation shows that the change in the growth of real consumption corresponds to a one-time $400 per-household transfer (tax) on 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. Fast-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 propagates the micro-level shocks. The most prominent network in this literature is a supply-chain network that translates the sectoral- and firm-specific shock (e.g., Acemoglu et al. 2016; Barrot and Sauvagnat 2016; Carvalho et al. 2016; Bigio and La'O 2017). Other studies emphasize the trade network across regions that translate the regional shock (e.g., Adao et al. 2018a; Caliendo et al. 2018; Stumpner 2019). In financial economics, several studies analyze the linkages created by inter-bank and intra-bank 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 previous studies by identifying a novel regional network arising from multi-market, multi-product firms, which translate a non-local shock across locations and have a non-negligible impact on the local consumption.

Most closely related to our study, an important work by 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 decrease in response to not only directly negative local demand shock but also indirect negative demand shocks originating from its other *production facilities*. We complement their analysis by providing a new intra-firm network created by firms that *sell* multiple products in multiple markets. Specifically, Giroud and Mueller (2019) shows that their intra-firm network presents in non-tradable sectors but not in tradable sectors. By providing a different intra-firm network that applies to tradable sectors, our evidence generalizes such intra-firm spillover effects to both tradable and non-tradable sectors in the U.S. economy. Similarly, for non-tradable sectors, Gilbert (2017) provides descriptive evidence that retailers' intra-firm networks synchronize the consumption across regions through their product entry and exit decisions. Related to the study of retailers, DellaVigna and Gentzkow (2017) and Cavallo (2018) document the uniform pricing behavior within retailers, which potentially spillover and smooth the local shock. On the other hand, our work aims to establish the causal statement about the shock spillover through the producers' intra-firm networks and their choice of product quality. In Appendix, we show that both the establishment linkage and the retailer margin discussed in previous studies do not confound our identified multi-market intra-firm network.

At the international level, the importance of multi-market firms (exporters) and multi-establishment firms (multinationals) in explaining the international comovement is well-documented in di Giovanni et al. (2018). Related to this study, Cravino and Levchenko (2017) shows how multinationals could explain a positive international business cycle co-movement across countries, and Boehm et al. (2019) show that firm-level input-output network spillover the shock across countries. Although the direction of spillover through multinationals and 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 the negative shock spillover through exporters (e.g., Ahn and McQuoid 2017; Almunia et al. 2018). This literature tends to infer the cost structure of firms through the spillover of exporters. Unlike previous studies, we seek to broaden the understanding of such spillover by analyzing domestic multi-market firms within the United States, where the detailed barcode-level data is available, and infer the consumption inequality across states.[5]

Our theoretical predictions on the consumption redistribution resembles the previous studies that examine the role of credit market (e.g., Asdrubali et al. 1996; Lustig and Nieuwerburgh 2005, 2010) and the 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 study variety and quality adjustments, product turnover, and innovation by firms in the context of economic growth, 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; Dingel 2017; 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 (2017). 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. 2016; Guren et al. 2020), price and price-cost markups (Stroebel and Vavra 2019), and employments (Mian and Sufi 2014; Giroud and Mueller 2017). We complement these studies by showing the novel spillover effect arising from the fall in house prices.

[5]Given that our mechanism only works through the barcode-level product replacement, it is hard for our work to infer the direction of international spillover across all countries, where the common barcode-level products are rare. However, at the international-level, we expect our identified spillover effect applies for those countries that share many of the same barcode-level products, such as the North American Free Trade Agreement (NAFTA) and European Union (EU). For the model, we are agnostic on the cost of production by assuming conventional constant marginal cost; Compared to standard models, we only allow fixed cost that varies across different quality, consistent with our empirical evidence and the models with a quality choice of firms (e.g., Faber and Fally 2017).

The rest of this paper is structured as follows. Section 2 describes the data and summary statistics, Section 3 explains the empirical strategy and construction of variables, and Section 4 presents the main spillover and decomposition results. In Section 5, we discuss the mechanism that underlies our results: the channel of uniform product replacements from high- to low-value products. Section 6 develops the multi-region model with endogenous quality adjustment by firms and discusses the distributional implications. Section 7 concludes.

2 Data and Summary Statistics

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 its establishment-level information obtained from the GS1 database and the National Establishment Time-Series (NETS) database. This allows us to construct a firm's county-specific sales and its connection to other counties where the firm generates sales, together with various firm-level information including its primary industry code, establishment location, and credit ratings. To measure local demand shocks, we leverage the large differential collapse in local housing markets during the Great Recession and supplement our dataset with county- and state-level house prices in 2007-09 from the Zillow database. 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.[6] The data contain approximately 2.6 million barcode-level product prices and quantities recorded weekly from about 35,000 participating grocery, drug, mass merchandise, convenience, and liquor stores in all U.S. 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 the 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 period of the Great Recession and the housing market collapse. It mainly includes consumer packaged goods, such as food, nonfood 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 multi-market firm behavior. First, the database records product sales at the barcode-level, which

[6] Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), 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.

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 coming through the intensive margin from continuously existing products and the extensive margin from product creation and destruction. Using a broader product category classification (as definition of product) would not allow us to identify the extensive margin effect emphasized in this paper.[7] Second, use of the database results in fewer measurement error problems. For example, compared to similar data that rely on consumer surveys (Homescan Panel database), the ACNielsen Retail Scanner data directly record expenditures when consumers purchase and scan products at stores. Thus, our data do not suffer from household non-response and misreporting, which is common problem in survey data used in economic research (Meyer et al. 2015). Also, unlike most firm-level international trade and balance sheet data that infer regional (domestic) sales by subtracting other regional (international) sales from total firm sales, Nielsen collects sales information independently across each region. This feature prevents the mechanical regional sales correlation problem raised in Berman et al. (2015) when we conduct the structural regression exercise described in Section 6.

We integrate the prices and quantities of each product with its producer information using the GS1 US Data Hub and the National Establishment Time-Series (NETS). GS1 is the only official source of barcodes in the United States and issues barcodes to producers.[8] 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 various producer-level information from the NETS data.[9] NETS is the U.S. establishment-level longitudinal database made available by Walls & Associates. The original source of the data is Dun and Bradstreet (D&B) archival data, which is collected primarily for marketing and credit scoring. The data allows 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 time period. We use this information to compare firms that operate in the same primary industry, to analyze heterogeneous treatment effects to investigate the mechanism that lies behind the spillover results, and to address concerns related to supply-side or collateral channel. 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 on the NETS data.[10]

[7]For example, we can define "product" using the broader "product group" categories in the ACNielsen data (instead of barcode level), and decompose local sales growth into the intensive and extensive margin. As shown in Table OA.2 in Online Appendix B, the spillover effect is entirely driven by the intensive margin from product group categories existed in both pre- and post- shock periods instead of the entry and exit of the product group categories.

[8]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 enjoys significant discounts in the cost per barcode (see http://www.gs1us.org/get-started/im-new-to-gs1-us).

[9]We use the Reclink2 command available in Stata to merge the GS1 database and the NETS database. A detailed description of the merging process is presented in Online Appendix A.

[10]According to Barnatchez et al. (2017), the NETS dataset is useful for studying cross-sectional business activities, but its value is more limited in studies of business dynamics. Thus, we only use a cross-sectional pre-recession "snapshot" of information in our analysis and abstain from using the data's dynamic perspective.

We supplement our combined database with house price indexes at the county-level from the Zillow database, the housing supply elasticity established by Saiz (2010), and the "nonlocal mortgage lending shock" constructed by García (2018) to capture the local market demand condition.[11] To explore the role played by financial friction in spillovers, we further augment our data with the industry-level "external financial dependence index" from Rajan and Zingales (1998).

We report the summary statistics of the final sample used in the regression analyses in Table 1. Our combined dataset consists of 4171 number of firms and covers 991 US counties from 2007 to 2009.[12] Three features of the data are worth highlighting. 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 to study spillover effects across counties through intra-firm networks: there is large variation across firms in their initial exposure to different counties, and these counties were differentially hit by local shocks. Second, there is extreme firm heterogeneity, as Hottman et al. (2016) have documented. A firm in the 90th percentile of the distribution has about 3000 times more sales, produces about 55 times more products, and sells in about 160 times more counties than a firm in the 10th percentile of the distribution. In the empirical analysis, we control for these firm-characteristics. Lastly, many firms sell their products in each county. On average, 848 firms sell their products in each county, and even in a county in the 10th percentile of the distribution, 341 firms sell their products. As discussed in more details in Section 3.4, this aspect suggests that it is unlikely that an individual firm could affect local economic conditions, due to its small share in each county.

3 Empirical Strategy

This section presents the empirical framework we use to identify the spillover effects of regional shocks through intra-firm networks. We start by discussing key variables, and then we present empirical specifications. At the end of this section, we briefly discuss potential threats to identification and how we address those concerns. We use the terms "(local) market" and "region" interchangeably. Our baseline definition of the local market is the county, but we also present results that use state for the sake of robustness.

[11] We thank Daniel García for sharing his dataset.

[12] As discussed in more details in Online Appendix A, our final combined sample covers about 40% of total sales in the Nielsen data. We show the robustness of our results using the full Nielsen sample as well as the Homescan Panel database in Table OA.3 in Online Appendix B and Table A.9 in Appendix A, respectively.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Panel A: County-firm variables						
$\tilde{\Delta}\text{HP}_{rf,07-09}$ (other)	840681	-.169	.042	-.209	-.170	-.122
$\tilde{\Delta}\text{Sale}_{rf,07-09}$	840681	-.041	.799	-1.176	.017	.942
$\tilde{\Delta}\text{Sale}^{\text{continue}}_{rf,07-09}$	840681	-.061	.543	-.702	-.037	.534
$\tilde{\Delta}\text{Sale}^{\text{replace}}_{rf,07-09}$	840681	.021	.53	-.528	0	.571
$\text{Sales}_{rf,07}$ (in thousand dollar)	840681	65.423	739.854	.107	2.346	70.288
$\text{Sales}^{\text{exist}}_{rf,07}$ (in thousand dollar)	840681	56.524	631.472	.061	1.639	58.916
$\text{Sales}^{\text{exit}}_{rf,07}$ (in thousand dollar)	840681	8.899	129.795	0	.197	8.684
$\text{Sales}_{rf,09}$ (in thousand dollar)	840681	68.068	768.49	.071	2.347	74.756
$\text{Sales}^{\text{exist}}_{rf,09}$ (in thousand dollar)	840681	52.375	528.692	.037	1.475	56.332
$\text{Sales}^{\text{enter}}_{rf,09}$ (in thousand dollar)	840681	15.693	283.807	0	.216	14.266
# of UPCs in 2007	840681	34.18	106.989	1	9	70
Panel B: Firm variables						
$\tilde{\Delta}\text{HP}_{f,07-09}$	4171	-.161	.087	-.269	-.156	-.067
$\text{Sale}_{f,07}$ (in million dollar)	4171	15.586	147.974	.005	.278	14.677
# of UPCs in 2007	4171	54.239	231.783	2	12	110
# of counties in 2007	4171	513.243	669.991	10	155	1655
# of product groups in 2007	4171	2.701	3.421	1	2	6
Panel C: County variables						
$\tilde{\Delta}\text{HP}_{r,07-09}$	991	-.092	.138	-.258	-.079	.044
$\text{Sale}_{r,07}$ (in million dollar)	991	55.499	131.941	.524	15.849	143.861
# of UPCs in 2007	991	28995.06	15382.66	7994	28730	49854
# of firms in 2007	991	848.316	353.868	341	876	1306

Note. All the sales and house price variables are defined in Section 3. $\tilde{\Delta}\text{Sale}^{\text{total}}_{rf,07-09}$ is the county-firm sales growth in 2007-09, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{rf,07-09}$ is the county-firm sales growth arising from product replacements in 2007-09, and $\tilde{\Delta}\text{Sale}^{\text{continue}}_{rf,07-09}$ is the county-firm sales growth arising from continuing products in 2007-09. $\text{Sale}_{rf,07}$ is the total county-firm sales in 2007, $\text{Sale}^{\text{exist}}_{rf,07}$ is the 2007 sales of products existed in both 2007 and 2009, and $\text{Sale}^{\text{exit}}_{rf,07}$ is the 2007 sales of products existed in 2007 but exited in 2009. $\text{Sale}_{rf,09}$ is the total sales in 2009, $\text{Sale}^{\text{exist}}_{rf,09}$ is the 2009 sales of products existed in both 2007 and 2009, and $\text{Sale}^{\text{enter}}_{rf,09}$ is sales of products newly entered in 2009. $\tilde{\Delta}\text{HP}_{r,07-09}$ is the county-level house price growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{f,07-09}$ is the firm-level exposure of house price growth, which is defined as 2007 sales share weighted average of $\tilde{\Delta}\text{HP}_{r,07-09}$ across counties where the firm generates sales, and $\tilde{\Delta}\text{HP}_{rf,07-09}$ (other) is the spillover shock defined as the initial sales-weighted $\tilde{\Delta}\text{HP}_{r,07-09}$ in the other counties where the firm generates sales. Firm variables are measured using information from all regions, including those without house price information.

3.1 Dependent Variables

Let $\text{Sale}_{rf,t}$ denote firm f's sales in region r at time t. We measure the region-firm-specific sales growth in 2007-09 as

$$\tilde{\Delta}\text{Sale}_{rf} \equiv \frac{\text{Sale}_{rf,09} - \text{Sale}_{rf,07}}{\overline{\text{Sale}}_{rf}} \tag{3.1}$$

where $\overline{\text{Sale}}_{rf} \equiv \frac{1}{2}(\text{Sale}_{rf,07} + \text{Sale}_{rf,09})$ is a 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 the employment growth at the establishment-level (e.g., Davis et al. 1996). This growth rate definition 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.[13,14]

Given the prevalence of multi-product firms, we investigate the role that product creation and destruction of these firms play in shock spillovers. Following Broda and Weinstein (2010), we decompose the sales growth defined in equation (3.1) 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) :

$$\tilde{\Delta}\text{Sale}_{rf} = \tilde{\Delta}\text{Sale}_{rf}^{\text{continue}} + \tilde{\Delta}\text{Sale}_{rf}^{\text{replace}} \tag{3.2}$$

where $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}} \equiv \frac{\text{Sale}_{rf,09}^{\text{continue}} - \text{Sale}_{rf,07}^{\text{continue}}}{\overline{\text{Sale}}_{rf}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}} \equiv \frac{\text{Sale}_{rf,09}^{\text{enter}} - \text{Sale}_{rf,07}^{\text{exit}}}{\overline{\text{Sale}}_{rf}}$. $\text{Sale}_{rf,t}^{\text{continue}}$ is the region-firm-time-specific sales from products that continuously existed in region r throughout 2007-09, $\text{Sale}_{rf,07}^{\text{exit}}$ is the sales from products that existed in region r in 2007 but exited in 2009, and $\text{Sale}_{rf,09}^{\text{enter}}$ 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 the sales growth: $\text{Sale}_{rf,07} = \text{Sale}_{rf,07}^{\text{continue}} + \text{Sale}_{rf,07}^{\text{exit}}$ and $\text{Sale}_{rf,09} = \text{Sale}_{rf,09}^{\text{continue}} + \text{Sale}_{rf,09}^{\text{enter}}$. The products that entered or exited region r account for less than one-fourth of total sales in 2007 and 2009. Despite their relatively small fraction in total sales, these extensive margins in firm's local sales cause most of the spillover effect.

To understand whether the spillover effect is coming from the intensive or the extensive margins response (or both), we regress each of two margins on the spillover shock. We also regress each margin on the direct local shock to similarly decompose the direct effect.

[13] Another important benefit of using this growth rate is that it can accommodate both the entry and exit of firms at the local market level. Table A.12 in Appendix A shows the result that accommodates these margins.

[14] The qualitative results are robust to using the more conventional definition of the sales growth in which the denominator equals 2007 sales. See Table OA.5 in Online Appendix B.

3.2 The Spillover Shock

As discussed in more details in the following section, our main goal is to investigate whether a firm's local sales growth is affected by *indirect* regional shocks originating in the firm's other markets, conditional on direct local demand. To this end we define the region-firm-specific *spillover shock* as the average regional demand shock a firm faces from its other markets, weighted by its initial sales share in those markets. The method of construction is similar to the one proposed by Giroud and Mueller (2019)—who consider within-firm multi-establishment networks in the nontradable sector—weighted by initial employment share.

