

# 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 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. 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 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.<sup>1</sup> 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 (e.g., [Almunia et al. 2020](#)). In this case, a decrease in demand and sales in one market leads to an increase in sales in the other market. Second, if firms that face a negative demand shock in one market have 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 (e.g., [Berman et al. 2015](#)). Third, it is possible that firms make their decision entirely at the local level and do not spill over the regional shock, as standard international macro and trade models with constant marginal costs predict (e.g., [Backus et al. 1992](#); [Melitz 2003](#)). In these models, exogenous foreign demand shocks that affect 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.

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<sup>1</sup>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, suppose Coca-Cola generates sales in Manhattan (New York County) and Brooklyn (Kings County). In that case, we observe prices and quantities sold in Manhattan and Brooklyn separately for each barcode level product (e.g., cherry-flavored 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 indirect shock, which measures the average negative demand shock originating in the firm's other markets. Strikingly, a firm's county-level sales growth *decreases* by 3.5%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. Since a typical firm in our sample sells to many markets, the local demand shock is relatively small to most firms and does not likely alter the firm-level decisions.<sup>2</sup> Consistent with this intuition, we find a larger spillover effect when firms initially generate larger sales from non-local markets compared to the local market.

We conduct various robustness checks to confirm that the identified spillover effect is not driven by other mechanisms, such as common or geographically clustered regional shocks and the establishment, retailer, or industry linkages across regions. Our placebo tests reveal that the spillover effects we identified are muted under the alternative network structures that could generate a similar sales correlation. We also confirm that our results cannot be explained by similar household demographics across locations, potentially differential effects on exporters, and the possibilities of certain firms' market selection into regions that experience a larger drop in housing prices. Moreover,

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<sup>2</sup>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 indirect demand shock by measuring the average demand shock this firm faces in all other 154 markets.

our empirical results are largely robust to instrumenting the local housing price changes with the house supply elasticity (Saiz 2010), the house price sensitivity (Guren et al. 2020a), and the non-local mortgage lending shock (García 2018).

Behind responses of local firm sales to direct and indirect demand 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.<sup>3</sup> 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 firms that did not face the direct demand shock. Therefore, a decline in firm sales occurs even in a local market that is not directly affected by the shock.

We formalize the spillover mechanism and discuss aggregate implications by developing a stylized multi-market model with 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.<sup>4</sup> 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 that experience 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, 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

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<sup>3</sup>Defining the product at a more aggregated-level, we find that all the spillover effects work through the sales of continuing products. Using barcode-level data is crucial in analyzing the product entry and exit within firms.

<sup>4</sup>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 elasticities are generally larger than unity in the consumer packaged goods market (see, e.g., Broda and Weinstein (2010)).

and other broad features of the data, our model delivers the quality-adjusted real consumption distribution across states. Without the spillover, the standard deviations of the growth and level of real consumption are nearly 30% and 50% larger than those of the benchmark model with the spillover effect, respectively. A back-of-the-envelope calculation shows that the real consumption growth 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 propagate 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 studies by identifying a novel regional network arising from multi-market, multi-product firms, which translate a non-local shock across locations and substantially impact local consumption.

Closely related to this article, [Giroud and Mueller \(2019\)](#) study how the intra-firm network created by multi-establishment firms translates regional demand shocks. They find that firms' local employment decreases in response to both a local demand shock and indirect demand shocks originating from its other *production facilities*. We complement their analysis by providing a new and much stronger intra-firm network created by firms that *sell* multiple products in multiple markets.<sup>5</sup> Specifically, [Giroud and Mueller \(2019\)](#) show that their intra-firm network presents in non-tradable sectors but not in tradable sectors. By providing a novel intra-firm product replacement mechanism that applies to tradable sectors, our evidence generalizes such intra-firm spillover effects—which our theory shows to be fundamental in understanding the regional welfare redistribution—to both tradable and non-tradable sectors. Similarly, for non-tradable sectors, [Gilbert \(2017\)](#) provides

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<sup>5</sup>The multi-establishment intra-firm network effect in [Giroud and Mueller \(2019\)](#) is approximately one-third of the direct effect, whereas the multi-market intra-firm network effect we identified is approximately six times larger than the direct effect. This difference is likely to arise because firms sell to many counties but have establishments in a relatively small number of counties.

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 product quality choice. In Appendix A, 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 firm-level analyses in explaining the international co-movement 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. 2020](#)). This literature tends to infer the exporter's cost of producing quantity through the spillover.<sup>6</sup> Unlike previous studies, our analysis emphasizes the fixed cost associated with product quality to understand the behavior of domestic multi-market firms within the United States, where the detailed barcode-level data is available, and infer the real consumption inequality across states.<sup>7</sup>

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 business cycles and economic inequality (e.g., [Broda and Weinstein 2010](#); [Bernard et al. 2010](#); [Schmitt-Grohé and Uribe 2012](#); [Nakamura and Steinsson 2012](#); [Hottman et al. 2016](#); [Anderson et al. 2017](#); [Argente et al. 2018](#); [Jaravel 2018](#); [Anderson et al. 2018](#); [Jaimovich et al. 2019](#)). In particular, we allow the choice of quality by firms, as in [Feenstra and Romalis \(2014\)](#) and [Faber and Fally \(2020\)](#), and emphasize

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<sup>6</sup>In a related study, [Kim \(2020\)](#) emphasizes the heterogeneous slope of marginal costs across industries in understanding the international business cycle.

<sup>7</sup>Given that our mechanism 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, we expect our identified spillover effect applies to those sets of countries that share many of the same barcode-level products, such as the North American Free Trade Agreement (NAFTA) and European Union (EU). For the model, we are agnostic on the cost of production by assuming conventional constant marginal cost; we allow fixed cost that varies across the different quality of products, consistent with our empirical evidence and the previous models with a quality choice of firms (e.g., [Faber and Fally 2020](#)).

the economies of scale at the level of different product qualities, as in [Dingel \(2017\)](#). The firm-level product replacement mechanism arising from regional demand shocks resembles the international-level evidence with product variety changes in [Mayer et al. \(2014, 2016\)](#); we do not find supporting evidence for the variety channel in our study of the domestic markets. Our identification strategy follows the literature analyzing the collapse in the housing market during the Great Recession. Previous studies document that a fall in house prices leads to a decline in local consumer spending ([Mian et al. 2013](#); [Kaplan et al. 2020](#); [Guren et al. 2020a](#)), price and price-cost markups ([Stroebel and Vavra 2019](#)), and employments ([Mian and Sufi 2014](#); [Giroud and Mueller 2017](#)). We complement these studies by showing the novel spillover effect arising from the fall in regional house prices.

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

## 2 Data and Measurement of Variables

### 2.1 Data

Our dataset combines barcode-level prices and quantities sold in each county produced by public and private firms from the ACNielsen Retail Scanner database and various firm- and establishment-level information obtained from the GS1 the National Establishment Time-Series (NETS) database. The combined data allow us to construct a firm’s county-specific sales and its connection to other counties where the firm generates sales, together with various firm-level information including its primary industry code, establishment location, and credit ratings. We leverage the large differential collapse in local housing markets during the Great Recession and supplement our dataset with the county- and state-level house prices in 2007-09 from the Zillow database to measure local demand shocks. Correspondingly, our sample period is 2007 to 2009. A detailed discussion of each dataset and merging procedure can be found in Online Appendix A.

The barcode-level price and quantity information in each county comes from the ACNielsen Retail Scanner database, which was made available by the Kilts Marketing Data Center at the University of Chicago Booth School of Business.<sup>8</sup> The data contain approximately 2.6 million barcode-level product prices and quantities recorded weekly from about 35,000 participating grocery,

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<sup>8</sup>Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (U.S.), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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 began in 2006 and ended in 2015, covering the Great Recession period 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 U.S. grocery and drug stores and more than 30 percent of all U.S. 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 is likely to be the most granular scale at which the product can be defined. This feature allows us to decompose a firm’s local sales growth into the intensive margin (arising from continuously existing products) and the extensive margin (arising from product creation and destruction). Using a broader product category classification as a definition of product does not allow us to identify the extensive margin effect emphasized in this paper.<sup>9</sup> Second, the database has fewer measurement error problems. For example, unlike most firm-level international trade data that infer regional (domestic) sales by subtracting other regional (international) sales from total firm sales, Nielsen collects sales information independently across each region. This feature prevents the mechanical regional sales correlation problem raised in [Berman et al. \(2015\)](#). Compared to similar data that rely on consumer surveys, the Retail Scanner data directly record expenditures when consumers purchase and scan products at stores. Thus, our data do not suffer from household non-response and misreporting, which are common problems in survey data used in economic research ([Einav et al. 2010](#); [Meyer et al. 2015](#)). One disadvantage of the Retail Scanner data is the sample selection, as it is likely to cover more of large retailers. We confirm the robustness of our main intra-firm spillover results by leveraging the Homescan Panel data, which relies on household reporting but has a sample weight that can make the sample nationally representative, as shown in [Table A.9](#) in [Appendix A](#).

We integrate each product’s prices and quantities with its producer information using the GS1 US Data Hub and the National Establishment Time-Series (NETS). The GS1, a not-for-profit information standards organization, is the official source of barcodes for producers.<sup>10</sup> Their data record the company name and address for each barcode-level product, and we use this information to link barcode-level product information to producer-level information from the NETS data. NETS is

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<sup>9</sup>As an alternative specification, we instead define product using the broader product group categories available in the ACNielsen data 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 instead of the entry and exit of the product group categories.

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



the U.S. establishment-level longitudinal database made available by Walls & Associates. The 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 behind the spillover results and address concerns related to the supply-side effect or collateral channel.<sup>11</sup> Note that our sample excludes the participating retailers in the Retailer Scanner data as their UPC codes are masked for confidentiality and cannot be combined with the GS1 data.

We supplement our combined database with county-level house price index from the Zillow database, the housing supply elasticity measure from [Saiz \(2010\)](#), the housing price sensitivity measure from [Guren et al. \(2020a\)](#), and the mortgage lending information from [García \(2018\)](#) for our identification strategy.<sup>12</sup> We further augment our data with the [Rajan and Zingales \(1998\)](#) industry-level external financial dependence index to explore the role played by financial friction in spillovers. For the robustness check, we additionally use the NBER county distance database and the county-level variables used in [Mian and Sufi \(2014\)](#), such as the household income and debt-to-income ratio.

Table 1 provides the summary statistics of the final sample used in the empirical analyses. Our combined dataset consists of 4,171 firms and covers 991 US counties from 2007 to 2009.<sup>13,14</sup> 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 a large variation across firms in their initial exposure to different counties, and local shocks differentially hit these counties. Given the relatively smaller variation in product groups within firms, we sum up product groups for our main analysis. Still, the results are robust to comparing outcomes within product groups, as shown in Appendix A.

Second, each county has many firms that sell many products. On average, 848 firms sell their products in a county; even in a county in the 10th percentile of the distribution, 341 firms sell their products. Using the total Nielsen sample, the largest firm in a typical county has a sales share smaller

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<sup>11</sup>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. According to [Barnatchez et al. \(2017\)](#), the NETS database is useful for studying cross-sectional business activities, but its information is limited in studying business dynamics. Thus, we only use the data for the pre-recession period and abstain from using the data’s panel structure.