Following Mian et al. (2013), we leverage the large differential drop in local house prices during the Great Recession to measure local consumer demand shock. Let $\text{HP}_{r,t}$ 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 2007-09 as

$$\tilde{\Delta}\text{HP}_r \equiv \frac{\text{HP}_{r,09} - \text{HP}_{r,07}}{\overline{\text{HP}}_r} \tag{3.3}$$

where $\overline{\text{HP}}_r$ is a simple average of the housing price indexes in region r in 2007 and 2009.

Given the region-specific house price growth, we take the weighted average of this growth measure across regions r' within a firm f, excluding the particular region r, to measure firm f's (indirect) spillover shock for region r:

$$\tilde{\Delta}\text{HP}_{rf}\ (\text{other}) \equiv \sum_{r' \neq r} \omega_{r'f} \times \tilde{\Delta}\text{HP}_{r'} \tag{3.4}$$

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

3.3 Empirical Specification

Our goal is to investigate whether and how a multi-market firm's local sales respond to local demand shocks that originate in the firm's other local markets. To achieve this goal, we estimate the following equation:

$$\tilde{\Delta}\text{Sale}^i_{rf} = \beta^i_0 + \beta^i_1 \tilde{\Delta}\text{HP}_r + \beta^i_2 \tilde{\Delta}\text{HP}_{rf}\ (\text{other}) + \text{Controls}_{rf} + \varepsilon^i_{rf} \tag{3.5}$$

where $i = \{\text{(all), continue, replace}\}$. $\tilde{\Delta}\text{Sale}^i_{rf}$ indicates region-firm level sales growth measured by all products (i.e., $\tilde{\Delta}\text{Sale}_{rf}$) that arise from continuously existing products (the intensive margin) and from the net creation of products (the extensive margin), respectively. $\tilde{\Delta}\text{HP}_r$, which is our measure of direct local demand shock, is the region-level house price growth, while $\tilde{\Delta}\text{HP}_{rf}$ (other) is the average house price growth in the firm's other markets, measuring the spillover shock. Controls_{rf} is the vector of control variables that include SIC 4-digit sector fixed effects and various region-firm control variables.[15] Standard errors are double clustered at the state and sector level and regressions are weighted by initial region-firm level sales.[16]

Our coefficient of interest is β^i_2, which measures the spillover effect on various margins of the firm's local sales. Specifically, β_2 is the elasticity of the firm's local sales growth with respect to the average local demand shock that originates in the firm's other markets, *conditional on direct local demand*. A priori, β_2 can have any sign. If negative local demand shocks in other regions reduce (increase) the firm's local sales, then the sign of β_2 should be positive (negative). The other coefficient, β^i_1, measures the effect of direct local house price growth on various margins of firm's local sales. As β_1 captures the conventional effect emphasized in Mian et al. (2013) at the region-firm level, we expect β_1 to be positive. Finally, it is worth emphasizing that the effect of any nation-wide shock, including the effect of a common aggregate decline in house prices in all regions, is absorbed by the constant term β^i_0. That is, our estimation of β^i_2 exploits a *differential* drop in house prices across regions, not the common aggregate component.

3.4 Discussion of the Identification Assumption

The main identifying assumption for the consistent estimation of β^i_2 is that any confounding factor that affects the firms' local sales growth is not correlated with house price growth in the firm's other markets. This assumption can be violated if, for example, a particular firm is very influential in a local market that it can influence house prices in that market. But such reverse causality is not a major concern since even the largest firm in a typical county has a sales share less than 5%.[17]

However, there remain challenges that may threat our identification, and these can be classified into three broad categories: (i) sorting (selection) into particular markets by firms; (ii) common or clustered regional shocks; and (iii) other channels. We briefly discuss how we overcome such challenges.

[15] These include — (region controls) pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than 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 — and — (region-firm controls) log of initial county-firm 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.

[16] In Table A.10 in Appendix A, we report standard errors accounting for the shift-share correlation structure as in Adao et al. (2018b). The standard errors are more or less similar.

[17] Even this number if plausibly overestimated because there could be firms selling in those markets that are not captured by ACNielsen Retail Scanner database.

Table 2: 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). The sample includes 4,171 firm level observations.

3.4.1 Sorting into Particular Markets by Firms

To identify the spillover effect, it is important to compare local market performances of plausibly similar firms that differ only in their exposure to housing market conditions in other markets. If one firm systematically established its major markets in regions that experienced relatively higher house price growth compared to the other firm, and if such behavior is correlated with firm characteristics that affect firms' local performances, then the spillover effect we find might actually be a result of such differences in firm characteristics.

In Table 2, we provide a support that this is not a major concern by performing balance test. Specifically, we regress a number of firm-level initial characteristics on the within-firm average of the house price growth across counties (i.e., the firm-specific average shock) and the sector fixed effects.[18] As we can be seen from the table, we do not find a systematic correlation between a firm's average shock and its initial characteristics. This implies that firms that were exposed on average to adverse local housing market conditions during the Great Recession are not systematically different from those exposed to relatively favorable local housing market conditions.[19]

[18] All our analyses will include SIC 4-digit sector fixed effects.

[19] Borusyak et al. (2018) proposes balance checks at the shock level (i.e., in our case, at the county level). In Table OA.6 in Online Appendix, we present the regional shock level balance checks following Borusyak et al. (2018). None of the county-specific averages of initial firm characteristics are significantly correlated with the county level house price growth at the conventional level.

3.4.2 Common or Clustered Regional Shocks

The Great Recession was a period of large aggregate shocks that affected the entire economy. Also, it is well known that different industries were differentially affected during the crisis.[20] All our regressions include sector fixed effects, which take care of aggregate and/or sectoral shocks. Moreover, our most conservative specification includes county-by-sector fixed effects (instead of directly controlling county-level observables), which take care of not only sectoral shocks but also potential county-sector-specific shocks. County-by-sector fixed effects allow us to effectively compare the local sales growth of firms *within the same county* among firms in the same industry.

Yet another evident identification threat is the possibility of geographically clustered shocks that simultaneously affect multiple regions in which firms are selling. For example, if a firm had been selling in geographically clustered markets, and if such markets are hit by clustered shocks correlated with house prices, this will lead to a fall in house prices and sales jointly. In this case, such clustered shocks could explain the positive relationship between a firm's local sales growth, $\tilde{\Delta}\text{Sale}_{rf}$, and the house price growth in its other markets, $\tilde{\Delta}\text{HP}_{rf}$ (other). To address these concerns, in Section 4, we show the robustness of our result by constructing the spillover shocks by excluding nearby counties and considering only geographically distant counties.

3.4.3 Other Channels

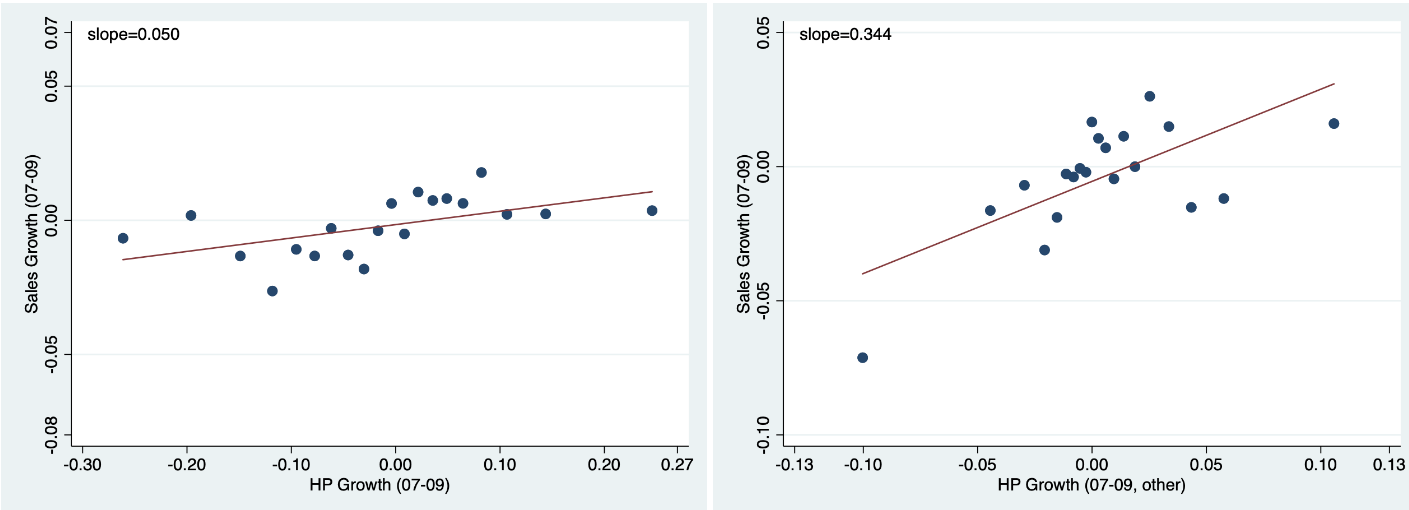
Finally, it is possible that our estimate of β_2^i is confounded by alternative channels or factors other than the spillover of local demand shocks. Such factors include the possibility that house prices could directly affect production facilities (i.e., supply-side or collateral channel), the endogeneity of house prices, common retailer through which households purchase products, and clientele effects. To address these concerns, we provide a number of Placebo tests and robustness analyses in Section 4.

4 Main Empirical Results

We show that a multi-market firm's local sales decrease in response to both direct negative local demand shock and the intra-firm spillover shock, which measures the average *indirect* local demand shock originating in its other markets. By decomposing a firm's local sales growth into the extensive and intensive margins, we show that the response of local sales to the spillover shock can be fully attributed to the extensive margin response associated with product creation and destruction, while the direct local shock affects local sales solely through the intensive margin from continuing products.

[20] Apart from the well-known construction bust, there is a substantial variation in employment drop in 2007-09 even within nondurable goods manufacturing sector from -25% (Textile mills) to 1% (Petroleum and coal products). See Barker (2011).

Figure 1: Local Sales Growth against (i) Direct Local Shock (Left) & (ii) Spillover Shock (Right) (All Residualized)



Note. These figures show bin scatter plots (20 bins based on ventiles) depicting the relationship between (residualized) county-firm level sales growth, $\tilde{\Delta}\text{Sale}_{(07-09)}$, against (i) (residualized) county-level house price growth, $\tilde{\Delta}\text{HP}_{(07-09)}$ (left panel), and (ii) (residualized) initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, $\tilde{\Delta}\text{HP}_{07-09}$ (other) (right panel). Residualized variables are constructed using regression corresponding to Column (1) of Table 3 using Frisch-Waugh theorem. The reported slop coefficients are based on simple linear regression using 20 bins.

4.1 Regional Spillover

We start by presenting the bin scatter plots that visualize the regression in equation (3.5). The left panel in Figure 1 plots a firm's local sales growth against the direct local demand shock, while the right panel plots it against the spillover shock. As can be seen from the positive slopes in both the left and right panels of the figure, a firm's local sales growth is positively associated with both the direct and the spillover shock.

Table 3 presents the formal regression results of equation (3.5), in which we measure a firm's local sales growth by including both continuing and replaced products. Column (1) shows that a firm's local sales growth positively respond to both the direct local shock—$\tilde{\Delta}\text{HP}_{(07-09)}(\%)$—and the indirect spillover shock—$\tilde{\Delta}\text{HP}_{(07-09)}(\%)$ (other)—that originates in its other markets. Both coefficients are positive and statistically significant. Importantly, the estimated elasticity of local sales with respect to the spillover shock, 0.35, turns out to be six times larger than that of the direct local shock. This is intuitive if one recalls that a typical firm sells in more than a hundred of counties. Thus, the spillover shock proxies the (leave-county-out) firm-specific demand shock that arises from the rest of a firm's other counties.

In Column (2), we show the estimation result of equation (3.5) in which we include sector-by-county fixed effects instead of directly controlling county-level observables. We obtain a highly significant positive coefficient of 0.40. This indicates that a 10%p decline in a firm's average local demand shock in the other markets reduces its local sales growth by 4%p.

Prior research shows that a decline in regional house prices during the Great Recession caused a drop in local consumer demand (e.g., Mian et al. (2013)). However, changes in regional house prices could have affected a firm's local sales by directly affecting production rather than through consumer demand. One example is the "collateral channel". Changes in regional house prices could affect a firm's collateral value, which, in turn, could affect production. Also, regional house prices could be correlated with regional productivity shocks, which again could directly affect production. Under these supply-side channels, intra-firm networks still matter, and not because they spill over local demand shocks, but because they spill over local "supply-side" shocks. In Column (3), we provide direct evidence consistent with the local consumer demand channel. Specifically, we construct the spillover shock by *excluding* counties in which the firm's establishments are located. Thus, regional house prices can only affect a firm's local demand and not the collateral value or productivity of its establishments.[21] The estimated coefficient is 0.38, which is highly statistically significant.

Another challenge to identifying the spillover effect is the possibility of geographically clustered regional shocks. Think about a firm that sells products in geographically close regions—for example Manhattan (New York County) and Brooklyn (Kings County), both of which are located in the state of New York. In this case, we might find that in one county the firm's local sales has a strong positive response to house price growth in the other county. This could occur not because of the spillover effect but because of clustered regional shocks that affect the New York area in general. Our estimate of the spillover effect could be confounded by such underlying common shocks if they generate positive comovement in house prices in New York area.

We address these concerns in two ways: (i) we exclude nearby counties when we construct the spillover shocks and show that the result is robust; and (ii) we repeat the analysis by defining the local market at the state-level. Column (4) shows the result when the spillover shock is measured only by considering counties located outside the state. We find a robust spillover effect under this specification. In Table A.1 in Appendix A, we construct the spillover shocks by excluding nearby counties within a radius of up to 150 miles. The results are robust to these alternative specifications.

In Column (5), we estimate equation (3.5) by defining the state as the unit of the local market. By defining the local market at the state-level, we aggregate regional demand shocks within each state (including any clustered regional shock that jointly affects counties within each state) and treat them as a state-level demand shock. We obtain a highly significant positive coefficient of 0.30. This result also indicates that our spillover effect is not particularly driven by firms who sell in multiple

[21]Formally, we measure the region-firm specific spillover shock by only including the firm's "other counties" where it (i) generates sales by selling its products and (ii) does not have establishments. We re-normalize the leave-out initial sales weights so that they sum up to one.

Table 3: The Effect of the Direct and the Spillover Shocks on Firm's Local Sales Growth

	(1)	(2)	(3)	(4)	(5)
			$\tilde{\Delta}\text{Sale}_{(07-09)}$		
			County-Firm		State-Firm
$\tilde{\Delta}\text{HP}_{(07-09)}$	0.059**				
	(0.028)				
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.345***	0.398***			0.303***
	(0.110)	(0.105)			(0.113)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, exclude-plant)			0.384***		
			(0.091)		
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, out-of-state)				0.335***	
				(0.088)	
Sector FE	✓	-	-	-	-
Region Controls	✓	-	-	-	-
Region-Firm Controls	✓	✓	✓	✓	✓
Sector x Region FE	-	✓	✓	✓	✓
R^2	0.201	0.392	0.398	0.393	0.357
Observations	840681	840681	821503	838812	83610

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the county-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, exclude-plant) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales and the firm has no establishments. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, out-of-state) is the initial sales-weighted house price growth between 2007 and 2009 in other counties located in other states. Sectors are defined based on SIC 4-digit. Region controls include pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than 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-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

counties located within a single state.

Importantly, what matters for the spillover is the connection to other markets *through the intra-firm market networks* and not other markets in general. Table A.2 in Appendix A presents Placebo tests that demonstrate the point. Instead of constructing the spillover shock using the true intra-firm networks, we construct *Placebo spillover shocks* using various Placebo networks. In Column (1) to Column (3) we construct Placebo spillover shocks using alternative weighting schemes (instead of a firm's initial sales share in those markets). As can be seen from the table, we cannot reproduce the spillover effect if we use alternative Placebo weighting schemes, such as equal weights, county level population weights, and county level median household income weights. In Column (4), we generate random intra-firm networks by randomizing each firm's intra-firm market networks.[22] Again, such random intra-firm networks do not generate the spillover effect. These results indicate that to successfully identify spillover effects we must (i) consider markets in which firms generated sales during the initial period *and* (ii) properly measure initial exposure across these markets through initial sales shares. Finally, Column (5) shows that spillover effects cannot be reproduced by identifying a firm's networks on the basis of the location of its establishments.[23]

To summarize, Table 3 provides strong evidence that regional shocks spill over through intra-firm networks and affect local performance of firms in other regions. We further confirm our result by conducting a number of robustness checks in Section 4.3.

4.2 Decomposition

We now decompose local sales growth into two components : those comming from common products that exist in both initial and end periods in the local market (the intensive margin); and those from the net creation of products (the extensive margin through product replacement). Our results show that the extensive margin significantly reacts to the shocks that hit other markets, while the direct local shock only affects the intensive margin.