<sup>12</sup>We are grateful to authors for uploading their estimates and sharing the data with us.

<sup>13</sup>The 991 US counties cover approximately 75% of the total US population. Our results are robust to defining the local market at the state level, which covers all states except Hawaii.

<sup>14</sup>As shown 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 in Table OA.3 in Online Appendix B.

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

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

than 5%. Given that each firm accounts for the small sales share in a county, it is unlikely that an individual firm could affect the local economic conditions, ensuring the validity of the indirect demand shock. Lastly, as already documented in [Hottman et al. \(2016\)](#), there is an extreme firm heterogeneity in the data. 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. We exploit this rich variation and confirm that the spillover effect is stronger for larger firms, consistent with the results in [Argente et al. \(2020\)](#).

## 2.2 Sales Growth and Decomposition

Our main dependent variable is the region-firm sales. Let  $S_{r,f,t}$  denote firm  $f$ 's sales in region  $r$  at time  $t$ . We measure the region-firm-specific sales growth in 2007-09 as

$$\tilde{\Delta}S_{rf} \equiv \frac{S_{rf,09} - S_{rf,07}}{\bar{S}_{rf}} \quad (2.1)$$

where  $\bar{S}_{rf} \equiv \frac{1}{2}(S_{rf,07} + S_{rf,09})$  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. This growth rate can accommodate both the entry and exit of firms at the region-level, and the main results are robust to such accommodations, as shown in Table A.12 in Appendix A. Also, 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.

To understand the underlying mechanism behind the regional shock spillover, we investigate the role of product creation and the destruction of these firms in shock spillovers. Following [Broda and Weinstein \(2010\)](#), we decompose the sales growth defined in equation (2.1) into two margins: the intensive margin associated with products that exist in both pre- and post-shock periods, and the extensive margin associated with product creation and destruction (i.e., net creation):

$$\tilde{\Delta}S_{rf} = \tilde{\Delta}S_{rf}^C + \tilde{\Delta}S_{rf}^R \quad (2.2)$$

where  $\tilde{\Delta}S_{rf}^C \equiv \frac{S_{rf,09}^{\text{exist}} - S_{rf,07}^{\text{exist}}}{\bar{S}_{rf}}$  and  $\tilde{\Delta}S_{rf}^R \equiv \frac{S_{rf,09}^{\text{enter}} - S_{rf,07}^{\text{exit}}}{\bar{S}_{rf}}$ .  $S_{rf,t}^{\text{exist}}$  is the region-firm-time-specific sales from products that continuously existed in region  $r$  throughout 2007-09,  $S_{rf,07}^{\text{exit}}$  is the sales from products that existed in region  $r$  in 2007 but exited in 2009, and  $S_{rf,09}^{\text{enter}}$  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:  $S_{rf,07} = S_{rf,07}^{\text{exist}} + S_{rf,07}^{\text{exit}}$  and  $S_{rf,09} = S_{rf,09}^{\text{exist}} + S_{rf,09}^{\text{enter}}$ .

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

For the extensive margin, we further decompose it into two components by classifying products into firms’ global and local products:

$$\tilde{\Delta}S_{rf}^R = \tilde{\Delta}S_{rf}^{R,M} + \tilde{\Delta}S_{rf}^{R,L} \quad (2.3)$$

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

### 2.3 The Indirect Demand Shock

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

In measuring the regional consumer demand shock, we exploit the sharp differential drop in local house prices during the Great Recession following the large literature studying the consequence of housing market disruptions.<sup>15</sup> It is well-known that there was a dramatic decline in housing prices in this period following the massive increase in housing prices in previous years, and the magnitude of the fall in housing prices varied widely across regions. The regions that faced a larger decrease in local housing prices experienced a greater fall in local consumption relative to its counterparts because of the lower household wealth or worsened credit condition arising from the depressed collateral (housing) values (see, e.g., Mian et al. 2013; Kaplan et al. 2019). The resulting depressed local consumption, in turn, lowers the wage and employment in the region and further shrink the local consumption. (the local general equilibrium effect; see, e.g., Guren et al. 2020b).

Let  $HP_{r,t}$  denote the house price index in region  $r$  at time  $t$ . Consistent with the measure of

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<sup>15</sup>Our measure of house price changes using the Zillow data follows Giroud and Mueller (2017, 2019); Kaplan et al. (2020). Giroud and Mueller (2017) document that at the MSA level, this measure is highly correlated with both the “the housing net worth shock” used in Mian et al. (2013); Mian and Sufi (2014) (86.3%) and the measure of house price changes from the Federal Housing Finance Agency (FHFA) data used in Adelino et al. (2015); Charles et al. (2018) (96.4%).

sales growth, we define the region-specific house price growth in 2007-09 as

$$\tilde{\Delta}\text{HP}_r \equiv \frac{\text{HP}_{r,09} - \text{HP}_{r,07}}{\overline{\text{HP}}_r} \quad (2.4)$$

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

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

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 to a firm, reflecting the idea that firms are more likely to be exposed to the consumer demand shock in a region  $r'$  if they initially sold more in region  $r'$  relative to other regions.

A primary concern in treating the local housing price as a shock is that a price is an equilibrium object, which is jointly determined by housing demand and supply and is associated with various confounding regional characteristics. The detailed county-firm data with the focus of the intra-firm spillover effects partially ease this concern. Our tightest specification allows region-sector fixed effects to absorb all regional and region-sector-specific characteristics potentially correlated with regional housing price changes. This specification, which compares firms within regions, aids the identification because the regional housing prices are likely to be exogenous to our sample of firms. The narrative evidence and previous studies suggest that the regional housing price changes in this period originate from the factors outside of the product market, especially the consumer packaged goods market this study considers. The two leading explanations of the fall in housing prices are the household credit expansion in the pre-recession period (e.g., [Mian and Sufi 2017](#)) and a sudden change in household expectation (e.g., [Adelino et al. 2018](#)). We are not aware of any evidence that firms, particularly consumer packaged goods firms, affect local housing prices by selling more or fewer products. Moreover, as discussed in [Section 2](#), the firms' share in our sample is small in a county, and each firm would likely play no role in affecting local housing price changes.

Given that our sample of firms takes the housing price as given, another concern is the possibility that firms with certain characteristics, which may affect their regional sales, select into those regions that experience larger drops in house prices. Given the high persistence of regional market share in the Consumer Packaged Goods industry (see, e.g., [Bronnenberg et al. \(2009, 2012\)](#)), it is unlikely that firms selected into counties for the reasons related to the house price changes in the Great Recession. One of our placebo tests reveals that the effect is muted when we only use those firms entering the

local market of interest at the beginning of the recession. We also test this possibility by correlating the firms' initial observed characteristics with the average degree of housing price changes they face. As shown in Appendix Table A.1, we find that the firm size, scope, age, and financial stability, which are likely to affect firm local sales, are uncorrelated with the average regional demand shocks in our sample. Moreover, we test and confirm that firms are not likely to select into regions based on their unobserved characteristics by utilizing the region and firm fixed effects in our regression specification.

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

The non-local mortgage lending shock utilizes the variation in the change in mortgage lender health, which does not originate from the county of interest, to generate the exogenous variation in the local economic house prices. More specifically, García (2018) brings in the rich region-lender mortgage credit information and separates the lender-specific credit change from the region-specific credit change by using a fixed effect methodology, similar to the methodology employed in Chodorow-Reich (2014) and Amiti and Weinstein (2018). He then takes a weighted average of the lender-specific credit changes across lenders within the county to construct a county-specific non-local mortgage lending shock, where the weight is the lagged market share of lenders.

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

**Table 2:** First-stage Regression Results

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

*Note.* The Housing supply elasticity<sub>rf</sub>, Housing price sensitivity<sub>rf</sub>, and the Non-local lending shock<sub>rf</sub> are the leave-one-out lagged share weighted average of the regional [Saiz \(2010\)](#) elasticity, [Guren et al. \(2020a\)](#) sensitivity estimates, and [García \(2018\)](#) non-local mortgage lending shock, respectively. Region indicates county and sector is defined based on SIC 4-digit. Region-Firm controls are initial log of county-firm sales, firm sales, firm’s number of markets, and firm’s product groups.  $\tilde{\Delta}HP_{rf}$  (other) is the indirect demand shock in equation (2.5). The regression is weighted by initial county-firm sales; standard errors are two-way clustered by state and sector. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

### 3 The Intra-firm Spillover Results

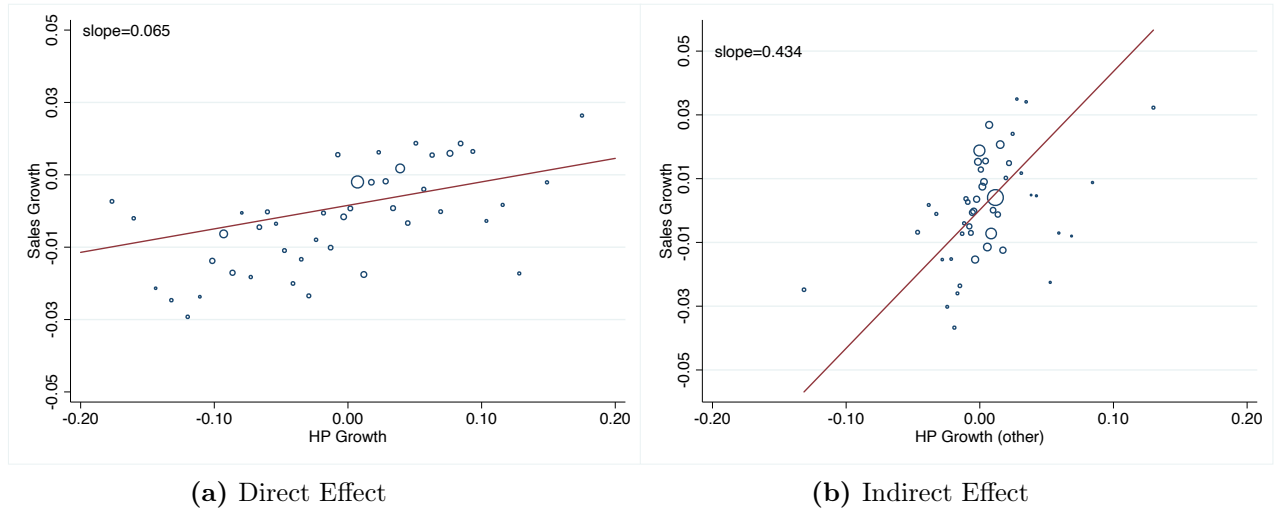
We use the following equation as the main specification throughout the empirical analyses:

$$\tilde{\Delta}S_{rf} = \beta_0 + \beta_1 \tilde{\Delta}HP_r + \beta_2 \tilde{\Delta}HP_{rf} \text{ (other)} + \mathbf{X}'_{rf} \boldsymbol{\beta}_3 + \varepsilon_{rf} \quad (3.1)$$

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

Our central coefficient of interest is  $\beta_2$ . This coefficient measures the elasticity of the firm’s local sales growth to the average regional demand shocks from the firm’s other markets, conditional on the direct local demand shock. A priori,  $\beta_2$  can have any sign; if the adverse regional demand shocks in other regions decrease (increase) the firm’s local sales, then the sign of  $\beta_2$  is positive (negative).  $\beta_2$  is zero if firms make their decisions at the local level. On the other hand,  $\beta_1$  measures the effect of direct regional housing price growth on a firm’s local sales, which is similar to what is studied in [Mian et al. \(2013\)](#); [Kaplan et al. \(2020\)](#). Our empirical analyses focus on the differential drop in housing prices by absorbing any nationwide changes, such as the aggregate decline in housing prices or the aggregate productivity changes, with the intercept  $\beta_0$ .