We first estimate equation (3.5) by replacing $\tilde{\Delta}\text{Sale}_{rf}$ with $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}}$, respectively. Columns (1)-(3) in Table 4 show the results. Notice that our definitions of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}}$ make the estimated coefficients in Column (1) identical to the sum of coefficients in Columns (2) and (3).[24]

As can be seen in Column (2), net creation does not respond to the direct local shock. Instead, it strongly (and positively) responds to the spillover shock with an estimated coefficient of 0.32. In contrast, sales growth that arises from common products significantly and positively responds to

[22] To be more specific, for each county-firm observation, we replace the firm's other connected counties (i.e., r''s with $\omega_{r'f} > 0$) with randomly selected counties. We then construct the placebo spillover shock based on such random network and estimate equation (3.5). We repeat this process 800 times and report the average coefficients and standard errors, respectively.

[23] This is consistent with Giroud and Mueller (2019) for tradable industry firms.

[24] We present the result decomposing $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ into creation and destruction in Table A.15 in Appendix A.

Table 4: Decomposition of Sales Growth: The Extensive vs. Intensive Margins

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$	0.059**	0.009	0.051**
	(0.028)	(0.014)	(0.024)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.345***	0.320***	0.025
	(0.110)	(0.093)	(0.067)
Sector FE	✓	✓	✓
Region Controls	✓	✓	✓
Region-Firm Controls	✓	✓	✓
R^2	0.201	0.284	0.223
Observations	840681	840681	840681
	(4)	(5)	(6)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.398***	0.419***	-0.021
	(0.105)	(0.102)	(0.045)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.392	0.408	0.427
Observations	840681	840681	840681

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the county-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region controls include pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than 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-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

the direct local shock, but it does not significantly respond to the spillover shock. Columns (4)-(6) repeat the analyses using equation (3.5). The results are similar. A 1%p decline in the spillover shock reduces the extensive margin by 0.42%p, and largely for this reason local sales respond to the spillover shock. In Table A.3 in Appendix A, we repeat the analysis at the state-firm level.

The decomposition results in this section point out that product replacements in local markets is the principal factor through which shock spillover occurs through intra-firm networks. In Section 5, we investigate why a firm's product replacements in a local market responds to the spillover shock that originates in its other markets and why such response results in decrease of local sales.

4.3 Robustness

Before we move on to the investigation of the mechanism behind our findings, in this section, we show the robustness of our results by addressing potential concerns that may confound our findings. First, we show that our spillover results are not driven by retailers through which firms sell products. Second, we use instrumental variable regression to show that the potential endogeneity of house prices does not affect our result. Third, to ensure that our results are not confounded by firms catering to different types of customers or markets, we perform additional robustness checks by controlling conditions in other markets. Fourth, we repeat our analyses using ACNielsen Homescan Panel data and show that using 2004 sales share to construct our shock and, additionally, controlling lagged-dependent variables (i.e., pre-trends in local sales) does not change our results. Finally, at the end of section, we briefly summarize further the robustness results we performed, such as accommodating local market entry/exit and allowing product group dimensions. We present all of the tables in this section in the Appendix.

4.3.1 Retailer Effects

One potential concern is that our spillover results may have been driven by retailers through which firms sell products. For example, lower sales growth in Coca-Cola of New York county relative to that of Pepsi might reflect the differential performance of retailers selling Coca-Cola's products relative to those selling Pepsi's products. To address this, we show the robustness of our results in Table A.4 by comparing the local sales growth of firms *within* the same retailer. Specifically, we add the retailer margin and construct county-firm (i.e., producer)-retailer level sales growth and run the regression by including sector×county×retailer fixed effects.[25] Thus, any county-retailer specific trend in local sales within SIC 4-digit producer sector will be absorbed by such fixed effects. Column (1) shows the result. our coefficient is 0.53, which is highly statistically significant.

However, it is still possible that, for example, the lower sales growth of Coca-Cola in a particular retailer in New York county relative to that of Pepsi could occur if that retailer faces larger Coca-Cola

[25] We define retailer using "parent code" in Nielsen Retail Scanner data.

specific negative shocks from its stores in other regions. Thus, in Column (2), we include the "average producer-specific demand shock" a retailer faces through its stores in other regions (where the producer's products are sold).[26] It turns out that change in county-firm-retailer specific sales is mainly driven by firm-level spillover shock and not the retailer-firm specific spillover shock. In Columns (3) and (4) we show the corresponding decomposition results.

4.3.2 Endogeneity of House Prices and IV Regression

Notice that the spillover shock we construct has the Bartik-type property. Thus, the spillover shock can be viewed as exogenous at the firm-level even if local house price change is not purely exogenous at the local market level. However, we also check the robustness of our result by instrumenting the spillover shock with similarly constructed instrumental variables that leverage widely-use instruments for house prices: (i) housing supply elasticity (Saiz (2010)) and (ii) nonlocal mortgage lending shocks (García (2018)).[27]

Table A.5 and Table A.6 in Appendix A present the results using these two instruments. All of the results are robust to these specifications.

4.3.3 Clientele Effects and Common Largest Market

It is also possible that the differential response of the local sales of two firms may arise not because of the differential local demand shocks they face in their other markets but because they cater to different types of customers. Different demographic segments of the population might have been affected differently during the Great Recession, and in such case, our spillover effect can be confounded by such clientele effects. In Table A.7, we account for clientele effects by including average demographic conditions in the firm's other markets. The results are robust to such specification.

In Table A.8 in Appendix A, we also show that our results are not driven by comparing the local sales of two firms that have their major markets concentrated in different regions in the US (e.g., east coast vs. west coast).[28] Although such variation is one of the sources of differential demand shocks across firms (which we utilize), we show the robustness of our results by comparing firms that

[26]Specifically, we run the following regression:

$$\tilde{\Delta}\text{Sale}_{rfs} = \beta_0 + \beta_2 \tilde{\Delta}\text{HP}_{rf}\ (\text{other}) + \beta_3 \tilde{\Delta}\text{HP}_{rfs}\ (\text{other}) + \text{Controls}_{rfs} + \epsilon_{rfs}$$

where r indicates region (i.e., county), f indicates firm (i.e., producer), and s indicates retailer. Here, $\tilde{\Delta}\text{HP}_{rfs}$ (other) $\equiv \sum_{r' \neq r} \omega_{r'fs} \times \tilde{\Delta}\text{HP}_{r'}$ where $\omega_{r'fs} \equiv \frac{\text{Sale}_{r'fs,07}}{\sum_{r' \neq r} \text{Sale}_{r'fs,07}}$. $\tilde{\Delta}\text{HP}_{rfs}$ (other) captures the average producer f-specific demand shock that retailer s faces through its stores in other regions (where the producer f's products are sold).

[27]Specifically, we replace $\tilde{\Delta}\text{HP}_{r'}$ in (3.4) with the county-level housing supply elasticity or nonlocal mortgage lending shocks.

[28]For example, some unobserved characteristics of firms might have led one firm to have its major markets located in, for example, the west coast side of the United States and the other to have its major markets located in the east coast.

share a common *largest market* (defined at the census division level). The results are robust under the specification with sector-by-largest market fixed effects.

4.3.4 Using Lagged-initial Sales and Controlling Lagged-dependent Variables

We also repeat our analyses using ACNielsen Homescan Panel data and show that using the 2004 sales share to construct the spillover shock and additionally, controlling lagged-dependent variables (i.e., pre-trends in local sales) does not change our results. The ACNielsen Homescan Panel dataset is constructed by Nielsen from a demographically representatitve sample of approximately 33,000 households in the United States.[29] We collapse the data into state-firm level and perform the analyses.[30]

Columns (1)-(3) of Table A.9 repeats Columns (4)-(6) in Table 4, where the spillover shocks are constructed using firms' 2004 sales share across local markets.[31] We get similar results. In Columns (4)-(6), we additionally control lagged-dependent variables. The results barely changes.

4.3.5 Additional Robustness Analyses

As discussed in Adao et al. (2018b) and Borusyak et al. (2018), it is important to consider the presence of correlated errors in shift-share research design. In Table A.10 in the Appendix, we report standard errors that account for the shift-share correlation structure as in Adao et al. (2018b). The estimated standard errors are more or less similar, and we find statistically significant spillover effects at the conventional level.

In Table A.11, we allow the product group dimension, which is a broad product category classification provided by ACNielsen.[32] By performing analyses at the county-firm-product group level, we can additionally include product group-by-county fixed effects. As can be seen in Table A.11, the results are robust to this alternative specification.

Table A.12 shows the result when a firms' local market entry and exit are taken into account. As the table shows, we find robust results.

[29] In this exercise, we use the entire ACNielsen Homescan Panel data without relying on the NETS data to minimize any distortion in the representativeness of the households through which the data are collected. This exercise also adds the external validity of our analyses because the ACNielsen Retail Scanner dataset and Hoemscan Panel dataset are collected by different entities (i.e., stores versus households, respectively).

[30] The ACNielsen Homescan Panel sample is demographically representative not only at the national level but also within subnational regions such as 9 census regions and 52 "scantrack markets" defined by Nielsen. Ideally, we would like to perform the analyses at the scantrack market-firm level, but as we do not have well-defined house price information at the scantrack market level, we perform the analyses at the state-firm level.

[31] All control variables are based on year 2004. Also, to compare plausibly similar firms, we group companies by their three largest product groups and classify them as operating in the same sector. To be more specific, if two firms share the same three largest product groups, we classify them as operating in the same sector. If a firm only sell products categorized into a single product group, we group these firms separately to those having two or more product groups.

[32] Product group is a broad categorization of products provided by ACNielsen. Examples of product groups are "Baby food", "Beer", "Cosmetics", "Glassware", "Laundry supplies", "Paper products", etc.

4.4 The Heterogeneous Treatment Effect

Our result indicates that in generating within-firm spillovers across regions, the firm-level factor plays a dominant role through product replacement rather than direct local market conditions. We provide two pieces of supporting evidence that emphasize the role of the firm-level factor behind our findings. First, we show that the identified spillover effects become stronger as firms become more financially constrained. Second, the within-firm spillover effects become stronger as the spillover shock better proxies the firm-level average demand shock.

We measure financial constraint using the initial paydex score provided by the NETS data.[33] For the robustness, we also use the financial constraint measure proposed by Rajan and Zingales (1998) (Table A.14 in Appendix A).

To gauge whether the spillover shocks proxy the firm level average demand shock, we measure the within-firm local sales shares (i.e., $\frac{Sale_{rf}}{\sum_r Sale_{rf}}$). If the within-firm local market share is sufficiently small, this means that the spillover shock arising from the other markets captures the bulk of the demand shocks the firm faces in the overall markets. In such cases, the spillover shock can be interpreted as the firm-level average demand shock (i.e., "global shock" from the firm's perspective).

Table A.13 in Appendix A summarizes the result. As can be seen in the first row, more financially constrained firms (i.e., higher ln(100-paydex)) experience stronger spillover. Notably, such interaction mainly works *through the product replacement channel*.

The second row shows that if a firm's local market has a smaller within-firm market share, the spillover effect becomes stronger. Specifically, we consider a dummy variable that has value one if the firm's local sales share is above the median of the distribution across all observations. We get significant negative coefficients for both the overall sales growth (Column (1)) and the extensive margin of sales growth from product replacements (Column (2)), which indicates that if the local sales share is sufficiently high (low), we will obtain a weaker (stronger) spillover effect.

5 Mechanism: Uniform Product Replacements from High- to Low-Valued Products

Our result suggests that product replacement within a firm in a local market is strongly affected by the overall demand conditions the firm faces in its other markets. Importantly, the result implies that newly introduced products in the local market generate lower sales than destroyed products, conditional on local demand. In this section, we explore the mechanism that underlies our findings.

[33] Paydex, a term used by Dun and Bradstreet, is a numerical score granted to businesses as a credit score for the promptness of their payments to creditors. Use of the Paydex score for commercial organizations resembles the use of the FICO score for individuals. A higher score indicates better financial conditions, and so we use ln(100-paydex) to measure degrees of financial constraint.

Table 5: Product Creation and Destruction Patterns

1. Local Market at the County level

(A) Product Destruction	Exits (>50%) of Mkt	Exits (>90%) of Mkt
	0.90	0.65
(B) Product Creation	Enters (>50%) of Mkt	Enters (>90%) of Mkt
	0.80	0.31

2. Local Market at the State level

(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 their initially sold markets 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 overall markets in 2009.

We show that the within-firm spillover effect across regions occurs because firms respond to negative demand shocks by replacing products uniformly across many markets, and in doing so, they replace high-valued products with low-valued products.[34] Thus, a region that is not directly hit by the shock also experiences a replacement of products from high- to low-valued products, resulting in a decline of local sales.

5.1 Uniform Replacement of Products across Multiple Markets

We start with descriptive statistics that show simultaneous product replacements across multiple markets, and then we formally show that the spillover effect is essentially driven by products replaced in multiple markets rather than in the local market only.

(1) When products exit or enter local markets, they do so in multiple markets uniformly.

[34]We formalize why negative demand shocks result in replacement from high- to low-value products through the lens of the model in Section 6. We argue that this reflects a downgrading of product quality that results from scale effect and nonhomothetic preferences. If production at the lower quality level requires lower fixed costs, firms find it optimal to downgrade product quality if they face lower demand shocks. Alternatively, if preferences are nonhomothetic, negative demand shock induces households to switch from high-quality goods to low-quality goods, in which case firms find it profitable to downgrade product quality.

Table 6: Extensive Margin Decomposition (County-level)

	(1) $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}^{\text{replace, local}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.419***	0.418***	0.000
	(0.102)	(0.101)	(0.000)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.408	0.408	0.216
Observations	840681	840681	840681

$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from products replaced in multiple counties, and $\tilde{\Delta}\text{Sale}^{\text{replace, local}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from products only replaced in the county. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

In Table 5, we investigate whether product creation and destruction involve the entry and exit of products in a majority of each firm's markets. Specifically, Panel (A) of Table 5 calculates the share of value lost by the destruction of products that is attributed to the products that exited more than 50% (90%) of their initially sold markets. As can be seen in Panel (A) of Table 5-1, about 90% of the value lost by product destruction arises from products that exit more than half of their initially sold counties. Even if we restrict products to those that exited more than 90% of initially sold counties, these products account for 65% of product destruction. As indicated in Panel (B). the product creation patterns are similar. About 80% of the value generated by product creation can be attributed to products that entered more than half of the firm's overall markets.

Table 5-2 repeats the analysis by defining the local market at the state level. Again, in the case of both product creation and destruction, about 90% of value created (destructed) can be attributed to products entering (exiting) uniformly across more than half of the firm's markets.

(2) The response of the extensive margin to the spillover shock is entirely attributed to the products replaced in multiple markets.

To investigate whether the extensive margin response to the spillover shock comes from products replaced in multiple markets, we decompose $\tilde{\Delta}\text{Sale}^{\text{replace}}_{rf}$ into two components: (i) $\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{rf}$, which captures local sales growth coming from products replaced in multiple markets; and (ii) $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$, which captures local sales growth that comes from products replaced in the county only.[35]

Columns (2) and (3) in Table 6 show the results from separate regressions that replace $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ with $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, multi}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$ as a dependent variable. Essentially all of the spillover effect comes from the response of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, multi}}$, while the response of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$ is negligible and statistically insignificant. We repeat the analysis by defining the local market at the state-level in Table A.18 in Appendix A, in which we get similar results.

To summarize, we confirm that firms replace their products in multple markets simultaneously, and that the extensive margin response of local sales to the spillover shock comes from products replaced in multiple markets. These evidences suggest that multi-market firms make non-localized decision when they introduce or destroy products, taking into account overall demand conditions from multiple markets.

5.2 Replacement from High- to Low-Valued Products

We first document that our result is not driven by a simple reduction in the number of varieties available in the local market. In fact, the number of products supplied does not respond to the spillover shocks. Instead, the "value difference" between newly entering products and exiting ones drives the reduction in local sales growth in response to the spillover shocks. The result is robust under various measures of values, including sales-per-product, unit price, and organic product turnover rates.

(1) The net number of varieties does not respond to the spillover shock.

We first investigate whether the extensive margin response of local sales comes from a simple reduction in the number of varieties supplied in local markets. We measure the region-firm level net entry in 2007-09 as follows:

$$\text{Net Entry}_{rf} \equiv \text{Entry}_{rf} - \text{Exit}_{rf} \tag{5.1}$$

where $\text{Entry}_{rf} \equiv \frac{\text{Num.UPC}_{rf,09}^{\text{enter}}}{\overline{\text{Num.UPC}}_{rf}}$ is the number of different products (i.e., varieties) that did not exist in region r in 2007 but newly entered in 2009, and $\text{Exit}_{rf} \equiv \frac{\text{Num.UPC}_{rf,07}^{\text{exit}}}{\overline{\text{Num.UPC}}_{rf}}$ is the number of different products that existed in region r in 2007 but no longer existed in 2009. All measures are normalized by $\overline{\text{Num.UPC}}_{rf}$, which is a simple average of the total number of varieties of firm f in region r in 2007 and 2009.