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



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

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

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

Table 3 column (1) confirms that the positive and statistically significant direct and indirect effects of regional demand shocks on local consumption and that the indirect demand effect is stronger.



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

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

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

The direct and indirect effects are 0.60 and 0.35, respectively. A 10%p drop in local house price growth leads to a 0.6%p decrease in the local firm sales growth, and the same decrease in the average of the other regional housing price growth lowers the local firm sales growth by 3.5%p.<sup>16</sup> We include all regional control variables used in [Mian et al. \(2013\)](#) as well as detailed firm-level variables that proxy firm size and scope.<sup>17</sup>

Columns (2)-(4) verifies our empirical findings using the various fixed effects to test and exclude unobserved confounding factors. Column (2) allows the firm fixed effects instead of the firm-level variables and the indirect demand shock, which variation mostly arises from the comparison across

<sup>16</sup>The magnitude of the estimated coefficient is smaller than the estimate reported in the previous study. For example, using the Nielsen Retail Scanner data, [Kaplan et al. \(2020\)](#) show that the estimate is 0.207 at the county-level, 0.239 at the MSA level, and 0.341 at the CBSA level. One key difference is the measure of the regional demand shock. If we use household net worth instead of housing prices as in [Kaplan et al. \(2020\)](#), our estimate of the local demand effect becomes 0.22.

<sup>17</sup>We do not include the variables from NETS data, such as the measures of financial constraints and firm age, because they decrease the sample size and do not have statistically significant effects on firm local sales conditioning on firm size and scope. The effects of direct and indirect shocks are robust to including such controls.

firms. The local demand shock’s quantitative effect remains the same with and without the firm fixed effects, suggesting that there is no selection of firms’ unobserved characteristics into the regional housing price changes conditional on control variables. If unobserved firm characteristics make some firms more exposed to the regional demand shock, adding the firm fixed effects would correct the bias and change the coefficient.<sup>18</sup> Column (3) instead allows regional fixed effects that absorb all the regional variations, including the local demand shock. The indirect effect is stable across columns (1) and (3), similar to the direct effect reported in columns (1) and (2), suggesting that there is no selection of unobserved regional characteristics into the indirect demand shock. Column (4) allows region times sector fixed effects that absorb all the region-sector variations that might confound the results, such as the regional clustering of manufacturing sectors that could co-move the differential manufacturing sales across locations. The indirect intra-firm spillover effect remains stable in this specification. Columns (5)-(8) bring in the instrumental variables and confirm the positive intra-firm spillover effects. As in previous literature studying the direct local effects, the IV estimates are larger than the OLS estimates, presumably due to the classical measurement errors that attenuate the coefficient size.<sup>19</sup> The first-stage F statistics are well above 10 in all specifications, and Hansen’s J-statistics cannot reject the instruments’ validity.

Among other concerns in identifying the indirect intra-firm spillover effects, one of the biggest threats is a common shock, which is often discussed in the international macroeconomics literature with more aggregate data (see, e.g., [Kose et al. 2003](#)). Although we rule out any common shocks to national, sectors, or region-sector clusters, there may be other geographically clustered shocks within broader regions, such as spatially correlated housing price changes. Such shocks could correlate with the indirect demand shocks and confound the results if the intra-firm initial networks are clustered in the same areas. Appendix A presents various robustness exercises and rules out the possibilities of the confounding effect of the clustered shocks. In measuring the indirect demand shocks, we exclude all counties near the local county of interest.<sup>20</sup> We also define a state as a region of analysis to exclude variations within the state, which could be more vulnerable to the clustered shocks. Regardless of using different definitions of nearby counties or using the state as a unit of analysis, we find that the indirect spillover effects remain strong.

We conduct placebo tests by varying the initial share weights when we measure the indirect demand shocks to inspect other common shock or other general mechanisms. Within the markets

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<sup>18</sup>This analysis is similar to the test of unobserved characteristics implemented in the banking literature. See, e.g., [Khwaja and Mian \(2008\)](#); [Chodorow-Reich \(2014\)](#).

<sup>19</sup>The sample size does not make much difference in the magnitude of the coefficients. The estimates from the elasticity and sensitivity instruments are larger than the estimate from the lending. One explanation of this difference is how different instrument affects different sub-sample based on the underlying channel. The elasticity and sensitivity instruments are likely to contain all the effect of housing prices on local consumption discussed in previous studies. In contrast, the lending instrument would affect households only through household mortgage borrowing.

<sup>20</sup>We try the radius of 50, 100, 150 miles in measuring the indirect demand shocks that exclude nearby counties. We also calculate it by excluding all counties located within the same state of the interested county.

firms operate, we consider the weight of equal share, household population, household median income, household debt-to-income ratio. We also use the initial share of entrants to explore firms' potential selection into the exposed regions and use the establishment-network to understand the supply-side effect arising from the land collateral or productivity shock. Lastly, we use the random weight; we randomize each firm's markets, measure the indirect shock, and run the regression. We do this exercise a thousand times and report the average estimated coefficients and standard errors. The coefficient will not equal to zero if there is any hidden structural correlation.

**Table 4:** Placebo Tests

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

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

Table 4 shows that the intra-firm spillover effects we find are muted under the potential alternative explanations. Column (1) shows the results using the equal sales weight of firms across regions. The spillover effects are negligible, suggesting that the firm's initial exposure is essential for the spillover effects, not the general correlation structure across regions within firms. Columns (2)-(4) consider weights of household characteristics, which are likely to make regional consumption more or less sensitive to the regional housing price changes, and we again find no significant effects. If there is a mechanism—other than the intra-firm behavior—that generates the correlation of sales across regions within firms, the household-characteristics-weighted housing price changes would affect the other region's sales through this mechanism. Our insignificant results rule out such a mechanism. Column (5) considers those firms that suffer from the indirect demand shock because they select into the markets in the year 2007. The results are again negligible, suggesting that the initial share variation we use in our main analysis is originated from the historical episodes. Column (6) considers the supply-side effects by using establishment-level employment information, and we do not find any

effect.<sup>21</sup> Appendix A.2 further reports the robustness of our main results to the supply-side effects by using the indirect demand shock that excludes the regions where firms produce their products, similar to the identification strategy employed in Baker et al. (2020).<sup>22</sup> Lastly, column (7) shows that using the random network does not generate any effect.

We conduct numerous additional robustness exercises to confirm our results, as shown in Appendix A. Our results are robust to the retailer behaviors, sales correlation of the granular product group across regions, controlling for the average household demographics firms face (clientele effect), and potentially differential change on exporters’ local sales. To address concerns on comparing firms with different characteristics, in addition to testing the selection of firms based on observed (Appendix Table A.1) and unobserved characteristics (Table 3), we compare firms that share the same Census division based on their largest markets; our results remain stable. We also confirm our intra-firm spillover results by using the ACNielsen Homescan Panel data, which has a more representative sample, along with the analyses of pre-trends.<sup>23</sup>

## 4 The Product Replacement Channel

Our reduced-form empirical results do not align with the predictions of the traditional models of international macroeconomics and trade, where firms make their decisions entirely at the market-level. The natural question is how firms spillover regional demand shocks across their markets.

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

To empirically investigate the underlying mechanism, we use a simple regression framework to decompose exactly the spillover effect into the product replacement effect and continuing product effect. As described in Section 2, we decompose the local sales into two parts: intensive and extensive margins. The intensive margin is entirely conventional and refers to the local firm sales growth from the continuing products, which exist in both the initial and end period. The extensive margin is the

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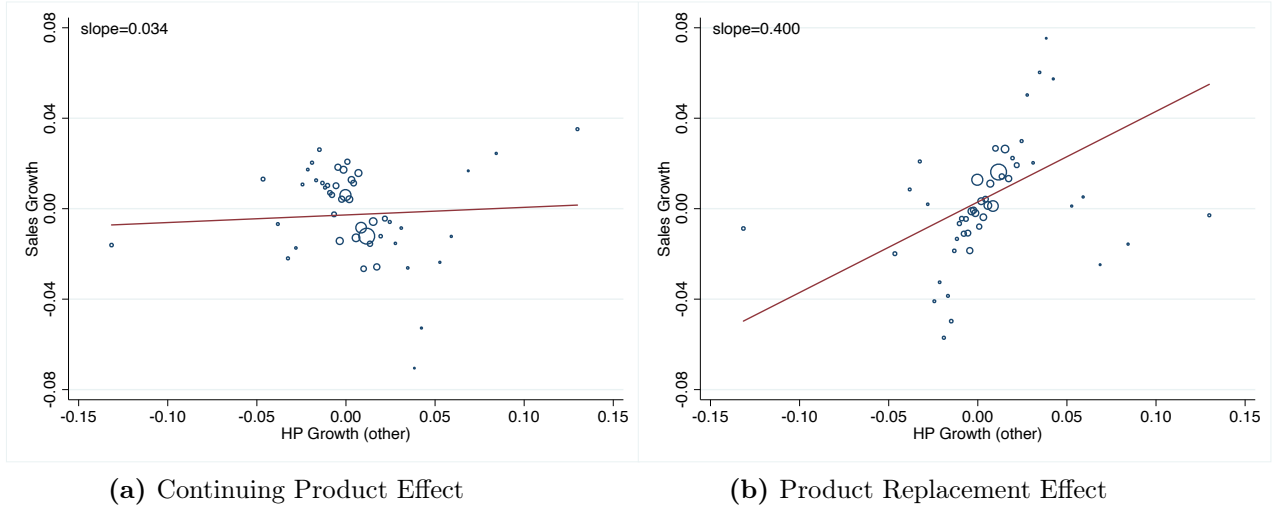
<sup>21</sup>This result is consistent with those of Giroud and Mueller (2019), who show that there is no multi-establishment network effect for tradable industries.

<sup>22</sup>Specifically, we measure the region-firm specific indirect shock by only including counties where (i) a firm sells its products and (ii) do not have establishments located. We re-normalize weights so that they sum up to one. We find similar intra-firm spillover effects by using this measure.

<sup>23</sup>In unpublished work, we also study the housing boom effect in 2004-2006 with the ACNielsen Homescan Panel data. We find very similar results for the intra-firm spillover effect. Still, they are not statistically significant at the conventional level, potentially because of the larger measurement errors in the data’s initial years.

local firm sales growth that arises from the product introduction and destruction in a given market. We regress each margin on the indirect demand shock to understand how firms that face a negative indirect demand shock change their local sales.