[35] By construction, $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}} = \tilde{\Delta}\text{Sale}_{rf}^{\text{replace, multi}} + \tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$ holds.

Table 7: Response of the Net Number of Varieties

	(1)	(2)
	Net Entry$_{(07-09)}$	Net Entry$_{(07-09)}$
$\tilde{\Delta}\mathrm{HP}_{(07-09)}$ (other)	-0.041	-0.059
	(0.138)	(0.166)
Region-Firm Controls	✓	✓
Sector x Region FE	✓	✓
Restriction	-	Entry & Exit>0
R^2	0.351	0.400
Observations	840681	461672

Note. Net Entry$_{(07-09)}$ is constructed as in equation (5.1). $\tilde{\Delta}\mathrm{HP}_{07-09}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 7 summarizes the result. Column (1) shows that the net entry remains unaffected by the spillover shock, as indicated by near-zero coefficient. In Column (2), we restrict the sample to local markets that experienced both positive entry and exit of varieties (i.e., $\mathrm{Entry}_{rf} > 0$ and $\mathrm{Exit}_{rf} > 0$). Again, the response of net entry is not distinguishable from zero, indicating that the number of products entering is more or less similar to the number of products exiting. This shows that our spillover effects are not driven by simple reductions in the number of varieties supplied in the local market.

(2) Firms respond to the negative spillover shock by replacing high-valued products with low-valued ones.

The fact that the net number of varieties does not respond to the spillover shock suggests that the "value differences" between newly entering products and exiting ones drive the reduction of local sales in response to the spillover shocks. To confirm this we investigate whether a firm replace high-valued products with low-valued ones in a local market in response to the spillover shock originating in its other markets.

Specifically, for a given measure of the region-firm specific value index v_{rf}—e.g., sales-per-product, unit price, and organic sales share — we measure the value difference between newly

Table 8: Replacement from High- to Low-value products at the Extensive Margin

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale-per-UPC}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Organic}^{\text{replace}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	1.017**	0.310***	0.344**	17.973**
	(0.435)	(0.065)	(0.128)	(8.893)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.397	0.417	0.428	0.622
Observations	461672	461672	461672	2603

Note. The dependent variables measure the value difference between the newly entering products and exiting products calculated by (5.2). Column (1)-(3) defines local market at the county level, while Column (4) defines local market at the state level. $\tilde{\Delta}\text{HP}_{07-09}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other regions where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial region-firm 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 region-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

entering products and exiting products as

$$\tilde{\Delta} v_{rf} \equiv \frac{v^{\text{enter}}_{rf,09} - v^{\text{exit}}_{rf,07}}{\overline{v}_{rf}} \tag{5.2}$$

where $\overline{v}_{rf} \equiv \frac{1}{2}(v^{\text{exit}}_{rf,07} + v^{\text{enter}}_{rf,09})$.

Table 8 shows the result. Column (1) shows that in response to the negative spillover shock, a firm destroys products that generate higher sales-per-product and introduces those that generate lower sales-per-product. Colunm (2) shows that the average unit price of newly entering products is lower than the price of exiting products. In Column (3) and Column (4), we use unit prices adjusted for product group average and organic product turnover rates, which are a proxy for product quality.[36]

It is worth emphasizing that the replacement from high- to low-valued products in a local market occurs in response to the shocks that originate in other markets (i.e., the spillover shock), *conditional on the direct local demand.* That is, such replacement occurs in the local market that did

[36] In Appendix C we discuss in detail how we construct these value measures. In Table A.16 and Table A.17 in Appendix A, we use an alternative definition of price indexes, which includes applying different weighting schemes and adjusting for package sizes, to check the robustness of the result. In Table OA.8 in Online Appendix B, we also confirm that the results are robust at a more disaggregated level by conducting the analysis at the county-firm-product group level with product group fixed effects.

not face direct local shock. At the same time a firm's local sales decrease in the local market due to such product replacement (in the absence of the direct local shock). This means that even though the newly entered products have lower price on average, they generate relatively lower sales than the exited products in the local market that did not face direct local shock. In Section 6, we show that this pattern can be justified by assuming that product replacements in response to the negative shocks are associated with downgrading of product quality.

6 The Model

This section presents a multi-region model with endogenous quality adjustments by firms that reflect product replacements in our empirical analyses. Building on Faber and Fally (2017), we explicitly extend their setup to a multi-region framework while we employ a number of simplifications for tractability. Individuals within each market share a common market-specific income level, and regional demand shocks are modeled as exogenous change in this income. On the demand side of the model, individuals enjoy utility from both quantity and quality from product bundles produced by a continuum of firms, and we allow nonhomothetic preferences so that consumers with different income can have different product quality evaluations. On the production side, monopolistic competitive firms optimally choose the quality of their products and prices, and production at different quality level incurs different production costs.

6.1 Demand

We consider a static economy with R markets indexed by $r \in \mathcal{R} \equiv \{1, 2, ..., R\}$.[37] Each market is populated by a continuum of mass L_r of individuals, each of whom is endowed with exogenous income I_r and dividends from production sector D_r.[38] We denote the total income of an individual in market r by $y_r \equiv I_r + D_r$. The economy consists of two broad sectors : consumer packaged goods (CPG) and an outside sector.[39] Like Handbury (2013) and Faber and Fally (2017), we consider a two-tier utility in which the upper-tier depends on utility from CPG shopping U and the consumption of an outside good z that will be our numeriare. We assume the constant elasticity of substitution (CES) upper-tier utility given by

$$V_r = \left[(1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} + \alpha(U_r)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{6.1}$$

[37] We use the term "market" and "region" interchangeably.

[38] Under the labor market structure described below, wage rate is equal to one. Thus, I_r can be interpreted as exogenous labor endowments, as in Fajgelbaum et al. (2011). Dividends are specified below following our description of the production sector.

[39] Consumer packaged goods (CPG) can be viewed as goods available in stores and supermarkets.

where $\eta > 1$.[40] By defining the share of total income y_r allocated to CPG expenditures as Θ_r, one can easily show that

$$\Theta_r = \frac{\alpha^\eta}{\alpha^\eta + (1-\alpha)^\eta (P_r)^{\eta-1}} \equiv \Theta(P_r) \tag{6.2}$$

where P_r is the CPG consumption bundle price index, which is defined below.[41] Note that for a given y_r, increase of P_r decreases CPG expenditure share. We define total CPG expenditures as

$$s_r \equiv \Theta_r y_r \tag{6.3}$$

We assume the following CES utility, U_r, for the CPG consumption :

$$U_r = \left[\int_{f \in G_r} (q_{rf}\zeta_{rf})^{\frac{\sigma-1}{\sigma}} df\right]^{\frac{\sigma}{\sigma-1}} \tag{6.4}$$

where f deonotes a firm (i.e., CPG producer), G_r denotes the set of firms selling in market r, q_{rf} is the quantity of product bundle produced by firm f that is consumed by an individual 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 substitution between product bundles.[42] Following Faber and Fally (2017), we assume that the perceived quality $\log \zeta_{rf}$ depends on an intrinsic quality choice $\log \phi_f$ by firm f and a multiplicative term γ_r :

$$\log \zeta_{rf} \equiv \gamma_r \log \phi_f \tag{6.5}$$

We introduce nonhomotheticity in the preferences by allowing γ_r to increase with income: $\gamma_r \equiv \gamma(I_r)$ with $\gamma'(\cdot) \geq 0$. We impose a simple log-linear functional form in $\gamma(\cdot)$:

$$\log \gamma_r \equiv \delta_1 + \delta_2 \log I_r \tag{6.6}$$

where $\delta_2 \geq 0$.

Important assumption we make here is that firm f's choice of intrinsic product quality, ϕ_f, does not vary across markets and thus do not have market subscript r. This assumption reflects the synchronized product replacement pattern discussed in Section 5.1.[43] We assume that change in the

[40] We set up the model with the flexible CES upper-tier utility so that aggregate regional CPG expenditures can vary even under a fixed y_r, mainly through change in P_r. The limiting case, $\eta \to 1$, implies the Cobb-Douglas upper-tier utility.

[41] Derivation can be found in Online Appendix C.1.

[42] In Online Appendix C.2, we show that such utility function can be derived from the aggregation of discrete-choice preferences across many agents choosing only one firm's product bundle.

[43] In Online Appendix D, we extend the model by allowing firms to optimally choose whether to uniformly adjust quality of their products and replace them in all their markets (*the uniform quality strategy*) or adjust quality of products market-specifically (*the market-specific quality strategy*). We show that firms optimally choose the uniform quality strategy if (i) the fixed costs associated with market-specific quality adjustment are sufficiently high or (ii)

quality of a product bundle involves the replacement of products in the bundle. That is, the quality of product bundle changes due to the exiting of original products and the entry of new products.[44]

Individuals solve for their optimal CPG consumption bundle by maximizing (6.4) subject to budget constraints given by

$$\int_{f\in G_r} p_{rf} q_{rf} df \leq \Theta_r y_r \equiv s_r \tag{6.7}$$

where p_{rf} is the price index of firm f's product bundle in market r.

By defining individual expenditures on firm f's product bundle in market r as

$$s_{rf} \equiv p_{rf} q_{rf} \tag{6.8}$$

the optimality implies

$$\begin{aligned} s_{rf} &= \frac{\left(\frac{\zeta_{rf}}{p_{rf}}\right)^{\sigma-1}}{\int_{f\in G_r}\left(\frac{\zeta_{rf}}{p_{rf}}\right)^{\sigma-1} df} s_r \\ &= (\zeta_{rf})^{\sigma-1}\left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} s_r \end{aligned} \tag{6.9}$$

where the (quality adjusted) CPG price index is given by

$$P_r \equiv \left[\int_{f\in G_r} (p_{rf})^{1-\sigma} (\zeta_{rf})^{\sigma-1} df\right]^{\frac{1}{1-\sigma}} \tag{6.10}$$

with $s_r = P_r U_r$.

One can easily see how the nonhomothetic preferences provide an incentive for firms to downgrade product quality when they face negative demand shocks. From (6.9),

$$\log\left(\frac{s_{rf}}{s_{rf'}}\right) = (\sigma - 1)\left[\gamma_r \log\left(\frac{\phi_f}{\phi_{f'}}\right) - \log\left(\frac{p_{rf}}{p_{rf'}}\right)\right] \tag{6.11}$$

If firm f has a higher product quality then firm f' (i.e., $\log\left(\frac{\phi_f}{\phi_{f'}}\right) > 0$), then the negative demand shock in market r, which lowers $\gamma_r \equiv \gamma(I_r)$, shifts consumer expenditures from firm f to firm f'. Thus, firm f finds it optimal to lower product quality to appeal to those consumers.

they sell in sufficiently many markets that they find it less profitable to pay recurring market-specific fixed costs.

[44] Thus, our interpretation of "change in the quality of product bundle" is different from "change in product appeal *within-UPC*" (e.g., Hottman et al. (2016)) in the sense that we are considering change in the quality of a product bundle that arises from the entry and exiting of UPCs that comprise the product bundle.

6.2 Outside Good Production and Labor Market

We assume that a unit of outside good is produced with a unit of labor input. The labor market is perfectly competitive and is not separated across CPG production and the outside good production. This implies that the cost of labor (wage) equals unity.

6.3 CPG Production: Environments

In the economy, 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. We abstract a firm's entry and exit decision to be consistent with our empirical analysis, which only considers existing firms in both pre- and post-shock periods.[45] When we bring the model to the data, we map the set of active firms in the model directly to those in the data.

6.3.1 Market Network

We start by defining a firm's *market network*, which we define as the set of markets in which a firm sells its product. Consistent with our empirical analysis, we assume that each firm's market network is given and fixed—an assumption that reflects the historical persistence of firm markets (Bronnenberg et al. (2009, 2012)). We bring each firm's market network directly from the data. We index the market network by k, and when we have to indicate a particular firm f's market network, we use notation k_f. The total measure of firms with market network k is denoted by N^k.

6.3.2 Cost Structures

There are two different costs: variable costs and fixed costs (both measured in terms of labor). Following Faber and Fally (2017), we allow the marginal and the fixed costs of production to increase in the quality of the good being produced (for a given amount of quantity). The latter captures potential overhead costs such as design, R&D, and marketing, which do not directly depend on the quantities being produced but do affect product quality. In turn, variable costs depend on the level of quality of the production and the entrepreneur's productivity, as in Melitz (2003).

Following Faber and Fally (2017), we assume the marginal cost of production of a firm f with productivity a_f as

$$mc(\phi_f; a_f) \equiv \frac{c(\phi_f)}{a_f} \tag{6.12}$$

where

$$c(\phi) = \phi^{\xi} \tag{6.13}$$

The parameter ξ captures the elasticity of the cost increase to the level of quality.

[45] We also calibrate the model so that all firms enjoy non-negative profit in the equilibrium.

The total fixed costs are given by $f(\phi_f) + f_0$, where $f(\phi_f)$ is the part of fixed costs that directly depends on quality. We assume a simple log-linear parametrization given by

$$f(\phi) = b\beta\phi^{\frac{1}{\beta}} \tag{6.14}$$

with $\beta > 0$.

6.4 CPG Production: Price and Quality Choice

We now characterize a firm's optimal quality and prices. Although firms choose a uniform product quality that applies to all their markets, we allow them to choose market-specific prices.

Firm f optimally chooses the intrinsic quality of product (i.e., product attribute) ϕ_f which applies uniformly across its markets, and market-specific price p_{rf}.

By combining (6.8), (6.9) and (6.5), we have firm f's sales and quantity sold in market r given by

$$\begin{aligned} S_{rf} &\equiv s_{rf} L_r \\ &= \phi_f^{(\sigma-1)\gamma_r} \left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} S_r \end{aligned} \tag{6.15}$$

and

$$\begin{aligned} Q_{rf} &\equiv q_{rf} L_r \\ &= \phi_f^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} P_r^{\sigma-1} S_r \end{aligned} \tag{6.16}$$

where $S_r \equiv s_r L_r$ denotes the total CPG expenditures in market r.

The quality and price setting problem by firm f can be formally written as follows:

$$\max_{\phi_f, \{p_{rf}\}_{r\in k_f}} \pi_f = \sum_{r\in k_f} \left(p_{rf} - mc(\phi_f; a_f)\right) Q_{rf} - f(\phi_f) - f_0 \tag{6.17}$$

subject to the demand condition in (6.16).

As shown in Appendix D, the optimal price is

$$p_{rf} = \left(\frac{\phi_f^{\xi}}{a_f}\right) \left(\frac{\sigma}{\sigma-1}\right) (\equiv mc(\phi_f; a_f) \times \mu) \tag{6.18}$$

and the optimal quality is

$$\phi_f = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta} \tag{6.19}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma - 1} \right)$ indicates the markup.

By combining (6.17), (6.14), and (6.19), we can derive the optimal profit as

$$\pi_f = \sum_{r \in k_f} \frac{1}{\sigma} \left[1 - \beta(\sigma - 1)(\gamma_r - 1) \right] S_{rf} - f_0 \tag{6.20}$$

The expression of firm f's local sales, S_{rf}, is derived using (6.15), (6.18) and (6.19) as

$$S_{rf} = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta(\sigma-1)(\gamma_r - \xi)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} P_r^{\sigma-1} S_r \tag{6.21}$$

The optimal price of firm f's local price is

$$p_{rf} = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta\xi} \left[\frac{\mu}{a_f} \right] \tag{6.22}$$

We can prove that under sufficiently small $\beta > 0$, the equilibrium is unique.

Proposition 1. *(Uniqueness of the Optimal Price and Quality)*

If $\beta > 0$ is small enough that $\beta(\sigma - 1)(\gamma_r - \xi) < 1$, then the optimal price and quality is uniquely determined.

Proof. The Proof can be found in Online Appendix C.3. □

In Online Appendix C.4, we also show that under the condition in Proposition 1, the equilibrium quality ϕ_f, local sales S_{rf}, and profit π_f increase monotonically with firm productivity a_f.