**Figure 2:** Decomposing the Intra-firm Spillover Effect



*Note.* Figure 2a and Figure 2b decompose the correlation between  $\tilde{\Delta}S_{r,f}$  and  $\tilde{\Delta}HP_r$  (other) in Figure 1 into the correlation between  $\tilde{\Delta}S_{r,f}^C$  and  $\tilde{\Delta}HP_r$  (other) and the correlation between  $\tilde{\Delta}S_{r,f}^R$  and  $\tilde{\Delta}HP_{r,f}$  (other), respectively. All variables are partialled out based on columns (2) and (3) of Table 5 and are weighted averaged by 50 equal-sized housing price growth bins. The bins are weighted by initial sales and the red lines fit the data linearly.

Figure 2 visualizes the importance of product replacement in understanding the intra-firm spillover effect. Figure 2a plots the entirely conventional price and quantity effect of the intra-firm spillover, which arises from the continuing products. Surprisingly, there is a near-zero linear relationship between sales growth and the indirect demand shock. Depending on how one treats the observations with the extreme indirect demand shock, there is at most a *negative* relationship.<sup>24</sup> On the other hand, Figure 2b shows the intra-firm spillover effect through the extensive margin. The figure presents a strong positive relationship and closely replicates the overall spillover effect visualized in Figure 1b.

Table 5 columns (1)-(3) not only validates the visualization but also shows a stark asymmetry: The direct demand effect works through the conventional intensive margin of price and quantity change, consistent with the price results in Stroebel and Vavra (2019), but the indirect demand effect

<sup>24</sup>For our baseline analyses, we seek to be agnostic on extreme values by including them but weight each observation by initial sales. Suppose we trim our sample based on the indirect demand shock. In that case, the indirect demand shock decreases the intensive margin of the local firm sales growth, consistent with the international market results in Almunia et al. (2020). However, the indirect demand shock's overall effect is still positive because there is a stronger positive intra-firm effect without extreme values, as shown in Figure 2b. This result is intuitive since many barcode-level products are shared across regions within the domestic markets, which generates the product replacement effect. In contrast, common products are rare at the international level.

**Table 5:** Decomposing the Intra-firm Spillover Effect

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

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

works through the product replacement. Column (1) replicates Table 3 column (1), and columns (2) and (3) exactly decompose coefficients in column (1) into the continuing product effect and the product replacement effect. Approximately 83% (0.05/0.06) of the direct demand effect arises from the continuing products, and approximately 92% (0.32/0.35) of the indirect demand effect occurs as a result of the product replacement. This asymmetry of direct and indirect effects ensures that the identified intra-firm spillover effect is unlikely to be confounded by the factors related to the local housing price changes, which affect local firm sales through continuing products. Note that the barcode-level definition of product is important in this decomposition; if we instead define the product as a broader category of the product group, all the effects seem to arise from the continuing products, as shown in Online Appendix OA.2.

Columns (4) and (5) present that the intra-firm spillover effect remains robust after including region times sector fixed effects. Comparing the firms that sell to the same local market and operate in the same sector, the firms that face more massive negative indirect demand shock decrease their local sales by replacing their products.

Columns (6) and (7) show that the intra-firm spillover effect results from the firms' synchronized product replacement decision across multiple markets, not due to the firms' market-specific product

replacement decision. The coefficients reported in columns (6) and (7) further decomposes the coefficient in column (5) by classifying products that are replaced in multiple markets and those replaced only in the local market. The local-market product replacement effect reported in column (7) is effectively zero, suggesting that all the effect arises from the products that are replaced in multiple markets simultaneously. This decomposition result is intuitive since almost all barcode-level products are sold in more than one market, and more than 80% of barcode-level products are replaced in multiple markets simultaneously in this period. The global-product replacement result rules out the possibility that firms replace their products in each market separately when they face the indirect demand shock.

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

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

$$\tilde{\Delta}v_{rf} \equiv \frac{v_{rf,09}^{\text{enter}} - v_{rf,07}^{\text{exit}}}{\bar{v}_{rf}} \quad (4.1)$$

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

$$\tilde{\Delta}N_{rf} \equiv \frac{N_{rf,09} - N_{rf,07}}{\bar{N}_{rf}} \quad (4.2)$$

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

their products.

**Table 6:** Changes in Product Value, Characteristic, and Variety

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

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

Table 6 show that the products that are newly entered in the local market by the firms that face the negative indirect demand shock have lower values—sales per product, price, and organic share—compared to the products that are destroyed by the same firm in the same market. Columns (1)-(6) consider different measures of values and characteristics by county, firm, and product entry and exit. Conditioning on the negative indirect demand shock, column (1) shows that the newly introduced products’ sales are lower than the destroyed products. Columns (2)-(4) use different weights and methods to construct the county-firm-level price index. Regardless of fixing the weight, varying the weight, or adjusting for the product group mean, the new products have a lower price than the old products due to the negative indirect demand shock. Columns (5) and (6) consider the sales share and number of organic products. The negative indirect demand shock makes firms introduce fewer organic products and generate fewer sales from these new organic products in the local market. Columns (7) and (8) consider the effect on variety, but we do not find any effect on the number of products firms sell with both full sample and the restricted sample of counties in which firms replace their products.<sup>25</sup>

Our analyses suggest that the negative indirect demand shock makes firms adjust their product value and characteristics, not their price-cost markups or varieties. At the barcode-level data, for firms to change their product features, they must replace their products. It is hard to interpret our

<sup>25</sup>For robustness checks, Table A.13 in Appendix A considers alternative definition of price indexes, and Table A.14 in Appendix A conduct the analysis at the county-firm-product group level with the product group fixed effects.



findings with the markup adjustment through the product replacement since those affected firms lower both price and sales in our data. If firms lower price and markups due to the indirect demand shock, as in the study of the variable markup (e.g., [Alessandria et al. \(2010\)](#)), they would generate more extensive sales and quantities.<sup>26</sup> We rule out the variety adjustment channel as we do not find any supporting evidence, as shown in [Table 6](#).<sup>27</sup>

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

**Table 7:** Heterogeneous Treatment Effect

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

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

[Table 7](#) shows that the intra-firm spillover effect is more substantial for (i) firms that have smaller local market share, (ii) counties where household income or housing prices are high, (iii)

<sup>26</sup>In unpublished work, we define the county-firm-level quantity and run the regression but do not find meaningful results.

<sup>27</sup>Although we show characteristics associated with intrinsic product values, firms may change the perceived product quality by the national advertising or marketing; our analyses are consistent as long as these changes apply to the newly introduced products. Similarly, firms may resize and repackage products. As long as such changes decrease the product value they sell and reduce their total local sales, the results are fully consistent with our intra-firm spillover effect. [Section 5](#) formalize the product replacement as a quality change, and quality is broadly defined as what changes the market share conditioning on the product price.

large firms, and (iv) financially constrained firms. Columns (1) and (2) additionally clarify why the intra-firm spillover effect is stronger than the direct effect, as shown in Figure 1 and Table 3. When the initial market share is small for a firm, the indirect demand shock closely proxy the total firm-level shock, making the intra-firm spillover effect stronger. Columns (3) and (4) provide additional empirical support for the product replacement of high- to low-valued products presented in Table 6. Assume that wealthy households, who have a high income or live in counties where house prices are high, prefer high-valued or high-quality products (see, e.g., [Handbury \(2013\)](#)). Then there would be a more massive decrease in firm sales in those counties where wealthy households dwell when firms provide low-valued (or low-quality) products. Column (5) presents that the intra-firm effect is stronger for large firms, consistent with the direct effect results in [Argente et al. \(2020\)](#); it is likely to be easier for such firms to replace products because they (i) produce more standardized products ([Holmes and Stevens 2014](#)) or (i) have a larger scope ([Argente et al. 2020](#)). Columns (6) and (7) show that the effect is marginally stronger for financially constrained firms, consistent with the multi-establishment network results in [Giroud and Mueller \(2019\)](#) and the international evidence in [Berman et al. \(2015\)](#). Such firms likely incur higher costs in keeping up with high-valued or high-quality products when facing the negative indirect demand shock, generating a bigger spillover effect.<sup>28</sup>

## 5 The Model

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

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

**Market Demand.** Consider a static economy with  $R$  markets indexed by  $r \in \mathcal{R} \equiv \{1, 2, \dots, R\}$ . Each market is populated by a continuum of mass  $L_r$  of individuals, each of whom is endowed with the total income of  $y_r$ , which is the sum of the exogenous income  $I_r$  and the dividends from the

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<sup>28</sup>We also consider the indirect demand shock interaction with the distance from its origination, but we do not find any meaningful results conditioning on firm size.

production sector  $D_r$ .<sup>29</sup> The regional demand shock is modeled as an exogenous change in individual income in the market  $r$ . The economy consists of two broad sectors: the Consumer Packaged Goods (CPG) sector, which is the focus of this paper, and an outside goods sector. Similar to [Handbury \(2013\)](#) and [Faber and Fally \(2020\)](#), we consider a two-tier Constant Elasticity of Substitution (CES) utility where the upper-tier depends on the utility from CPG goods ( $U$ ) and an outside good ( $z$ ), which serves as a numeraire. The optimal consumption of CPG goods by an individual in market  $r$  ( $s_r$ ) is the share of the income of the same individual ( $y_r$ ), where the share depends on the regional CPG price index, the elasticity between CPG and outside goods, and the individual preference parameter on CPG goods over outside goods.

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

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

where  $f$  denotes a CPG firm,  $G_r$  is the set of firms selling in market  $r$ ,  $q_{rf}$  is the quantity of product bundle produced by firm  $f$  and consumed by individuals in market  $r$ ,  $\zeta_{rf}$  refers to the perceived quality (or appeal, taste) of firm  $f$ 's product bundle in market  $r$ , and  $\sigma$  refers to the elasticity of substitution between the firms' product bundles.<sup>30</sup> We assume that the perceived quality depends on an intrinsic quality (i.e., product attribute) choice  $\log \phi_f$  by firm  $f$  and a multiplicative term  $\gamma_r$  that governs the non-homothetic preference:

$$\log \zeta_{rf} \equiv \gamma_r \log \phi_f \quad (5.2)$$

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

There are two simplifying assumptions in this setup to reflect our empirical analyses. First, given that we find no empirical evidence of product variety changes from the indirect demand shock, we do not explicitly model the multi-product firms. Instead, we interpret the change in the quality of a product bundle,  $\phi_f$ , as a product replacement within firms. Our empirical analyses on product values and organic shares suggest a change in product features that make it less desirable for consumer conditioning on product prices, which is precisely linked to the definition of the product quality in this model. Second, firm  $f$ 's choice of the intrinsic product quality,  $\phi_f$ , does not vary across markets.

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<sup>29</sup>Since the wage rate equals one under the labor market structure described below,  $I_r$  can be interpreted as exogenous labor endowments as in [Fajgelbaum et al. \(2011\)](#). For simplicity, we assume that the dividends are distributed proportionally to their exogenous income.