6.5 Local Price Index

Let $\mathcal{M}^r \equiv \{k \in 2^{\mathcal{R}} : r \in k\}$ denote the collection of market networks that contain market r. Then the equilibrium CPG price in market r is expressed as

$$P_r = \left[\int_{f \in G_r} \left[\phi_f^{-(\gamma_r - \xi)} \left(\frac{\mu}{a_f} \right) \right]^{1-\sigma} df \right]^{\frac{1}{1-\sigma}} \tag{6.23}$$

6.6 Profits and Dividends

Because we do not allow the entry and exit of CPG producers, there are aggregate profits in the economy:

$$\overline{\Pi} \equiv \int_f \pi_f df \tag{6.24}$$

We assume that the aggregate profits are rebated to the consumers as dividends. For the sake of simplicity, we assume that individuals receive dividends that are proportional to their exogenous income endowments. Thus, an individual in market r receives dividend D_r given by

$$D_r \equiv \frac{I_r}{\sum_{r\in\mathcal{R}} I_r L_r} \overline{\Pi} \tag{6.25}$$

which implies

$$y_r = I_r + D_r = I_r \left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right) \tag{6.26}$$

6.7 Bridging the Empirics and the Theory: Structural Equation of Market Interdependency

The model delivers a structural equation that shows within-firm market interdependency. This equation allows us to structurally interpret our reduced-form empirical analyses. The magnitude of the spillover is determined by four structural parameters that govern the elasticity of market share and the elasticity of fixed costs with respect to the change in product quality. The relationship is derived by expressing the equation (6.21) in terms of growth rates. We present the result here and provide the derivation in Appendix D.3.

By denoting the initial value of a variable x as x_0 and defining growth rate by $\hat{x} \equiv \log x/x_0$, the equation (6.21) implies

$$\hat{S}_{rf} = \Upsilon_{r,0} \sum_{r\in k_f} \left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] + (\sigma-1)\hat{a}_f + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r \tag{6.27}$$

where $\omega_{rf,0} \equiv \frac{S_{rf,0}(\gamma_{r,0}-\xi)}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$,[46] $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$, $X_{f,0} \equiv \sum_{r\in k_f} S_{rf,0}\left(\frac{1}{b}\frac{\gamma_{r,0}-\xi}{\mu}\right)$,

[46] Note that if $\gamma_{r,0} = \gamma_0$ 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.

$A_r \equiv (P_r)^{\sigma-1} S_r$, and $\Upsilon_{r,0}$ is defined by

$$\Upsilon_{r,0} = \underbrace{\beta}_{\substack{\text{Inverse-elasticity of} \\ \text{fixed cost w.r.t } \phi}} \times \underbrace{(\sigma-1)(\gamma_{r,0}-\xi)}_{\substack{\text{Elasticity of} \\ \text{market share w.r.t } \phi}} \tag{6.28}$$

Equation (6.27) shows that even if the shock does not directly hit market r, the shocks that hit other markets $r' \neq r$ could generate spillovers to market r through the firm's internal market network. The key mechanism is uniform quality adjustments across multiple markets. Note that a firm's local sales growth is related to both its average sales growth in all its market, $\sum_{r \in k_f} \omega_{rf,0} \hat{S}_{rf}$, and to the term $\sum_{r \in k_f} \theta_{rf,0} \hat{\gamma}_r$ with the same coefficient $\Upsilon_{r,0}$. These two terms capture different channels in the model that induce quality adjustments when firms face demand shocks. The first term $\sum_{r \in k_f} \omega_{rf,0} \hat{S}_{rf}$ shows the role played by the scale effect. Lower sales that are induced by negative demand shocks cause firms to lower product quality so that they could avoid high fixed costs associated with production at the high quality level. The second term $\sum_{r \in k_f} \theta_{rf,0} \hat{\gamma}_r$ captures the role of the nonhomothetic preferences. Negative demand shocks make consumers switch their consumption toward lower quality products, which induce firms to downgrade product quality to appeal to those consumers.

$\Upsilon_{r,0}$ summarizes how structural parameters determine the magnitude of spillovers. A higher β implies a lower elasticity of fixed cost with respect to intrinsic quality change. This implies a lower sensitivity of the cost-side of quality change, which precipitates a more sensitive quality change to the shock. This generates stronger spillover.

A higher $(\sigma-1)(\gamma_{r,0}-\xi)$ captures a higher elasticity of market shares with respect to intrinsic quality change.[47] As clear from (6.9), $(\sigma-1)$ captures how the market shares respond to change in a households' perceived quality $\zeta_{rf,0}$ conditional on prices. In turn, $(\gamma_{r,0}-\xi)$ reflects the trade off that arises from changing intrinsic product quality: (i) it increases households' perceived quality, which increases the market share; and (ii) it increases price, which decreases the market share. Specifically, $\gamma_{r,0}$ captures the elasticity of perceived quality $\zeta_{rf} \equiv (\phi_f)^{\gamma_{r,0}}$ with respect to a change in intrinsic quality, while ξ reflects the elasticity of the marginal cost $mc(\phi_f; a_f) \equiv \frac{\phi_f^{\xi}}{a_f}$ which passes through to the price. In sum, a higher $(\sigma-1)(\gamma_{r,0}-\xi)$ implies a higher sensitivity of the revenue-side of quality change, which causes firms to lower their intrinsic quality more sensitively to the same magnitude of negative demand shock.

The estimation of $\Upsilon_{r,0}$ requires recovering $\sum_{r \in k_f} \theta_{rf,0} \hat{\gamma}_r$ and properly instrumenting $\sum_{r \in k_f} \left[\omega_{rf,0} \hat{S}_{rf} + \theta_{rf,0} \hat{\gamma}_r\right]$. We revisit this in Section 6.9.1, which provides details of our structural

[47] This can be seen from (6.21), in which market share in r is $\frac{S_{rf}}{S_r} = \phi_f^{(\sigma-1)(\gamma_r-\xi)} \left[\frac{\mu}{a_f}\right]^{1-\sigma} (P_r)^{\sigma-1}$. Thus the elasticity of market share with respect to quality change is $(\sigma-1)(\gamma_r-\xi)$.

estimation procedure.

6.8 Partial Equilibrium Responses to the Exogenous Demand Shocks

What happens to a local market that did not face a direct shock if other markets linked through intra-firm networks are hit by demand shocks? Given the lack of analytical solutions, the full general equilibrium effects must be calculated numerically. Yet, we can derive the partial equilibrium responses of optimal quality, local sales, the local CPG price index, local CPG expenditures, and local welfare to change in income level in other markets. They are partial equilibrium responses in the sense that we shut down several general equilibrium adjustments, including the effect through a change in dividends. Thus, we treat y_r as exogenous during the partial equilibrium analysis.

Theorem 2. *(Exogenous Change in Local Income and Response of Quality and Local Sales)*

Let $r \in k_f$. Suppose (i) β is sufficiently small that $\beta(\sigma-1)(\gamma_r-\xi)<1$ and (ii) P_r, D_r are fixed. Then, $\frac{\partial \log \phi_f}{\partial \log y_r}>0$ and $\frac{\partial \log S_{rf}}{\partial \log y_r}>0$.

The results also hold by if we relax (ii) by allowing P_r to vary with y_r, as long as such variations are sufficiently small.

Proof. The proof can be found in Online Appendix C.5. □

Theorem 3. *(Change in Quality and Response of Local Sales)*

Let $r \in k_f$. Suppose (i) y_r is fixed (i.e., there is no direct local shock) and (ii) P_r is fixed. Then, $\frac{\partial \log S_{rf}}{\partial \log \phi_f}>0$.

Proof. The proof can be found in Online Appendix C.5. □

Theorem 4. *(Change in Quality and Response of Local CPG Prices, CPG Expenditures, and Welfare)*

Let $r \in k_f$. Suppose y_r is fixed (i.e., there is no direct local shock). Then, $\frac{\partial \log P_r}{\partial \log \phi_f}<0$, $\frac{\partial \log S_r}{\partial \log \phi_f}>0$, $\frac{\partial \log U_r}{\partial \log \phi_f}>0$, and $\frac{\partial \log V_r}{\partial \log \phi_f}>0$.

Proof. The proof can be found in Online Appendix C.5. □

Suppose a negative income shock hits market $r' \in k_f$. Theorem 2 implies that this will induce a firm that is selling in market r' to downgrade quality and experience lower sales in market r'. In turn, Theorem 3 implies that such quality downgrading will result in lower sales in market $r(\neq r') \in k_f$, which is not directly hit by the income shock. This is consistent with our empirical findings in Section 5.2 regarding regional spillovers that transpire through downgrading of products (i.e., replacement from high- to low-valued products). For example, a firm's local sales and local price in market $r(\neq r')$ will both decrease because of the lower quality, which is the result of the shock that hit market r'.

Finally, Theorem 4 shed lights on the distributional consequences of the intra-firm spillover across regions. The theorem implies that quality downgrading (induced by a negative income shock in market r') increases the "quality-adjusted" CPG price index in market r, which, in turn, reduces the "quality-adjusted" real CPG consumption and the overall welfare in market r. That is, our model implies that a market not directly hit by negative shock also experiences welfare loss through the quality downgrading by multi-market firms. But the flip side of the coin of this argument is that market r' (who faced the direct shock) will benefit from the existence of market r. Market r can be viewed as a market that is hit by zero shock (which is more favorable than the negative shock), and this will alleviate the quality downgrading in market r'. Thus, market r and market r' share the burden of the negative shock that hit market r', which generates a redistributive effect.

In Appendix E, we present the counterfactual economy in which all firms choose market-specific quality. Unlike the uniform quality choice, the market-specific quality choice generates independence across markets. The independence across markets under market-specific quality choice is summarized by Proposition 7 in Appendix E.

6.9 Counterfactual Analysis

To discuss the aggregate implications of our findings, we first structurally estimate the key parameters in the model and match broad features in the data and then perform a counterfactual analysis. We compare the benchmark economy, in which all firms adjust product quality uniformly across their markets with the counterfactual economy, in which all firms market-specifically adjust product quality.

We show that the identified intra-firm cross-market spillover effect generates substantial distributional consequences across regions. We calculate the state level quality-adjusted real consumption (per capita), which measures the regional welfare. We first compare the measured regional welfare growth with the one measured under the counterfactual economy. We then turn to the cross-sectional dispersion of the state level welfare in terms of level. We show that the channel we identified serves as a redistributive (or risk-sharing) mechanism across regions and substantially mitigates the quality-adjusted regional consumption inequality (in terms of both growth and level).

Not all parameters are estimated. Some of the parameters are calibrated using the values in the existing literature, while others are directly matched with the data. We start with those parameters, and then describe how we estimate the rest of the parameters.

6.9.1 Calibration

In this exercise, we define the local market at the state-level. This allows us to exactly match firm-level spatial networks across states using the data while substantially reducing computational burden. We include both single-market firms and multi-market firms in our analysis, which yields a total of 5186 firms that at most sell in 49 states.[48] Each firm's market network k_f (i.e., intra-firm

[48]The states included in our exercise can be found in Table A.23 in Appendix A.

network) is directly obtained from the data.[49]

Because we are not considering firm-level entry and exit, productivity heterogeneity plays a minor role in our model. Thus, in the numerical exercise, we do not introduce productivity heterogeneity and instead assume $a_f = 1$ for all firms.[50] For the initial I_r in the model, we use the 2007 state level average income obtained from the American Community Survey data. For the L_r, we use the 2007 state level population (in thousands). Since we introduced L_r to reflect the relative size of population across states, we abstract cross-state migration or population growth by assuming fixed L_r across time.

For the exogenous local demand shock, $\hat{I}_r$, we use state level house price growth multiplied by 0.23 as a proxy for exogenous demand shock. 0.23 is the consumption elasticity with respect to the house price shock reported by Berger et al. (2018).[51,52]

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. Using a larger η at the end only strengthens the implication that we find (i.e., it generates stronger mitigation of regional consumption and welfare inequality). We set the CPG expenditure share parameter α to 0.20, which is close to the United States counterpart.[53]

Finally, we bring the elasticity of substitution σ from Faber and Fally (2017), which is $\sigma = 2.2$. One caveat is that the estimate in Faber and Fally (2017) is the elasticity of substitution across firms *within a product module*.[54] Thus, we interpret the elasticity of substitution across firms in our model

[49] As some firms share the same market network (e.g., if firm A and firm B both sell in New York and California, they have the same market network $k_A = k_B = \{\text{New York, California}\}$), there are 2775 unique market networks in total.

[50] Although we do not allow productivity heterogeneity, we do (approximately) match the pooled distribution of the state-firm level sales in the following way. Note that in the model, the state level CPG expenditure S_r is equal to the aggregate state level CPG producers' sales, $S_r = \sum_{f\in G_r} S_{rf}$. Also, recall that $S_r \equiv s_r L_r = \Theta_r y_r L_r = \Theta_r I_r \left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right) L_r$. Thus, we have $I_r L_r = \frac{\sum_{f\in G_r} S_{rf}}{\Theta_r \left(1+\frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right)}$. Because we will use Cobb-Douglas upper-tier utility in the numerical exercise, $\Theta_r = \alpha$, we have $(I_r L_r) = \sum_{f\in G_r} S_{rf} \times \left[\alpha\left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r}\right)\right]^{-1}$. It turns out that 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 the correlation coefficient 0.93. Thus, given $(I_r L_r) \propto S_r$, we are matching the pooled distribution of the "average state-firm level sales" (averaged across firms within a state). More formally, we are matching the distribution of $\frac{\sum_{f\in G_r} S_{rf}}{N_r}$ across markets, where N_r is the number of firms in market r.

[51] One caveat is that the elasticity reported by Berger et al. (2018) measures aggregate consumption elasticity with respect to the aggregate house price shock, which can differ from regional elasticity. For our purposes, this number itself plays a minor role because we use this elasticity to simply re-scale house price growth into income growth, which in our model, translates into expenditure growth.

[52] Alternatively, we can use the change in state level average income between 2007 and 2009 as the measure of $\hat{I}_r$. This choice does not change any of our implications. We decided to use house price growth measure (multiplied by the consumption elasticity w.r.t. house price shock) to be more consistent with our reduced-form analyses.

[53] 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, Tobacco products and smoking supplies.

[54] 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".

as proxying the average of the within-module elasticity of substitution across firms.

6.9.2 Estimation

The remaining key parameters we need to estimate are β, ξ, δ_1 and δ_2 in $\gamma(\cdot)$. The first equation we use is the expression of $\Upsilon_{r,0}$ in (6.28), which can be recovered by estimating the structural equation (6.27).

The second equation is derived from (6.22). Following steps similar to those used in the derivation of (6.27), we obtain

$$\hat{p}_{rf} = \beta\xi \sum_{r \in k_f} \left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] - \hat{a}_f \tag{6.29}$$

If we can estimate the coefficient of the above structural equation, we will recover $\beta\xi$.

The challenge of estimating $\Upsilon_{r,0}$ and $\beta\xi$ in (6.27) and (6.29), respectively, lies in the fact that $\gamma_{r,0}$ and $\hat{\gamma}_r$ are not observed. Thus, we must first estimate $\gamma_{r,0}$ and $\hat{\gamma}_r$ and then subsequently estimate $\Upsilon_{r,0}$ and $\beta\xi$.

(1) Estimation of $\gamma_{r,0}$ and $\hat{\gamma}_r$

We start with the empirical counterpart of equation (6.9) aggregated at the state-firm-year level $S_{rft} = (\zeta_{rft})^{\sigma-1}\left(\frac{p_{rft}}{P_{rt}}\right)^{1-\sigma} S_{rt}$, where r indicates state, f indicates firm, and t indicates year.[55] By taking the log of both sides of the above equation and using the assumption $\log\zeta_{rft} = \gamma_{rt}\log\phi_{ft}$, we get

$$\log S_{rft} = (1-\sigma)\log p_{rft} + (\sigma-1)\gamma_{rt}\log\phi_{ft} + (1-\sigma)\log P_{rt} + \log S_{rt} \tag{6.30}$$

To filter out state-specific components, we calculate the difference of the above equation between the reference firm F, which we define as the largest firm in the sample, and the other firms f. This yields $\Delta'\log S_{rft} = (1-\sigma)\Delta'\log p_{rft} + (\sigma-1)\gamma_{rt}\Delta'\log\phi_{ft}$, where $\Delta' x_{rft} \equiv x_{rFt} - x_{rft}$. By rearranging terms, we arrive at

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

where $\Xi_{rft} \equiv \frac{1}{(\sigma-1)}\left[\Delta'\log S_{rft} - (1-\sigma)\Delta'\log p_{rft}\right]$. Under the calibration of $\sigma = 2.2$, we can directly measure Ξ_{rft}. The model predicts that the larger the firm size, the greater the product quality, implying $\gamma_{rt}\Delta'\log\phi_{ft} > 0$. This turns out to hold in the data. By taking the log of both sides, we

[55] Recall that (6.9) is expressed in per individual units. Thus, we define state-firm level sales as $S_{rf} = s_{rf}L_r$ and state level sales as $S_r = E_rL_r$.

obtain

$$\log \Xi_{rft} = \log \gamma_{rt} + \log \left(\Delta' \log \phi_{ft}\right) \tag{6.31}$$

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

With the measured $\log \gamma_{rt}$ in hand, we obtain the "predicted" $\log \gamma_{rt}$, which we denote $\log \gamma_{rt}^{predict}$, by first regressing $\log \gamma_{rt}$ on $\log I_{rt}$ to estimate δ_1 and δ_2 in the equation (6.6) and then calculating $\log \gamma_{rt}^{predict} = \hat{\delta}_1 + \hat{\delta}_2 \log I_r$. This allows us to filter out noise contained in γ_{rt} and establish a monotone relationship between $\log I_r$ and $\log \gamma_r$, as in the model.[56]

Table A.19 in Appendix A summarizes the result: we use either the log of state level average income or the log of state level 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 state level average income yields a much clearer association. This may indicate that income (rather than house price per se) is the primary factor that determines the degree of nonhomotheticity.

We use the simplest specification in Column (1) as our benchmark, which is a pooled regression across state and year with year fixed effects. The predicted $\log \gamma_{rt}^{predict}$ obtained from specification Column (1) serves as our measure of $\log \gamma_{rt}$.[57] This also implies $\delta_2 = 0.166$ in (6.6).

(2) Estimation of β and ξ

With the $\gamma_{r,0}$ and $\hat{\gamma}_r$ in hand, we can estimate Υ_0 and $\beta\xi$ by estimating (6.27) and (6.29), respectively, where $\Upsilon_0 \equiv \beta(\sigma-1)(\gamma_0 - \xi)$ can be interpreted as the average estimate of $\Upsilon_{r,0}$ across states obtained by running a state-firm level regression. Below we discuss in detail our IV strategy to obtain a consistent estimate of Υ_0 and $\beta\xi$, but first explain how we recover β and ξ using the consistent estimates of Υ_0 and $\beta\xi$.

Once we obtain consistent estimates of $\Upsilon_0 \equiv \beta(\sigma-1)(\gamma_0 - \xi)$ and $\beta\xi$, we can easily recover ξ using the relationship

$$\xi = \frac{\sigma - 1}{\kappa + \sigma - 1} \gamma_0 \tag{6.32}$$

obtained by rearranging $\left(\frac{\Upsilon_0}{\beta\xi} \equiv\right) \kappa = \frac{\beta(\sigma-1)(\gamma_0-\xi)}{\beta\xi}$. Since we have values for κ, σ and γ_0 (which is

[56]Such noise may reflect pure measurement errors as well as variations that arise from demographic heterogeneity.

[57]Note that in the counterfactual analysis, we use $0.23 \times \tilde{\Delta} HP_r$ as a proxy of 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 state level house price). This 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 spillover shock $\tilde{\Delta} HP_{rf}$(other), which is constructed by the house price growth.

the average $\gamma_{r,0}$ across states), we can recover ξ. Then, β is recovered using $\beta = \frac{\beta\xi}{\xi}$.[58]

We now discuss how we estimate Υ_0 and $\beta\xi$. A consistent estimate of Υ_0 can be obtained by running a fixed effect regression that is similar to the one used in the reduced-form analysis (3.5). The difference is that instead of directly regressing a firm's local sales growth on the spillover shock, we regress a firm's local sales growth on $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ instrumented by the spillover shock.

Specifically, the state fixed effects that take care of $\hat{A}_r$ (and the common component in $(\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r$), while adding various state-firm level controls and industry fixed effects allows us to compare plausibly similar companies, at least partially taking care of $(\sigma-1)\hat{a}_f + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r$. Most importantly, instrumenting $\sum_{r \in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ using the spillover shock, which measures the leave-out average demand shocks that arise in other markets, allows us to further avoid potential endogeneity associated with unobserved error terms.[59]

Table A.20 in Appendix A presents the result. In Column (1), we simply regress a firm's local sales growth on $\sum_{r \in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ with state and sector fixed effects. We get a coefficient of 0.996, indicating that local sales growth is highly correlated across regions within a firm. In Column (2), we instrument $\sum_{r \in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ with the spillover shock, where the estimated coefficient is $\Upsilon_0 = 0.618$.

We can estimate $\beta\xi$ using a similar strategy. We regress a firm's local price index on $\sum_{r \in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ instrumented by the spillover shock. Column (3) of Table A.20 reports an OLS estimate of $\beta\xi$, and Column (4) reports the IV estimate. Our estimate is $\beta\xi = 0.317$.[60]

We summarize the resulting parameter values in Table 9. In Table A.21 in Appendix A, we show that the estimated model can successfully replicate the elasticity of firm's local sales growth with respect to both the direct local shock and the spillover shock. We show this by estimating equation 3.5 at the state-firm level using the model generated data (i.e., generated by feeding in the observed house price growth as the state-level exogenous shock in the model).

[58] Note that the calculation of the independent variable $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ requires knowledge of ξ because of $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r' \in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$. Thus, in practice, we start with a guess value of ξ, measure $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ and run the regression, and then check if (6.32) returns the same value of ξ.

[59] Our various robustness analyses in Section 4.3 make us confident that the spillover shock is not systematically correlated with direct local market factors as well as supply-side factors such as productivity (i.e., $\hat{a}_f$).

[60] In Table A.22 in Appendix A, we show the estimation result under the assumption that $\gamma_{rt} = \gamma$ for all r and t. This implies homogeneous utility function across regions with homothetic preferences. Under this assumption, (6.27) and (6.29) become $\hat{S}_{rf} = \Upsilon\left(\sum_{r \in k_f}\omega_{rf,0}\hat{S}_{rf}\right) + (\sigma-1)\hat{a}_f + \hat{A}_r$ and $\hat{p}_{rf} = \beta\xi\left(\sum_{r \in k_f}\omega_{rf,0}\hat{S}_{rf}\right) - \hat{a}_f$, respectively, where $\Upsilon \equiv \beta(\sigma-1)(\gamma-\xi)$ and $\omega_{rf,0} \equiv \frac{S_{rf,0}}{\sum_{r' \in S_{r'f,0}}}$ 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.20 reflecting small variations in $\left(\sum_{r \in k_f}\theta_{rf,0}\hat{\gamma}_r\right)$ relative to $\left(\sum_{r \in k_f}\omega_{rf,0}\hat{S}_{rf}\right)$ (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 the nonhomotheticity plays a limited role under our estimation.

Table 9: Parameter Values

Parameter	Value	Description	Source
Υ_0	0.62	Elasticity of Local Sales wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$ (avg)	Own Estimation
$\beta \times \xi$	0.32	Elasticity of Local Price wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$ (avg)	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
γ_0	1.03	Elasticity of Perceived Quality wrt Quality	Own Estimation
δ_2	0.17	Elasticity of γ wrt Income	Own Estimation
b (benchmark)	1	Fixed Cost Parameter	Normalize
b (counterfactual)	0.04	Fixed Cost Parameter	Matched s.t. Avg. Quality Equal Benchmark
η	1	EoS across CPG and Outside Goods	Cobb-Douglas
α	0.20	CPG Share Parameter	Matched so that CPG share equals 0.20 under η

6.9.3 Implication: Regional Redistribution

By leveraging the estimated model, we calculate state level quality-adjusted real consumption (per capita), which measures regional welfare. We first compare the measured regional welfare growth with the one measured under the counterfactual economy. Next we turn to the cross-sectional dispersion of the state level welfare (in terms of level). We show that the channel we identified serves as a redistributive (or risk-sharing) mechanism across regions, thus substantially mitigating the quality-adjusted regional consumption inequality in terms of both growth and level.

We start by investigating the dispersion of the quality-adjusted regional consumption growth, which measures regional welfare growth. We use two measures, (i) quality-adjusted real CPG consumption per capita U_r (i.e., "CPG welfare"); and (ii) real (composite) consumption per capita, aggregating CPG goods and the outside good V_r (i.e., "overall welfare"). The results are summarized in Table 10. For the purpose of brevity, we only present four states *and* the summary statistics across all states. Results for all states can be found in Table A.23 in Appendix A.

The first measure captures the welfare effect that arises through CPG consumption, which is the principal focus of our empirical and theoretical analyses. Yet, households can switch their consumption to other types of goods if they find CPG less appealing because of the quality change. The overall effects that incorporate such substitutions are captured by $\hat{V}_r$. We view our measure of $\hat{V}_r$ as the lower-bound of the welfare effect because we are assuming that our channel exists only in CPG consumption. In reality, a similar mechanism could exist in other types of consumption.

Table 10: Regional Redistribution across States

State	$\hat{HP}_r(\%)$	$\hat{I}_r(\%)$	$\hat{U}_r(\%)$			$\hat{V}_r(\%)$			Pop. Weight (%)
			Benchmark	Counterfactual	Abs. Diff.	Benchmark	Counterfactual	Abs. Diff.	
IA	0.18	0.04	-1.40	0.17	1.57	-0.20	0.12	0.32	1.00
SD	0.72	0.16	-1.26	0.38	1.64	-0.07	0.26	0.33	0.27
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
AZ	-38.13	-8.77	-13.67	-15.40	1.72	-9.73	-10.09	0.36	2.12
CA	-33.11	-7.61	-11.70	-13.40	1.71	-8.40	-8.76	0.36	12.20
(All States)									
Mean	-16.60	-3.82	-6.65	-6.61	0.97	-4.34	-4.34	0.20	Sum: 100
St.Dev	12.97	2.98	4.03	5.21		3.20	3.44		

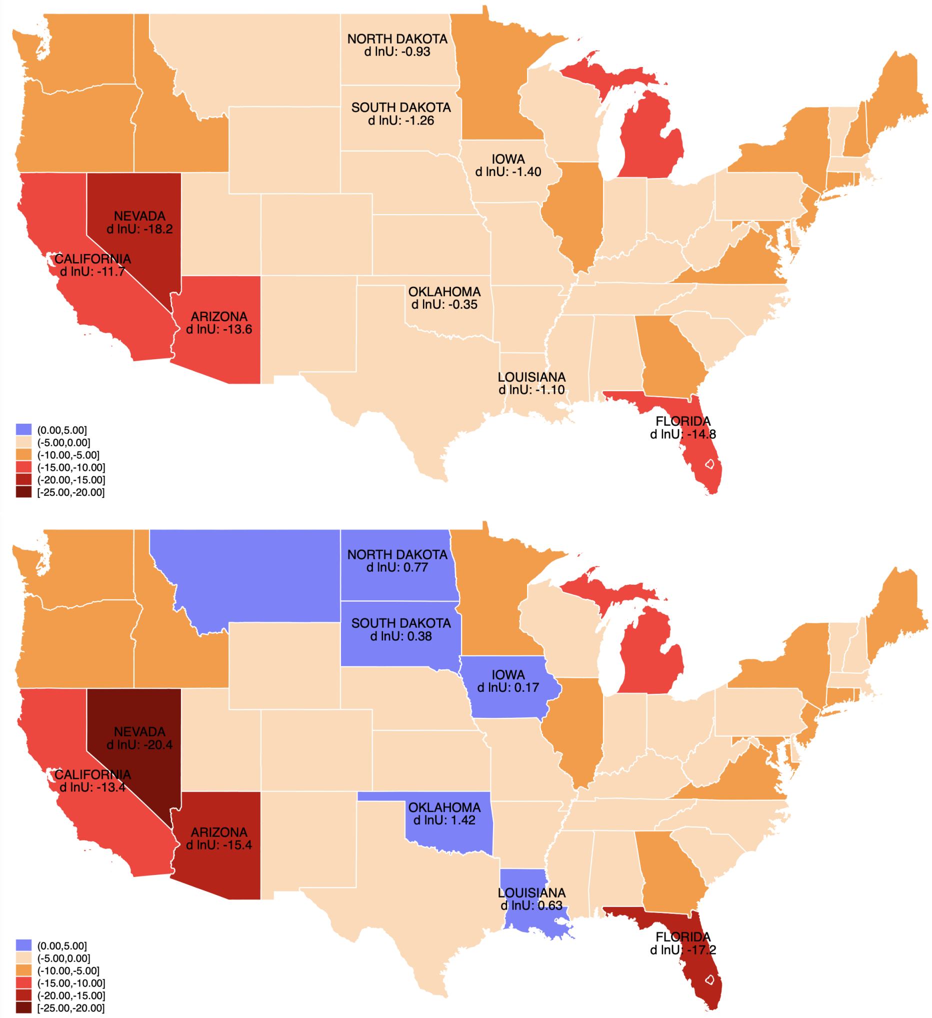
Note. $\hat{HP}_r(\%)$ is the state-level house price growth. $\hat{I}_r(\%)$ is the exogenous regional income growth which is calculated as $\hat{HP}_r(\%) \times 0.23$. Benchmark indicates the model with uniform quality choice in Section 6, and counterfactual indicates the model with market-specific quality choice in Appendix E. $\hat{U}_r(\%)$ 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.

Also, we would like to emphasize that our assumption of the Cobb-Douglas upper-tier utility is a conservative choice, and that introduction of a larger elasticity of substitution between CPG and the outside good will strengthen our implication. Like $\hat{V}_r$, which serves as the lower-bound, we view $\hat{U}_r$ as the upper-bound of the welfare effect.

We first focus on CPG welfare $\hat{U}_r$. States that experienced increase of local house prices such as Iowa (IA) and South Dakota (SD) experienced a large decline of CPG welfare due to spillovers from states that were hit by large housing market disruptions. For example, the benchmark economy implies that Iowa experienced a 1.40% *loss* of CPG welfare, while under the counterfactual economy, it could have experienced a 0.17% *increase* of CPG welfare. This shows that regions not directly hit by negative shocks can also experience a decline of welfare due to uniform quality downgrading by multi-market firms.

While states that have been less affected by negative shocks experience deterioration of welfare due to spillovers from severely hit states, the opposite holds for states that went through severe negative shocks. For example, Arizona (AZ) experienced a 13.67% decline of CPG welfare under the benchmark economy, but under the counterfactual economy it would have fared worse, with a 15.40% loss of CPG welfare. similarly, California (CA) experienced a 11.70% decline of CPG welfare under the benchmark economy, while it could have experienced a 13.40% loss of welfare in the counterfactual economy. This means that states that were hit by severe negative shocks benefit from regions that were less hit because multi-market firms downgrade product quality less under the benchmark than they do under the counterfactual economy.

Figure 2: Regional Redistribution across States: Benchmark (Up) vs. Counterfactual (Down)



Note. This figure plots the state-level CPG welfare growth, $\hat{U}_r(\%)$, in the benchmark and the counterfactual economies. Benchmark indicates the model with uniform quality choice in Section 6, and counterfactual indicates the model with market-specific quality choice in Appendix E.

On average, the absolute difference in CPG welfare growth between the benchmark and the counterfactual economy is given by 0.97 percentage points. That the average decline of CPG welfare in the benchmark economy is 6.65% implies that shutting down our channel generates an additional 15% welfare increase (decrease) in regions that have been hit by below-average (above-average) exogenous income growth.

The dispersion of welfare growth across states can be summarized by the standard deviation of welfare growth across states. Under the benchmark economy with our channel, the standard deviation is 4.03, while in the counterfactual economy it is 5.21. Thus, the result implies that the standard deviation of the welfare growth across states increases by 29% in the counterfactual economy.

To quantify the dollar amount effect, we do a simple back-of-the-envelop calculation. Specifically, we reduce the dispersion of regional shocks across states up to the point that the standard deviation of welfare growth across states equals that of the benchmark. On average this requires 2.5 percentage point decrease (increase) of house price growth in states that experienced above-average (below-average) house price growth, or 0.58 percentage point (=2.5 percentage point$\times$0.23) decrease (increase) of exogenous income growth in corresponding states. Since the cross-state average of the median household income in 2007 was approximately \$69000, the dollar transfer is $\$400 \approx \$69000 \times 0.0058$. This indicates that the redistribution effect generated by intra-firm spillovers through uniform quality adjustments correspond to a one-time \$400 per-household transfer (tax) on a state that experienced below-average (above-average) house price growth. This is comparable to the tax rebate checks authorized by the US Congress in 2008 (Economic Stimulus Act of 2008), which were also one-time payments that ranged from \$300 to \$1200 per qualifying household. Therefore, the magnitude of redistribution induced by our identified channel is economically meaningful and compares in size to transfer policies. This highlights the important role that the intra-firm network and the spillover through it plays in alleviating the regional consumption inequality.