<sup>30</sup>As documented in [Anderson et al. \(1987\)](#), this utility function can be derived from the aggregation of discrete-choice preferences across many agents choosing only one firm's product bundle. See Online Appendix D.2 for the proof.

This assumption reflects our main empirical findings of the synchronized product replacement across many markets presented in Section 4. In Appendix Figure A.1 and Table A.20, we additionally document that most of the products in the CPG industries are nationally sold, and there is a general synchronized product replacement pattern in these industries.<sup>31</sup>

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

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

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

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

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

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

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

where the parameter  $\xi$  is the elasticity of the cost to the level of product quality. Note that we assume the standard constant marginal costs of quantity production. This assumption reflects our empirical finding that there is no intra-firm spillover effect through continuing products within the domestic markets. Assuming the increasing or decreasing marginal costs of quantity would generate the spillover effect through continuing products because firms would sell different quantities in the

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<sup>31</sup>Explicitly considering the choice of the market-specific quality in the model reveals that firms choose the uniform product quality across markets when (i) their fixed costs of market-specific quality adjustment are high or (ii) they sell to many markets and find it less profitable to pay market-specific fixed costs. See Online Appendix E for this extension.

local market when the change in marginal costs is induced by the demand shocks arising from their other markets.

The total fixed costs are given by  $f(\phi_f) + f_0$ , where  $f(\phi_f)$  is the part of fixed costs that directly depends on quality. This part captures potential overhead costs such as design, R&D, and marketing, which do not directly depend on the quantities being produced but affect product quality. We assume a simple log-linear parameterization given by

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

where  $\beta$  measures the responsiveness of fixed cost with respect to the supply of high product quality, and  $b$  is a constant parameter that rescales the quality part of the total fixed costs.

Firm  $f$  optimally chooses the intrinsic quality of product  $\phi_f$ , which applies uniformly across its markets, and price  $p_{rf}$  by maximizing their profit

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

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

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

and

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

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

Combining the local firm product demand (5.3), the definition of product quality (5.2), and the

equilibrium firm local price (5.8), we derive the following local firm sale equation:

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

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

With sufficiently small  $\beta$ , the equilibrium price and quality are unique and the equilibrium firm product quality  $\phi_f$ , local sales  $S_{rf}$ , and profit  $\pi_f$  increase monotonically with firm productivity  $a_f$ . See Online Appendices D.3 and D.4 for the proof.

## 5.1 From Theory to Empiric

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

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

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

The first part in the right-hand side of the equation (5.11) presents and decomposes the inter-dependency of markets through the multi-market firms' internal networks, which is linked to our empirical analyses. The inter-dependency works through the firms' uniform product quality decision across their markets, which makes their local sales to respond to both their overall sales growth ( $\sum_{r \in k_f} \omega_{rf} \hat{S}_{rf}$ ) and the change in overall household preference on quality ( $\sum_{r \in k_f} \omega_{rf} \hat{\psi}_r$ ). The firm sales affect its local sales because of the scale effect: firms downgrade their product quality when they do not have enough revenue to recover the high fixed cost of producing high-quality products. The overall change in household preference affects local firm sales through the non-homothetic preference:

as households prefer low-quality products, firms lower their product quality to meet their demand and to save the associated costs. The initial weight,  $\omega_{rf}$ , reflects the importance of each market to the firm by their sales ( $S_{rf}$ ) and the net benefit of the high-quality products ( $\psi_r$ ). The overall shock firms face  $\left(\sum_{r \in k_f} \omega_{rf} \left[\hat{S}_{rf} + \hat{\psi}_r\right]\right)$  mirror the indirect demand shock in the empirical analyses. As emphasized in Section 3, CPG firms sell to many markets, approximately 513 counties on average. The local market share is negligible at the firm-level, and almost all the variation of the global firm-level shock arises from the indirect demand shock. Consistent with this notion of the indirect demand shock, the intra-firm spillover effect we identified is stronger as the indirect demand shock better proxies the global firm-level shock, as shown in Table 7.

The responsiveness of local firm sales to both the overall sales growth and the preference change is  $\Upsilon_r$ , which consists of the inverse-elasticity of fixed cost ( $\beta$ ) and the elasticity of market share  $((\sigma - 1)(\gamma_r - \xi))$  with respect to quality. Given that the indirect demand shock closely proxies the overall firm-level shock, the structural parameters in  $\Upsilon_r$  effectively control the strength of the intra-firm spillover effect we identified in the data.<sup>32</sup> From the cost-side, if a firm can raise its product quality by paying a small amount of fixed costs (high  $\beta$ ), they would raise quality and local sales more than its counterpart conditioning on the same firm sales growth. From the demand-side, if firms can acquire enormous market share by raising their product quality (high  $(\sigma - 1)(\gamma_r - \xi)$ ), such firms that face overall sales growth would increase the quality and local sales more than their counterparts. As described in the equation (5.10), the effect of quality on market share depends on the substitutability of products ( $\sigma$ ), individual preference ( $\gamma$ ), and the marginal cost of quality that pass-through to output price ( $\xi$ ). Consistent with the prediction on  $\gamma_r$ , the spillover effect is larger for high-income regions as reported in Table 7.

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

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

*Proof.* See Online Appendix D.5. □

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

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

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<sup>32</sup>Fixing  $\gamma$  across counties, it is straightforward to recover the empirical equation (3.1) by replacing the housing price growth in the indirect demand shock with the sales growth.

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

*Proof.* See Online Appendix D.5. □

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

## 5.2 Regional Redistribution

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

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

*Proof.* See Online Appendix D.5. □

Proposition 3 shows the risk-sharing of quality-adjusted consumption across regions through multi-market firm behavior. Conditioning on the regional demand shock, decreasing firm-level product quality raise the regional quality-adjusted price index and decrease local sales and the quality-adjusted CPG consumption.<sup>33</sup> Thus, our model predicts that a market that did not experience any negative regional shock can experience welfare loss through the quality downgrading of multi-market firms. At the same time, market  $r'$ , which faces the direct negative demand shock, benefits from the other market  $r$ , which did not face the negative demand shock. Since the market  $r$  face non-negative demand shock, the quality downgrading in market  $r'$  is alleviated. Thus, market  $r$  and market  $r'$  share the burden of the negative demand shock that affects market  $r'$ .

**General Equilibrium Analyses.** Armed with an economic intuition in Proposition 3, we numerically solve the full general equilibrium effect of the intra-firm network on the consumption redistribution across states.<sup>34</sup> We include both single-market firms and multi-market firms in our analyses, which yields in total 5,186 firms that at most sell in 49 states. We compare our baseline

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<sup>33</sup>The total consumption, which includes both CPG consumption and outside goods, also decrease due to the decrease in product quality adjustment in CPG industries.

<sup>34</sup>Our reduced-form empirical results are robust to defining the market as a state, as shown in Appendix Table A.2.



economy with the counterfactual economy, which shuts down the intra-firm network channel by assuming the firm’s market-specific quality choice. As stated in Proposition 6 in Appendix D, this economy features no spillover through intra-firm network as in conventional models of international economics. See Appendix D for the full description of the counterfactual economy.

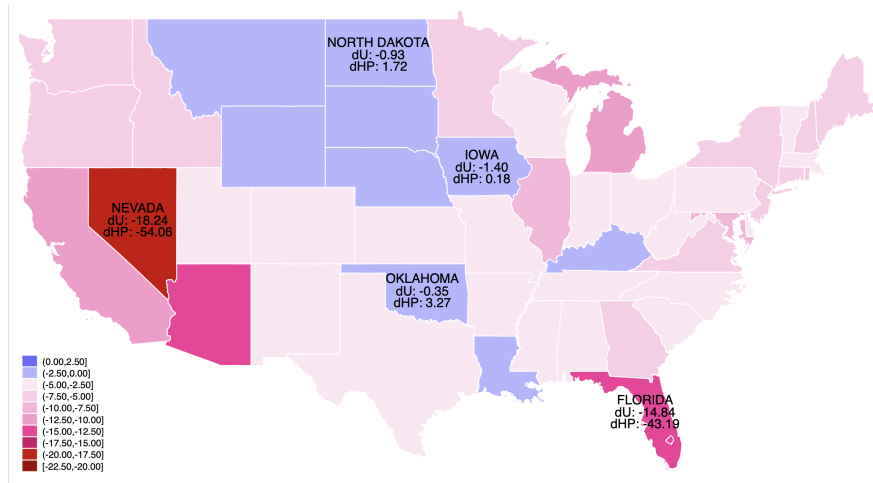
Appendix E presents the full description of the calibration and estimation of parameters. We leverage Equation (5.11) by using the indirect demand shock from empirical analyses as an instrumental variable to estimate the key parameter  $\Upsilon$ . We rely on the relationship between housing price and consumption identified in Berger et al. (2018) to feed the 2007-09 state-level housing price growth in the model. Calibration and estimation of other parameters mostly follow the previous literature, and a summary of resulting parameter values are reported in Appendix Table A.21. We check the validity of the model and parameters by feeding the state-level housing price growth in the model, generate data from the model, and estimate Equation (3.1). As shown in Appendix Table A.17, the estimated model replicates the elasticity of the firm’s local sales growth concerning both the direct and the indirect demand shocks.

Figure 3 shows that the intra-firm spillover effect we identified in the data decreased a substantial amount of the real CPG consumption inequality across states. We plot both the baseline and counterfactual model-generated quality-adjusted CPG consumption per capita across states in Figures 3a and 3b, respectively; Figure 3a allows the intra-firm spillover effect, whereas Figure 3b shuts down the effect. Despite the same level of housing price changes across two different economies, the counterfactual economy features a substantially larger variance of CPG consumption sales growth per capita across states relative to the baseline economy. Under the counterfactual economy, the standard deviation of the CPG consumption growth per capita is 5.21, approximately 29% larger than the standard deviation of 4.03 in the benchmark economy. Using the total consumption, we find the same qualitative results. Appendix Figures A.2 and A.3 additionally compare the cross-sectional dispersion of the *level* of CPG and total consumption, and we find that the standard deviation increases approximately 50% in the counterfactual economy.