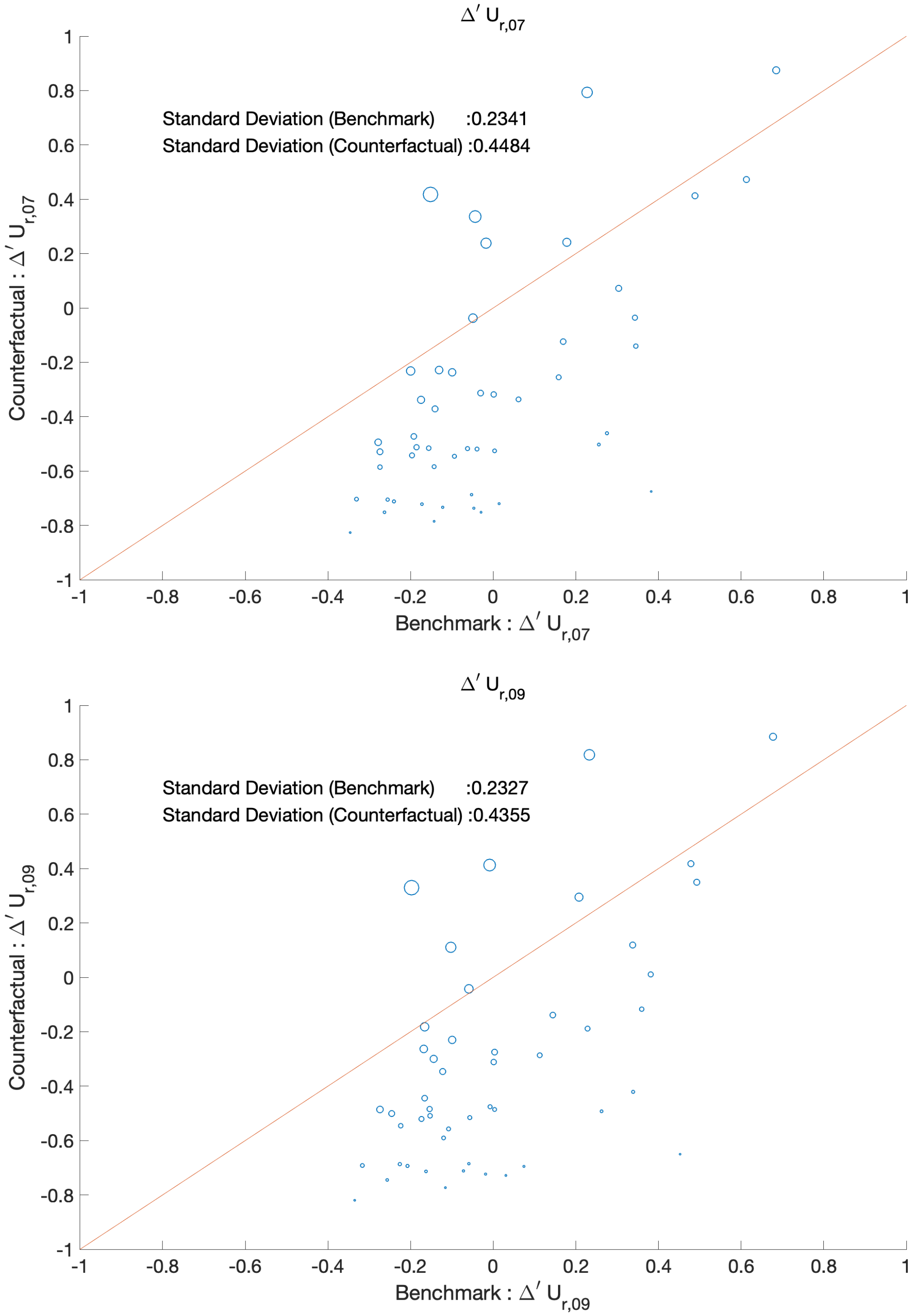
In Figure 2, we visualize the state-level CPG welfare growth in the benchmark economy (upper panel) and the counterfactual economy (lower panel). We confirm that the benchmark economy features more equalized welfare growth across states than the counterfactual economy.

Even if we take into account potential substitution to the outside good, we still find non-negligible welfare consequences. Iowa (IA) and South Dakota (SD) could have experienced an overall welfare increase under the counterfactual economy, but they experienced a decline of welfare due to our channel. For example, Iowa (IA) experienced a 0.20% *loss* of overall welfare in the benchmark, while it could have experienced a 0.12% *increase* of welfare under the counterfactual economy.

In contrast, Arizona (AZ) and California (CA) could have experienced an overall welfare loss of 10.09% and 8.76%, respectively, yet they actually experienced smaller welfare declines of 9.73% and 8.40%, respectively. The average absolute difference in welfare growth between the two economies is given by 0.20 percentage points. The average decline of overall welfare in the benchmark economy is 4.34%, which implies that shutting down our channel generates an additional 5% increase (decrease) of overall welfare in regions that experienced below-average (above-average) exogenous income growth. Finally, the standard deviation of the overall welfare growth across states increases by 8% if we move from the benchmark (3.20) to the counterfactual economy (3.44).

We now compare the cross-sectional dispersion of the state level welfare, which is measured by the quality-adjusted regional consumption per capita (in terms of level). Again, we use two measures, (i) quality-adjusted real CPG consumption per capita U_r (i.e., "CPG welfare") and (ii) real (composite) consumption per capita, aggregating CPG goods and the outside good V_r (i.e., "overall

Figure 3: 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 size of the circle reflects population weights. The mean, Avg.$U_{r,t}$, and the reported standard deviations are weighted by state level population.

welfare").

Figure 3 shows the scatter plot of regional CPG welfare between the benchmark and the counterfactual. We calculate the deviation of regional CPG welfare from its cross-sectional average. The upper panel plots the 2007 snap shot and the lower panel shows that of 2009. In both years, the observations associated with lower welfare (relative to the cross-sectional average) lie below the 45-degree line, while those associated with higher welfare lie above the 45-degree line. This indicates that the counterfactual economy generates a larger dispersion of welfare across states, implying a larger quality-adjusted regional consumption inequality. In both years, the counterfactual economy produces a standard deviation of regional welfare distribution that is almost two times that of the benchmark. In Figure A.2 in Appendix B, we show the result using the overall welfare V_r. Similar patterns hold, with the counterfactual economy generating 10% larger standard deviation compared to that of the benchmark.

In summary, the multi-market firms' product replacement decision, which involves uniform quality adjustments, mitigates the regional quality-adjusted consumption and welfare inequality in terms of both growth and level. These results indicate that the identified intra-firm spillover through uniform quality adjustments serves as a redistributive (or risk-sharing) mechanism across regions. Given that firms introduce uniform product quality across markets and that they take into account average demand conditions in all their markets to decide product quality choice, regions with higher demand face relatively lower product quality compared to the counterfactual economy because of regions that have lower demand. In contrast, regions with lower demand enjoy relatively higher product quality due to the regions that have higher demand. This mitigates the quality-adjusted regional consumption inequality.[61]

7 Conclusion

In this paper, we study whether and how intra-firm spatial networks created by multi-market firms spill over regional shocks across US local markets. We show that a firm's local sales decrease in response to not only the direct negative local demand shock but also the indirect negative local

[61] In fact, the scale effects and the nonhomothetic preferences generate different welfare implications, although they both provide incentives for firms to downgrade product quality when they face negative demand shocks. Under the homothetic preferences, uniform quality adjustments indeed mitigate quality-adjusted regional consumption inequality because regions with higher demand face lower product quality than the counterfactual economy, while regions with lower demand enjoy relatively higher product quality. But under the nonhomothetic preferences both high demand and low demand regions can experience decreases of welfare because both regions face unfavorable product quality. That is, higher demand regions would like to have higher product quality as in the counterfactual economy, while lower demand regions would like to have lower product quality because they are poor. Thus, both regions experience additional level effects that lower the welfare. However, such level effects do not change the main implications of the model for two reasons. First, quality-adjusted regional consumption inequality is mainly related to the "dispersion" of those measures across regions, and the role played by level effects is small. Second, our estimation result assigns a dominant role to the scale effects, and the role of the nonhomothetic preferences turns out to be limited.

demand shocks that affect its other markets. In particular, the intra-firm spillover effect is mostly attributed to the extensive margin response of local sales that arises from the product creation and destruction. As the key mechanism behind the spillover, we emphasize the role of synchronized product replacements across multiple markets by each firm wherein high-valued products are replaced with lower-valued products in response to the negative shocks. Through the lens of a multi-region model with endogenous quality adjustments by firms that reflect product replacements, We show that the identified intra-firm spillover serves as a redistributive mechanism across local markets and substantially mitigates the quality-adjusted regional consumption inequality.

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Appendix A Additional Tables

Table A.1: Excluding Nearby Regions

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(4) $\tilde{\Delta}\text{Sale}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, out-of-state)	0.335^{***}			
	(0.088)			
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, $\geq$50mi)		0.400^{***}		
		(0.080)		
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, $\geq$100mi)			0.396^{***}	
			(0.077)	
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, $\geq$150mi)				0.359^{***}
				(0.080)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.393	0.394	0.395	0.395
Observations	838812	840235	839548	838641

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{(07-09)}$ (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 on them and re-normalizing the remaining weights to one), $\tilde{\Delta}\text{HP}_{(07-09)}$ (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 on them and re-normalizing the remaining weights to one). Region-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Placebo Tests

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(4) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(5) $\tilde{\Delta}\text{Sale}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, equal weight)	0.126				
	(0.209)				
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, pop. weight)		0.027			
		(0.176)			
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, income weight)			0.107		
			(0.182)		
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, random network)				-0.006	
				(0.379)	
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, estab. network)					-0.052
					(0.112)
Region-Firm Controls	✓	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓
R^2	0.391	0.391	0.391	0.392	0.391
Observations	840681	840681	840681	840681	840681

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, equal weight) is the placebo spillover shock measured by calculating the equal-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, pop weight) and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, income weight) are similarly constructed placebo spillover shocks, where we use county-level population (measured by total number of households) and median household income as weights, respectively. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, random network) is the placebo spillover shock measured by considering randomly generated intra-firm networks. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, estab. network) is the placebo spillover shock measured by calculating the initial employment-weighted house price growth between 2007 and 2009 in the other counties where the firm has establishments. Region-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Decomposition of Sales Growth (State level)

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.303**	0.376***	-0.074
	(0.113)	(0.085)	(0.058)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.357	0.449	0.426
Observations	83610	83610	83610

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the state-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial state-firm 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 state-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Allowing Retailer Dimension: County-Firm (Producer)-Retailer level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (firm, other)	0.533***	0.520***	0.537***	-0.017
	(0.007)	(0.022)	(0.022)	(0.041)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (firm-retailer, other)		0.071	0.055	0.016
		(0.130)	(0.142)	(0.071)
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. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm-retailer specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm-retailer specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the county-firm-retailer specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (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 SIC 4-digit. Region-Firm controls include log of initial county-firm-retailer 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-retailer specific initial sales. Standard errors (in parentheses) are three-way clustered at the state, sector, and retailer level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.5: Saiz (2010) Housing Supply Elasticity IV Regression

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	(4) $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.417***	0.601***	0.398**	0.203
	(0.127)	(0.139)	(0.188)	(0.206)
IV	-	✓	✓	✓
First-stage F stat	-	541.2	541.2	541.2
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.402	0.036	0.044	0.008
Observations	448604	448604	448604	448604

Note. This table presents variants of the specification in Columns (4)-(6) of Table 4 by instrumenting $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) using similarly constructed IV. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are three-way clustered at state, sector, and "other state" level, where "other state" indicates state containing each county-firm observation's largest other county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.6: García (2018) Nonlocal Mortgage Lending Shock IV Regression

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	(4) $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.389***	0.408**	0.401**	0.007
	(0.106)	(0.199)	(0.194)	(0.070)
IV	-	✓	✓	✓
First-stage F stat	-	540.5	540.5	540.5
Region-Firm Controls	✓	✓	✓	✓
Sector x Region FE	✓	✓	✓	✓
R^2	0.398	0.037	0.044	-0.000
Observations	658607	658607	658607	658607

Note. This table presents variants of the specification in Columns (4)-(6) of Table 4 by instrumenting $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) using similarly constructed IV. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are three-way clustered at state, sector, and "other state" level, where "other state" indicates state containing each county-firm observation's largest other county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Control Firms' Customer Types

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.637**	0.598***	0.039
	(0.258)	(0.150)	(0.244)
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. This table presents a variant of the specification in Columns (4)-(6) of Table 4 with 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. All regressions are weighted by county-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.8: Control Largest Market

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.423***	0.349***	0.073
	(0.121)	(0.070)	(0.114)
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. This table presents variants of the specification in Columns (4)-(6) of Table 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. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are double clustered at state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.9: Homescan Panel (State-level): Controlling Lagged-dependent Variables

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (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)
$\tilde{\Delta}\text{Sale}_{(04-06)}$				0.086***		
				(0.009)		
$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(04-06)}$					0.100***	
					(0.010)	
$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(04-06)}$						-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 ACNielsen Homescan Panel database. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from continuing products. $\tilde{\Delta}\text{Sale}_{04-06}$, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{04-06}$, and $\tilde{\Delta}\text{Sale}^{\text{continue}}_{04-06}$ are corresponding growth rates between 2004 and 2006. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the lagged-initial 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 them operating in the same sector. Region-Firm controls include 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 double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.10: Using Shift-Share Robust Standard Error

	County-level		
	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.398**	0.419***	-0.021
	(0.169)	(0.087)	(0.129)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.392	0.408	0.427
Observations	840681	840681	840681
	State-level		
	(4)	(5)	(6)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.303***	0.376***	-0.074
	(0.112)	(0.081)	(0.069)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.357	0.449	0.426
Observations	83610	83610	83610

Note. This table repeats Columns (4)-(6) of Table 4 under alternative definitions of markets (county and state) using shift-share robust standard error proposed by Adao et al. (2018b). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.11: County-Firm-Product Group level Regression:
County-Firm level Spillover Shock

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, firm)	0.173**	0.306***	-0.133
	(0.070)	(0.033)	(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. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm-product group specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm-product group specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ 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. Region-Firm controls include 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. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.446***	0.486***	-0.040
	(0.113)	(0.124)	(0.070)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.434	0.434	0.442
Observations	1455914	1455914	1455914

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from continuing products, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. While constructing each growth rate, we accommodate firms' local market entry and exit by assigning 2 (entry) and -2 (exit), respectively. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 specific average sales (across 2007 and 2009) to avoid assigning zero weight on newly entered local market in 2009. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.13: The Heterogeneous Treatment Effects

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other) x ln(100-paydex)	2.143*	2.692***	-0.549
	(1.195)	(0.868)	(2.055)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other) x I(Local Sales Share>P(50))	-0.524***	-0.590***	0.066
	(0.169)	(0.115)	(0.205)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	-6.150	-7.845**	1.695
	(3.953)	(3.006)	(6.930)
ln(100-paydex)	0.209	0.484***	-0.275
	(0.220)	(0.129)	(0.336)
I(Local Sales Share>P(50))	-0.126***	-0.126***	-0.000
	(0.036)	(0.022)	(0.039)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Market	County	County	County
R^2	0.376	0.410	0.402
Observations	771840	771840	771840

Table A.14: Interaction with Financial Constraint (Rajan and Zingales (1998))

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other) x RZ	5.325	4.503**	0.821
	(3.449)	(2.015)	(2.932)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	-0.422	-0.237	-0.185
	(0.543)	(0.288)	(0.456)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Market	State	State	State
R^2	0.326	0.458	0.404
Observations	51856	51856	51856

Table A.15: Creation and Destruction

	(1)	(2)
	$\text{Creation}_{(07-09)}$	$\text{Destruction}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.145***	-0.273***
	(0.044)	(0.079)
Region-Firm Controls	✓	✓
Sector x Region FE	✓	✓
R^2	0.572	0.437
Observations	840681	840681

Note. $\text{Creation}_{(07-09)}$ is the county-firm specific sales generated by products that didn't exist in region r in 2007 but existed in 2009 (i.e., $\frac{\text{Sales}^{\text{enter}}_{rf,09}}{\text{Sales}_{rf}}$), and $\text{Destruction}_{(07-09)}$ is the county-firm specific sales generated by products that existed in region r in 2007 but no longer exist in 2009 (i.e., $\frac{\text{Sale}^{\text{exit}}_{rf,07}}{\text{Sale}_{rf}}$). $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ in Column (5) of Table 4 is identical to $\text{Creation}_{(07-09)}$-$\text{Destruction}_{(07-09)}$. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.16: Price Response at the Extensive Margin