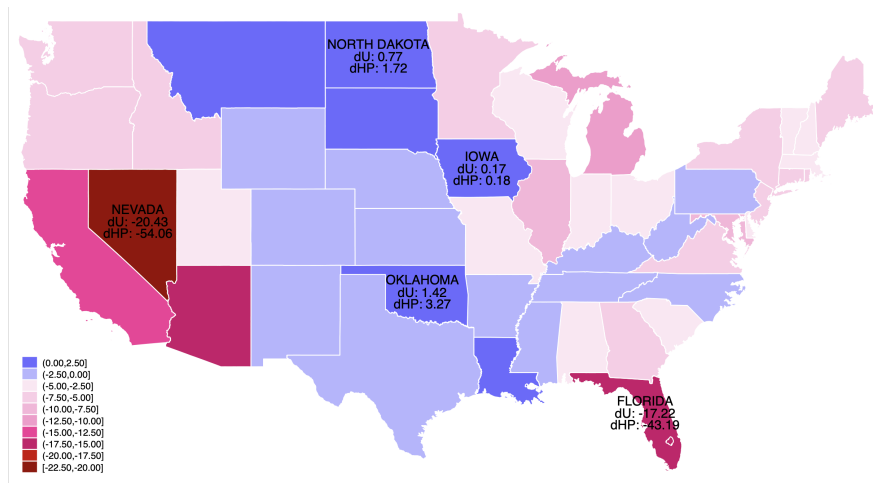
The underlying mechanism behind the consumption redistribution is the intra-firm product quality decision across markets. Firms supply the same product quality to both negatively and positively affected states in the benchmark economy, but in the counterfactual economy, firms offer lower product quality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

**Figure 3: Regional Redistribution across U.S. States**

(a) Benchmark Economy



(b) Counterfactual Economy



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

17.32 percent. The results are similar for total consumption.<sup>35</sup>

<sup>35</sup>Note that the scale effects and the non-homothetic preference effect generate different regional consumption distributive effects. With the homothetic preference, the uniform quality adjustments mitigate the quality-adjusted regional consumption inequality because regions with higher demand face lower product quality than the counterfactual economy, while areas with lower demand enjoy relatively higher product quality. But under non-homothetic preferences, both high-income and low-income markets can experience decreases in real consumption because both regions face the same unfavorable product quality. High-income markets prefer higher product quality, while low-income markets would like to have lower product quality because they are poor. Thus, both types of markets experience additional level effects that lower consumption. However, such level effects do not change the main results. First, the quality-adjusted regional consumption inequality is mainly related to the dispersion of those measures across markets, and the role

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

## 6 Conclusion

This paper studies whether and how multi-market firms spillover regional shocks across U.S. local markets through their intra-firm network with detailed barcode-level data. We find that a firm’s local sales decrease in response to the direct negative local demand shock and more strongly to the indirect adverse local demand shocks, which affect its other markets. We observe a stark asymmetry in this finding: the direct effect works through the continuing products, but the intra-firm spillover effect is mostly attributed to product creation and destruction. To explain the intra-firm spillover effect, we propose the product replacement mechanism: firms that face negative regional demand shock replace their high-valued products with low-valued products, and in doing so, they do it in multiple markets and spillover the shock. We provide empirical supports and formalize the mechanism with a stylized model. Counterfactual analyses reveal that the identified intra-firm spillover serves as a redistributive mechanism and substantially mitigates the regional consumption inequality.

Our work underscores the importance of multi-market, multi-product firm behavior in understanding regional consumption inequality. Integrating the importance of such firms would deepen our understanding of the regional welfare distribution.

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played by the level effects is small. Second, our estimation result assigns a dominant role in the scale effects, and the role of the non-homothetic preferences turns out to be limited.

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## Appendix A Additional Tables

**Table A.1:** Balance Checks

Variable	Firm-level Avg. $\tilde{\Delta}$ HP		
	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.

**Table A.2:** The Direct and the Indirect Effect on Firm's Local Sales Growth

	(1)	(2)	(3)	(4)	(5)
			$\tilde{\Delta}S_{(07-09)}$		
			County-Firm		State-Firm
$\tilde{\Delta}HP_{(07-09)}$	0.059** (0.028)				
$\tilde{\Delta}HP_{(07-09)}$ (other)	0.345*** (0.110)	0.398*** (0.105)			0.303*** (0.113)
$\tilde{\Delta}HP_{(07-09)}$ (other, exclude-plant)			0.384*** (0.091)		
$\tilde{\Delta}HP_{(07-09)}$ (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.* Columns (1) and (2) repeat column (1) and (4) in Table 3. The regression specifications in columns (3)-(4) are the same as what are in Table 3 column (4), where we replace  $\tilde{\Delta}HP_{(07-09)}$  (other) with  $\tilde{\Delta}HP_{(07-09)}$  (other, exclude-plant) and  $\tilde{\Delta}HP_{(07-09)}$  (other, out-of-state).  $\tilde{\Delta}HP_{(07-09)}$  (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.  $\tilde{\Delta}HP_{(07-09)}$  (other, out-of-state) is the initial sales-weighted house price growth between 2007 and 2009 in other counties located in other states. The regression specification in column (5) is the same as what is in Table 3, where we define local market at the state-level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A.3:** Excluding Nearby Regions

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

*Note.* The regression specification is the same as what is in Table 3 column (4).  $\tilde{\Delta}HP_{(07-09)}$  (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),  $\tilde{\Delta}HP_{(07-09)}$  (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). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A.4:** Decomposition of Sales Growth (State level)

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

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

**Table A.5:** Extensive Margin Decomposition (State-level)

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

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

**Table A.6:** Allowing Retailer Dimension: County-Firm (Producer)-Retailer level

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

*Note.*  $\tilde{\Delta}S_{(07-09)}$  is the county-firm-retailer specific sales growth between 2007 and 2009,  $\tilde{\Delta}S_{(07-09)}^R$  is the county-firm-retailer specific sales growth between 2007 and 2009 arising from product replacements,  $\tilde{\Delta}S_{(07-09)}^C$  is the county-firm-retailer specific sales growth between 2007 and 2009 arising from continuing products,  $\tilde{\Delta}HP_{(07-09)}$  (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, and  $\tilde{\Delta}HP_{(07-09)}$  (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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table A.7:** Control Firms' Customer Types

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

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

**Table A.8:** Control Largest Market

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

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

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

	(1)	(2)	(3)	(4)	(5)	(6)
	$\tilde{\Delta}S_{(07-09)}$	$\tilde{\Delta}S_{(07-09)}^R$	$\tilde{\Delta}S_{(07-09)}^C$	$\tilde{\Delta}S_{(07-09)}$	$\tilde{\Delta}S_{(07-09)}^R$	$\tilde{\Delta}S_{(07-09)}^C$
$\tilde{\Delta}HP_{(07-09)}$ (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)
$\tilde{\Delta}S_{(04-06)}$				0.086***		
				(0.009)		
$\tilde{\Delta}S_{(04-06)}^R$					0.100***	
					(0.010)	
$\tilde{\Delta}S_{(04-06)}^C$						-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.  $\tilde{\Delta}S_{(07-09)}$  is the state-firm specific sales growth between 2007 and 2009,  $\tilde{\Delta}S_{(07-09)}^R$  is the state-firm specific sales growth between 2007 and 2009 arising from product replacements,  $\tilde{\Delta}S_{(07-09)}^C$  is the state-firm specific sales growth between 2007 and 2009 arising from continuing products.  $\tilde{\Delta}S_{04-06}$ ,  $\tilde{\Delta}S_{04-06}^R$ , and  $\tilde{\Delta}S_{04-06}^C$  are corresponding growth rates between 2004 and 2006.  $\tilde{\Delta}HP_{(07-09)}$  (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 two-way clustered at the state and sector. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



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

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

*Note.* The regression specification is the same as what is in Table 3 column (4), where we use shift-share robust standard error proposed by [Adao et al. \(2018b\)](#). We use alternative definitions of local markets at either county- or state-level. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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

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

*Note.*  $\tilde{\Delta}S_{(07-09)}$  is the county-firm-product group specific sales growth between 2007 and 2009,  $\tilde{\Delta}S_{(07-09)}^R$  is the county-firm-product group specific sales growth between 2007 and 2009 arising from product replacements,  $\tilde{\Delta}S_{(07-09)}^C$  is the county-firm-product group specific sales growth between 2007 and 2009 arising from continuing products,  $\tilde{\Delta}HP_{(07-09)}$  (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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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

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

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

**Table A.13:** Replacement from High- to Low-value Products: Alternative Price measures

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

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

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

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

*Note.* The regression specification is the same as what is in Table A.11. The measure of value (price) change,  $\tilde{\Delta}v_{rf}$ , is defined as in (4.1). In left panel,  $\tilde{\Delta}\text{Price}_{(07-09)}$  is the county-firm-product group specific price growth at the replacement margin between 2007 and 2009. The simple and weighted price index in columns (1) and (2) are the simple and the sales-weighted geometric price across UPCs within the product module and firm. The simple index is the conventional price index part of the nested CES demand system in Hottman et al. (2016), and the weighted index is used to adjust for the importance of each UPC, as in the Cobb-Douglas utility function. In right panel, price index additionally subtracts the average module price similar to the quality index used in Argente et al. (2018). \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table A.15:** Relationship between  $\gamma_{rt}$  and Log of State Income Level

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln \gamma_{rt}$	$\ln \gamma_{rt}$	$\ln \gamma_{rt}$	$\ln \gamma_{rt}$	$\ln \gamma_{rt}$	$\ln \gamma_{rt}$
$\ln(\text{Income}_{rt})$	0.166*** (0.033)	0.202*** (0.045)	0.147** (0.058)			
$\ln(\text{HP}_{rt})$				0.033** (0.013)	0.089*** (0.022)	0.012 (0.013)
Year Dummy (2009)	0.002 (0.012)	0.002 (0.011)	0.002 (0.002)	0.007 (0.013)	0.016 (0.011)	0.003 (0.003)
Constant	-1.825*** (0.373)	-2.222*** (0.500)	-1.610** (0.650)	-0.381** (0.159)	-1.067*** (0.269)	-0.114 (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.*  $\ln(\text{Income}_{rt})$  is the log of state level average income in year  $t$ , and  $\ln(\text{HP}_{rt})$  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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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

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

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

**Table A.17:** Goodness of Fit: State-Firm level Regression - Data vs. Model

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$	0.159*** (0.051)	0.150*** (0.004)		
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.203* (0.103)	0.191*** (0.021)	0.238*** (0.085)	0.236*** (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. The regression specification is the same as what is in Table 3 column (4), where we define local market at the state-level instead of county. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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

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

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



**Table A.19:** Regional Redistribution across States

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

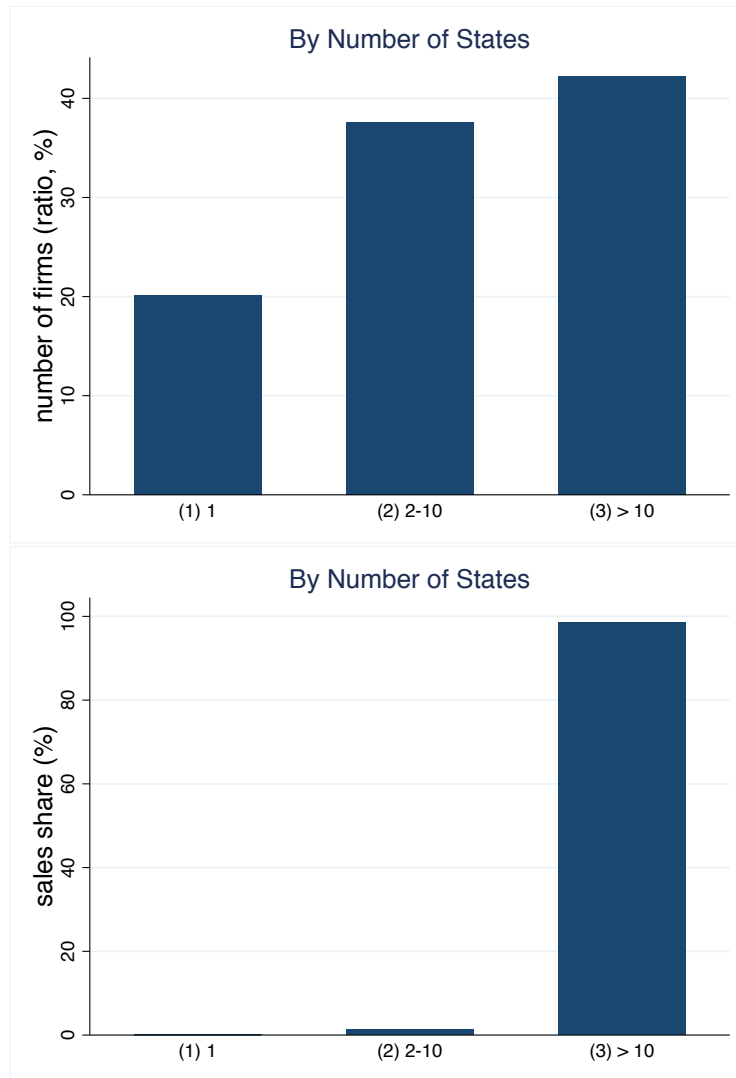
**Table A.20:** Product Creation and Destruction Patterns

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

*Note.* Panel (A) calculates the share of value lost by the destruction of products that is attributed to the products that exited more than 50% (90%) of 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. Consistent with our model calibration, we define local markets at the state-level.

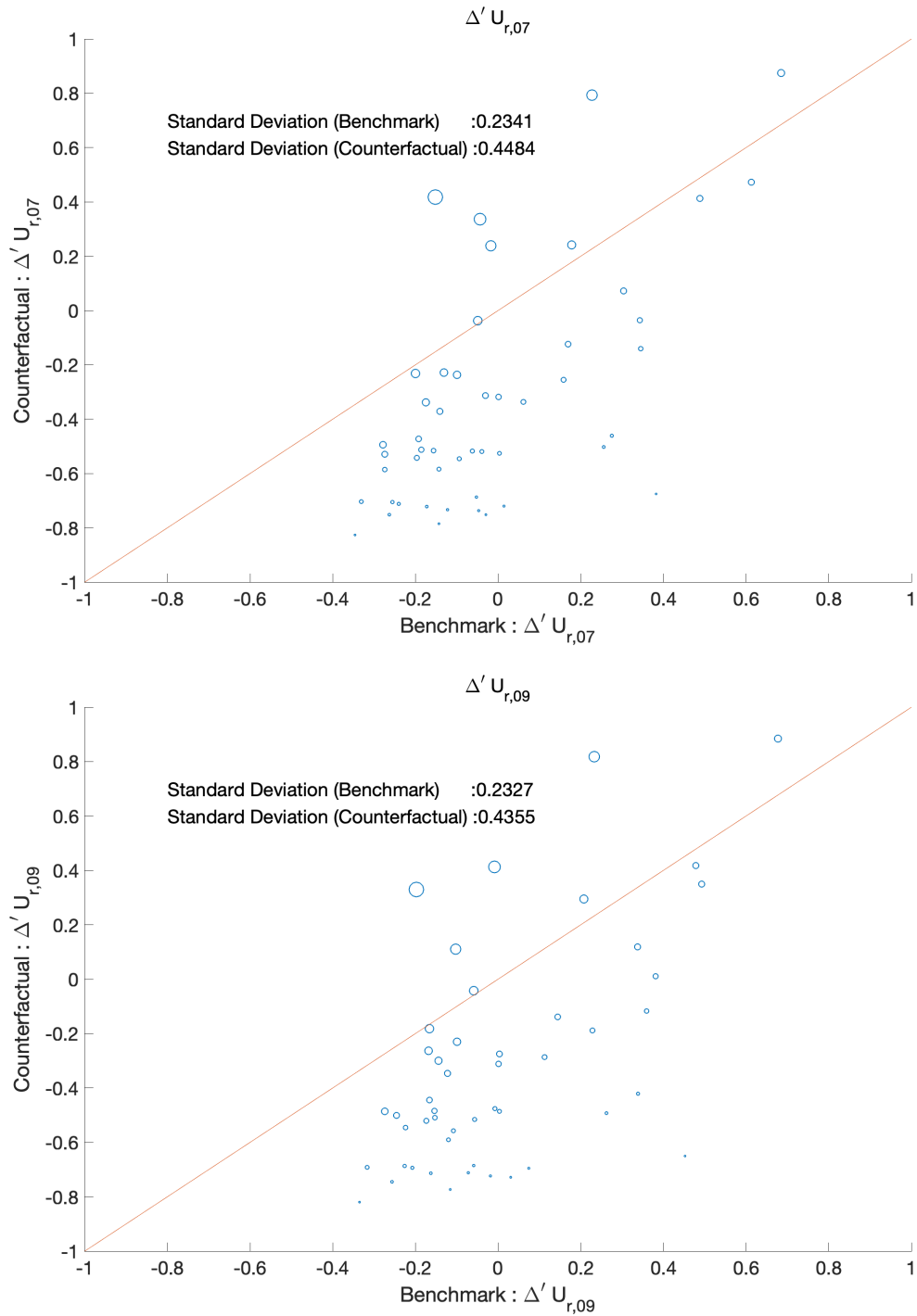
## Appendix B Additional Figures

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



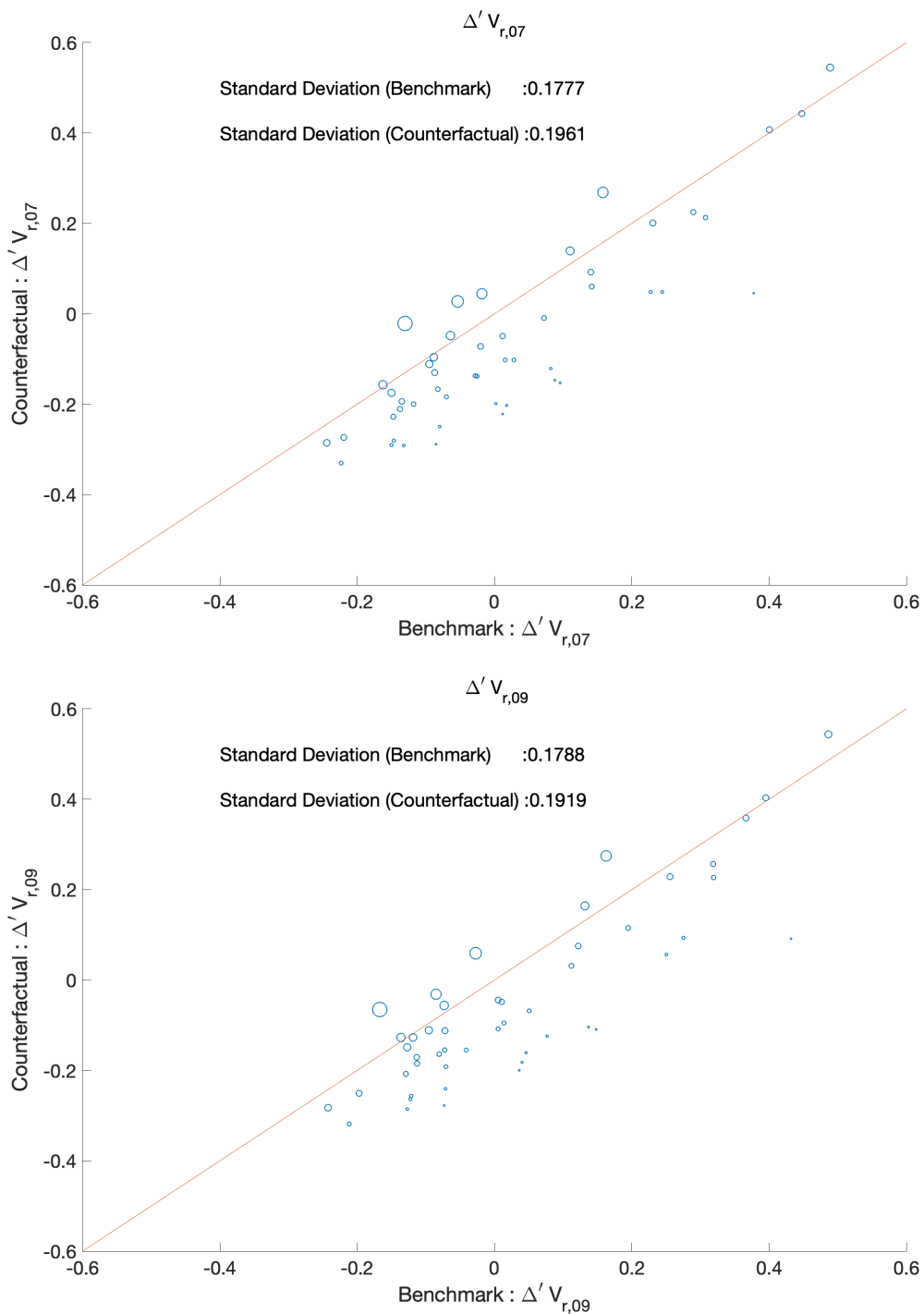
*Note.* Calculation based on ACNielsen Retailer Scanner database combined with GS1 database.

**Figure A.2:** Cross-sectional Dispersion of Regional 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,  $\text{Avg}.U_{r,t}$ , and the reported standard deviations are weighted by state level population.

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



*Note.*  $\Delta' V_{r,t} \equiv (V_{r,t} - \text{Avg}.V_{r,t})/\text{Avg}.V_{r,t}$  measures the cross-sectional dispersion of regional overall welfare at time  $t$ . The 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 Derivation of Optimal Prices and Quality

From the profit function (5.7), we have

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

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

To obtain the first-order conditions with respect to  $p_{rf}$  and  $\phi_f$ , 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 D.3.

### C.1 First-order Conditions in Prices

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

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

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

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

This implies optimal price

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

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

## C.2 First-order Conditions in Quality

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

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

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

By multiplying  $\phi_f$  on both side of the equation, we get

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

By rearranging terms, we get the optimal quality choice

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

### C.3 Structural Equation of Market Interdependency - Derivation

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

Put logarithm in both side of (5.10):

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

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

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

Linearization with respect to the hat-variables 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 defining  $\psi_{r,0} \equiv \gamma_{r,0} - \xi$  and using  $x = x_0 e^{\hat{x}}$ , we get

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

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

$\omega_{rf,0} = \frac{S_{rf,0}}{\sum_{r' \in k_f} S_{r'f,0}}$  becomes the initial sales weight.

Thus, we get

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

The following alternative expression of (C.4) also turns out to be useful when we do estimation:

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

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



## Appendix D Counterfactual: Market-specific Quality Choice

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

### D.1 Price and Quality Choice

We denote market-specific choice of quality by  $\phi_{rf}$ . To distinguish optimal prices under market-specific quality with those under uniform quality, we denote optimal price under market-specific quality by  $p_{rf}^m$ . We denote corresponding quantity, sales, and profit by  $Q_{rf}^m$ ,  $S_{rf}^m$ , and  $\pi_f^m$ . The market-level aggregates are denoted by  $Q_r^m$  and  $S_r^m$ .