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.310***	0.456***	0.165***
	(0.065)	(0.142)	(0.048)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Index	Equal Weight	Sales Weight	Size Adj.
R^2	0.417	0.397	0.420
Observations	461672	461672	461672

Note. $\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$ is the county-firm specific price growth at the replacement margin between 2007 and 2009 defined in Appendix C, and $\Delta\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.17: Quality Response at the Extensive Margin

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.344**	0.481***	0.209**
	(0.128)	(0.144)	(0.102)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Index	Equal Weight	Sales Weight	Size Adj.
R^2	0.428	0.419	0.403
Observations	461672	461672	461672

Note. $\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$ is the county-firm specific quality growth at the replacement margin between 2007 and 2009 defined in Appendix C, and $\Delta\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm 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 state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.18: Extensive Margin Decomposition (State-level)

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace, local}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.376***	0.389***	-0.013
	(0.085)	(0.078)	(0.009)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.449	0.450	0.144
Observations	83610	83610	83610

Note. $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from products replaced in multiple states, and $\tilde{\Delta}\text{Sale}^{\text{replace, local}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from products only replaced in the state. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial state-firm 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 state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.19: 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 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. weighted by state level sales. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.20: Regression of the Structural Equation: State-Firm level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$
$(\tilde{\Delta}\text{Sale}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)})$ (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. $\tilde{\Delta}\text{Sale}_{(07-09)}$ 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 defined in Appendix C, and $(\tilde{\Delta}\text{Sale}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)})$ (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 $(\tilde{\Delta}\text{Sale}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)})$ (avg) using $\Delta\text{HP}_{(07-09)}$ (other), which is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. State-Firm controls include log of initial state-firm 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 state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.21: Goodness of Fit: State-Firm level Regression - Data vs. Model

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(4) $\tilde{\Delta}\text{Sale}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$	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) uses the actual data, and Column (2) and Column (4) uses model generated variables by feeding in the observed house price growth as the state-level exogenous shock in the model. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the state-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Region-Firm controls include log of initial state-firm 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, and sector fixed effects (at SIC 4-digit). In Column (2) and Column (4), we bring firm's initial number of product groups and sector fixed effects directly from the data and map it with corresponding firm in the model, while the rest of the control variables are generated from the model. All regressions are weighted by state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.22: Regression of the Structural Equation under Homogeneous Utility Function across Regions with Homothetic Preferences: State-Firm level

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$	$\tilde{\Delta}\text{Price}_{(07-09)}$
$(\tilde{\Delta}\text{Sale}_{(07-09)})$ (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. $\tilde{\Delta}\text{Sale}_{(07-09)}$ 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 defined in Appendix C, and $(\tilde{\Delta}\text{Sale}_{(07-09)})$ (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 $(\tilde{\Delta}\text{Sale}_{(07-09)})$ (avg) using $\Delta\text{HP}_{(07-09)}$ (other), which is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. State-Firm controls include log of initial state-firm 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 state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

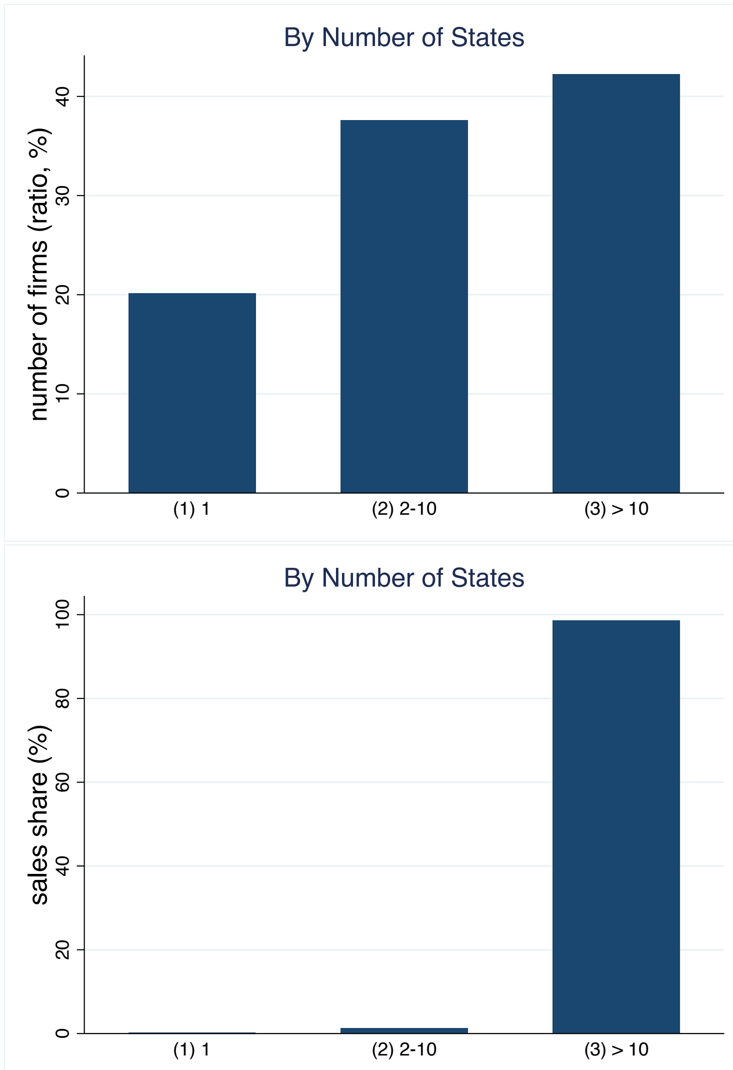
Table A.23: Regional Redistribution across States - All States

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.	Pop. 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 6, and counterfactual indicates the model with market-specific quality choice in Appendix E. $\hat{U}_r(\%)$ 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.

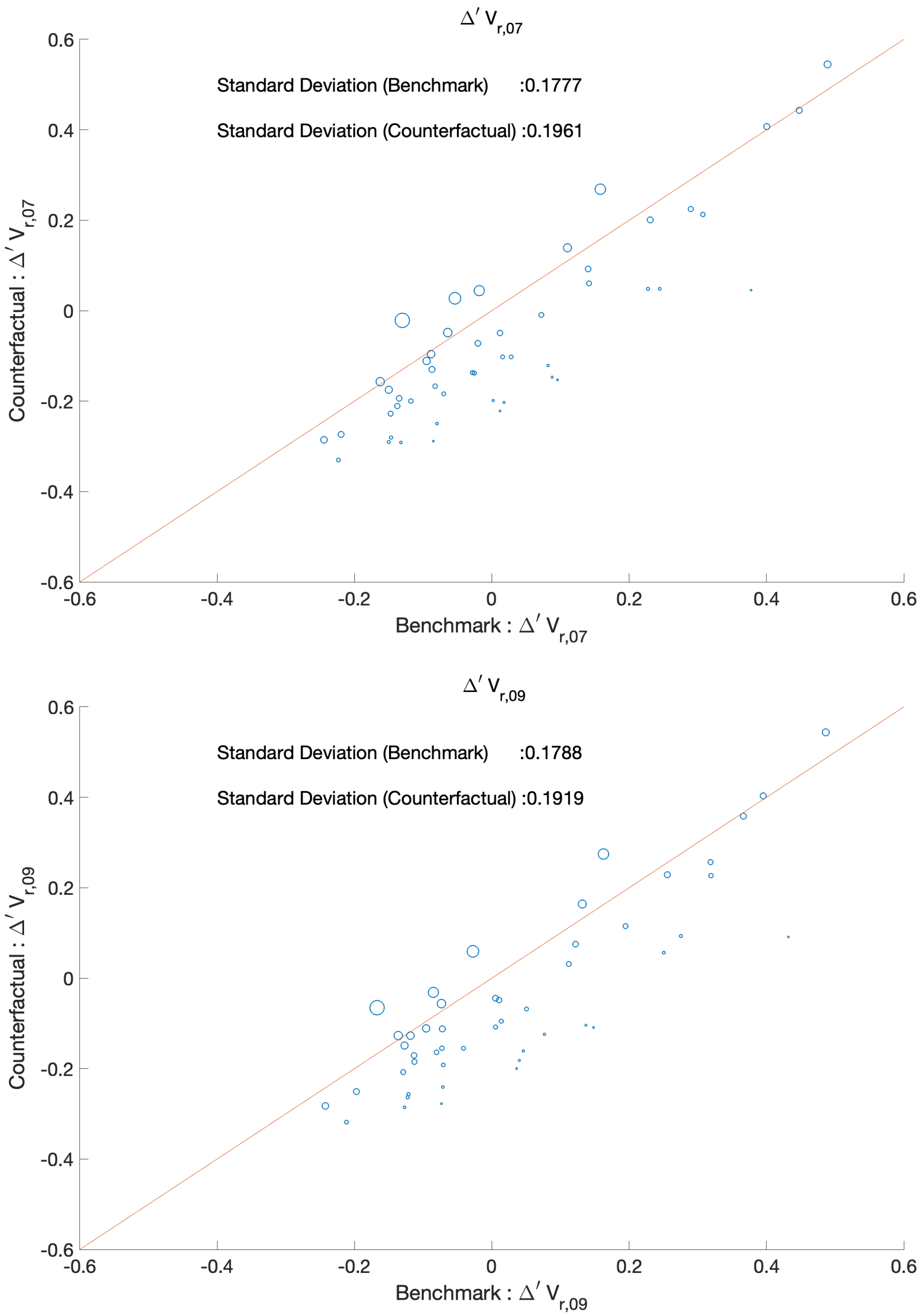
Appendix B Additional Figures

Figure A.1: Share of consumer goods producers by the number of states they sell: the number of firms in ratio (Up) and sales share of firms (Down)



Note. Calculation based on ACNielsen Retailer Scanner database combined with GS1 database.

Figure A.2: 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 size of the circle reflects population weights. The mean, $\text{Avg.}V_{r,t}$, and the reported standard deviations are weighted by state level population.

Appendix C Measuring Values : Price and Quality

Let $p_{r,u,g,f,t}$ refer to the unit price of a product, where r region, u indicates product, c product group (category), f firm, and t time. We first define *county-firm-category* specific price for classification $i \in \{\text{common, exit, enter}\}$ at time t, $p^i_{r,g,f,t}$, as

$$p^i_{r,g,f,t} \equiv \Pi_{u\in\Omega_{i,r,t}} \left(p_{r,u,g,f,t}^{\omega_{u,i}^{r,g,f,t}} \right) \tag{C.1}$$

where we use either $\omega_{u,i}^{r,g,f,t} \equiv \frac{1}{N^i_{r,g,f,t}}$ (equal weight) or $\omega_{u,i}^{r,g,f,t} \equiv \frac{S_{r,u,g,f,t}}{\sum_{u'\in\Omega_{i,r,t}} S_{r,u',g,f,t}} \equiv \frac{S_{r,u,g,f,t}}{S^i_{r,g,f,t}}$ (sales weight). $\Omega_{i,r,07}$ indicates set of products in 2007 in county r that either commonly exist in both periods (i = common) or exit in 2009 (i = exit), and $\Omega_{i,r,09}$ indicates set of products that either commonly exist in both periods (i = common) or newly enter in 2009 (i = enter). Now by aggregating across i, we define *county-firm-category* specific price $p_{r,g,f,t}$ at time t as

$$p_{r,g,f,t} \equiv \Pi_i \left(p^i_{r,g,f,t}\right)^{\omega_i^{r,g,f,t}} \tag{C.2}$$

where $\omega_i^{r,g,f,t} \equiv \frac{S^i_{r,g,f,t}}{\sum_{i'} S^{i'}_{r,g,f,t}} \equiv \frac{S^i_{r,g,f,t}}{S_{r,g,f,t}}$. Similarly, *county-category* specific price $p_{r,g,t}$ at time t is defined as

$$p_{r,g,t} \equiv \Pi_f \left(p_{r,g,f,t}^{\omega_f^{r,g,t}} \right) \tag{C.3}$$

where $\omega_f^{r,g,t} \equiv \frac{S_{r,g,f,t}}{\sum_{f'} S_{r,g,f',t}} \equiv \frac{S_{r,g,f,t}}{S_{r,g,t}}$.

We define *county-firm-category* specific quality for classification $i \in \{\text{common, exit, enter}\}$ at time t, $\phi^i_{r,g,f,t}$, as

$$\phi^i_{r,g,f,t} \equiv \frac{p^i_{r,g,f,t}}{p_{r,g,t}} \tag{C.4}$$

This captures how far the prices of products (classified as i) in category c produced by firm f are from the average price level of products in the same category in county r at time t.

We define *county-firm* specific price and quality for classification $i \in \{\text{common, exit, enter}\}$ at time t, $p^i_{r,f,t}$ and $\phi^i_{r,f,t}$, as

$$p^i_{r,f,t} \equiv \Pi_g \left(p^i_{r,g,f,t}\right)^{\omega_{g,i}^{r,f,t}} \tag{C.5}$$

$$\phi^i_{r,f,t} \equiv \Pi_g \left(\phi^i_{r,g,f,t}\right)^{\omega_{g,i}^{r,f,t}} \tag{C.6}$$

where $\omega_{g,i}^{r,f,t} \equiv \frac{S^i_{r,g,f,t}}{\sum_{g'} S^i_{g',r,f,t}} \equiv \frac{S^i_{r,g,f,t}}{S^i_{r,f,t}}$.

Finally, we define *county-firm* specific quality and price at time t, $p_{r,f,t}$ and $\phi_{r,f,t}$, as

$$p_{r,f,t} \equiv \Pi_i \left(p^i_{r,g,f,t}\right)^{\omega_i^{r,f,t}} \tag{C.7}$$

$$\phi_{r,f,t} \equiv \Pi_i \left(\phi^i_{r,g,f,t}\right)^{\omega_i^{r,f,t}} \tag{C.8}$$

where $\omega_i^{r,f,t} \equiv \frac{S^i_{r,f,t}}{\sum_{i'} S^{i'}_{r,f,t}} \equiv \frac{S^i_{r,f,t}}{S_{r,f,t}}$.

In addition to the benchmark price and quality measures, we also consider "size-adjusted" measures based on the unit price *after adjusting package size and unit differences*. Finally, under the rationale that organic products have higher quality compared to the non-organic products, we also measure value of products based on organic product turnover rates.

Appendix D Derivation of Optimal Prices and Quality

From the profit function (6.17), 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 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 for the uniqueness (i.e., second-order conditions) can be found in Online Appendix C.3.

D.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

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

This implies optimal price

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

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

D.2 First-order Conditions in Quality

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

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

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

By multiplying ϕ_f on both side of the equation, we get

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

By rearranging terms, we get the optimal quality choice

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

D.3 Structural Equation of Market Interdependency - Derivation

We start with the equation (6.21). 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 $S_{rf,0}$.

Put logarithm in both side of (6.21):

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

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 imply

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

Now lets 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 using $x = x_0 e^{\hat{x}}$, we get

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

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 $\sum_{r\in k_f}\omega_{rf,0} = 1$, and $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$ with $\sum_{r\in k_f}\theta_{rf,0} > 1$. 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 get

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

Appendix E 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.

E.1 Price and Quality Choice

We denote market-specific choice of quality by ϕ_{rf}. To distinguish optimal prices under market-specific quality with those under uniform quality, we denote optimal price under market-specific quality by p^m_{rf}. We denote 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 costs structure 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 incurring market-specific fixed costs. We assume for supplying ϕ_r quality of 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 cost that do not depend on the choice of quality. Superscript m is used to indicate cost associated with market-specific quality strategy. We parametrize $f^m(\phi_{rf})$ as

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

where we allow 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.[62]

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

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

subject to demand condition

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

We can show that the optimal price is

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

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

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

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

where

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

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 (E.5) into (E.1), we obtain the expression of 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

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

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

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

This implies

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

where we assume $\beta_m > 0$ 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

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

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

Proposition 5. *(Productivity and Quality, 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 $a_f = a_{f'}$. Also, if $\beta_m > 0$ is sufficiently small that $\beta_m(\sigma-1)(\gamma_r - \xi) < 1$, we have

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

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

Proof. We only need to prove $\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0$. We know $\frac{\partial \log S^m_{rf}}{\partial \log a_f} > 0$ under $\beta_m(\sigma-1)(\gamma_r - \xi) < 1$. Note that (E.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 6. *Under the conditions in Proposition 5, the equilibrium profit π^m_f under market-specific quality strictly monotonically increases with firm productivity a_f.*

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

E.2 Market Independence under Market-specific Quality

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

Proposition 7. *(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 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 (E.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 shutting 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 (E.4) and (E.5) and $\frac{\partial \log S^m_{rf}}{\partial \log y_{r'}} = 0$. □