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  $\phi_r$  quality of product bundle in market  $r$ , the firm pays fixed costs of  $f^m(\phi_{rf}) + f_{0r}^m$ . We let the term  $f_{0r}^m$  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

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

where we allow fixed cost parameters  $b_m$  and  $\beta_m$  under market-specific quality to have different values from corresponding parameters  $b$  and  $\beta$  under uniform quality.<sup>36</sup>

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

$$\max_{\{\phi_{rf}, p_{rf}^m\}_{r \in k_f}} \pi_f^m = \sum_{r \in k_f} [(p_{rf}^m - mc(\phi_{rf}; a_f)) Q_{rf}^m - f^m(\phi_{rf}) - f_{0r}^m] \quad (\text{D.2})$$

subject to demand condition

$$Q_{rf}^m = \phi_{rf}^{(\sigma-1)\gamma_r} (p_{rf}^m)^{-\sigma} (P_r^m)^{\sigma-1} S_r^m \quad (\text{D.3})$$

We can show that the optimal price is

$$p_{rf}^m = mc(\phi_{rf}; a_f) \times \mu \quad (\text{D.4})$$

---

<sup>36</sup>Only for the cases of  $b_m$  and  $\beta_m$  we use subscript  $m$  instead of superscript to avoid notational confusion with raising power of  $b$  and  $\beta$ .

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

$$\phi_{rf} = \left[ S_{rf}^m \left( \frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m} \quad (\text{D.5})$$

where

$$S_{rf}^m = (\phi_{rf})^{(\sigma-1)\gamma_r} \left( \frac{p_{rf}^m}{P_r^m} \right)^{1-\sigma} S_r^m \quad (\text{D.6})$$

The profit under market-specific quality can be rearranged as

$$\pi_f^m = \sum_{r \in k_f} [(1 - \mu^{-1}) S_{rf}^m - f^m(\phi_{rf}) - f_{0r}^m]$$

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

$$\pi_f^m = \sum_{r \in k_f} \left[ \frac{1}{\sigma} [1 - \beta_m(\sigma - 1)(\gamma_r - \xi)] S_{rf}^m - f_{0r}^m \right] \quad (\text{D.7})$$

The expression of sales of firm  $f$  in market  $r$ ,  $S_{rf}^m$ , is derived using (D.4), (D.5), and (D.6) as

$$S_{rf}^m = \left[ S_{rf}^m \left( \frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m(\sigma-1)(\gamma_r-\xi)} \left[ \frac{\mu}{a_f} \right]^{1-\sigma} (P_r^m)^{\sigma-1} S_r^m \quad (\text{D.8})$$

This implies

$$S_{rf}^m = \left( \frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right)^{\frac{\beta_m(\sigma-1)(\gamma_r-\xi)}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \left[ \frac{\mu}{a_f} \right]^{\frac{1-\sigma}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} [(P_r^m)^{\sigma-1} S_r^m]^{\frac{1}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \quad (\text{D.9})$$

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

$$p_{rf}^m = \left[ S_{rf}^m \left( \frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m \xi} \left[ \frac{\mu}{a_f} \right] \quad (\text{D.10})$$

Note that from (D.9),  $S_{rf}^m = S_{rf'}^m$  if  $a_f = a_{f'}$ . Also, it is clear from (D.9) that  $\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0$  as long as  $\beta_m(\sigma - 1)(\gamma_r - \xi) < 1$ . Also, from (D.5) and (D.10), we have that if  $a_f = a_{f'}$ , then  $\phi_{rf} = \phi_{rf'}$  and  $p_{rf}^m = p_{rf'}^m$ . 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 4.** (*Productivity and Quality, Sales under Market-specific Quality Choice*)

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

$$\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0 \quad (\text{D.11})$$

$$\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0 \quad (\text{D.12})$$

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

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

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

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

*Consider a firm under market-specific quality. Let  $r, r' \in k$  and  $r \neq r'$ . Suppose we shut down general equilibrium adjustments by fixing  $P_r^m$  and  $D_r^m$  (and thus treat  $y_r$  as exogenous). Then,  $\frac{\partial \log S_{rf}^m}{\partial \log y_{r'}} = 0$ ,  $\frac{\partial \log \phi_{rf}}{\partial \log y_{r'}} = 0$ , and  $\frac{\partial \log p_{rf}^m}{\partial \log y_{r'}} = 0$ .*

*Proof.*  $\frac{\partial \log S_{rf}^m}{\partial \log y_{r'}} = 0$  is immediate from (D.9) and the fact that  $\frac{\partial \log P_r^m}{\partial \log y_{r'}} = \frac{\partial \log S_r^m}{\partial \log y_{r'}} = 0$  since we shutting down the general equilibrium effect through  $P_r^m$ .  $\frac{\partial \log \phi_{rf}}{\partial \log y_{r'}} = \frac{\partial \log p_{rf}^m}{\partial \log y_{r'}} = 0$  follows from (D.4) and (D.5) and  $\frac{\partial \log S_{rf}^m}{\partial \log y_{r'}} = 0$ .  $\square$

## Appendix E Parameters Calibration and Estimation

Table A.21: Parameter Values

Parameter	Value	Description	Source
$\tilde{\Upsilon}$	0.62	Elasticity of Local Sales wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$	Own Estimation
$\beta \times \xi$	0.32	Elasticity of Local Price wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$	Own Estimation
$\sigma$	2.20	EoS across Firm's Product Bundle	Faber & Fally (2017)
$\xi$	0.39	Elasticity of Marginal Cost wrt Quality	Derived from Own Estimation
$\beta$	0.81	Elasticity of Fixed Cost wrt Quality	Derived from Own Estimation
$\bar{\gamma}$	1.03	Elasticity of Perceived Quality wrt Quality	Own Estimation
$\delta_2$	0.17	Elasticity of $\gamma$ wrt Income	Own Estimation
$b^{\text{benchmark}}$	1	Fixed Cost Parameter	Normalize
$b^{\text{counterfactual}}$	0.04	Fixed Cost Parameter	Mean Quality = Benchmark Value
$\eta$	1	EoS across CPG and Outside Goods	Cobb-Douglas
$\alpha$	0.20	CPG Share Parameter	CPG share = 0.20 given $\eta$

### E.1 Calibration

Since our empirical results are robust to using state-firm-level variation, as shown in Appendix Table A.2, we define state as a market for the numerical analyses. The state-level analyses reduces computational burden substantially in matching the firm-level spatial network. We include both single-market firms and multi-market firms in our analysis, which yields in total 5186 firms that at most sell in 49 states.

We match  $I_r$  and  $L_r$  in the model using the 2007 state level average income obtained from the American Community Survey data and state population. Each firm's market network  $k_f$  is directly obtained from the data. For the exogenous local demand shock,  $\hat{I}_r$ , we use state level house price growth multiplied by 0.23, which is the consumption elasticity with respect to the house price shock estimated in Berger et al. (2018).<sup>37</sup> Although we utilize house price growth to be consistent with the empirical analyses, using the change in state-level average income does not change the main implications of the model. In this exercise, we abstract away the productivity heterogeneity (i.e.,  $a_f = \bar{a}$ ) since it plays a minor role with the set of balanced firms we consider. Still, for each firm, we

<sup>37</sup>Berger et al. (2018) reports the aggregate consumption elasticity, which might differ from the regional elasticity. At the same time, this number plays a minor role for our analyses because we use this elasticity to re-scale house price growth into income growth, which translates into expenditure growth in the model.

match the sales distribution across states by using the sales per firm in each state.<sup>38</sup>

For the elasticity of substitution parameter  $\eta$  in the upper-tier utility, we impose the limiting case  $\eta \rightarrow 1$  which implies the Cobb-Douglas upper-tier utility function.<sup>39</sup> Using a larger  $\eta$  only strengthens the implication that we find (i.e., it generates stronger mitigation of regional consumption and welfare inequality). We bring in the elasticity of substitution  $\sigma$  from Faber and Fally (2020), which is  $\sigma = 2.2$ . Since the estimate is based on the pooled estimation of the within-module cross-firm elasticity of substitution,  $\sigma$  is interpreted as a proxy of the average within-module elasticity of substitution across firms.<sup>40</sup>

## E.2 Estimation

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

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

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

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

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

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

where  $\Xi_{rft} \equiv \frac{1}{(\sigma-1)} [\Delta' \log S_{rft} - (1 - \sigma) \Delta' \log p_{rft}]$ . Note that the model predicts that the larger the firm size, the greater the product quality, implying that  $\gamma_{rt} \Delta' \log \phi_{ft} > 0$ . This turns out to hold

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<sup>38</sup>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, note that  $S_r \equiv s_r L_r = \Theta_r y_r L_r = \Theta_r I_r \left(1 + \frac{\bar{\Pi}}{\sum_{r \in \mathcal{R}} I_r L_r}\right) L_r$ , where  $\Theta_r$  is the share of CPG goods as described in Online Appendix C. Thus, we have  $I_r L_r = \sum_{f \in G_r} S_{rf} \left[\Theta_r \left(1 + \frac{\bar{\Pi}}{\sum_{r \in \mathcal{R}} I_r L_r}\right)\right]^{-1}$ . Because we use the Cobb-Douglas upper-tier utility in the numerical exercise,  $\Theta_r = \alpha$ , we have  $(I_r L_r) = \sum_{f \in G_r} S_{rf} \times \left[\alpha \left(1 + \frac{\bar{\Pi}}{\sum_{r \in \mathcal{R}} I_r L_r}\right)\right]^{-1}$ . 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  $(I_r L_r) \propto S_r = \sum_{f \in G_r} S_{rf}$ , and that we are directly bringing information  $(I_r L_r)$  and  $N_r$  (number of firms in market  $r$ ) using the data, we are matching the pooled distribution of the ‘‘average state-firm level sales’’ (averaged across firms within a state). More formally, we are matching the distribution of  $\frac{\sum_{f \in G_r} S_{rf}}{N_r}$  across markets.

<sup>39</sup>We set the CPG expenditure share parameter  $\alpha$  to 0.20, which is close to the United States counterpart. This number is calculated based on the BLS report—*Consumer Expenditures in 2007*. We categorize the following major categories as CPG expenditures: Food, Alcoholic beverages, Apparel and services, Personal care products and services, Tobacco products and smoking supplies.

<sup>40</sup>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’’.

with out estimated values.

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

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

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

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

$$\log \gamma_{rt} \equiv \delta_1 + \delta_2 \log I_{rt} \quad (\text{E.3})$$

where  $\delta_2$  governs the strength of the non-homotheticity. It measures the responsiveness of the quality demanded to a change in individuals income in market  $r$ . With the measured  $\log \gamma_{rt}$ , we obtain the predicted  $\log \gamma_{rt}$ , which we denote  $\log \gamma_{rt}^{predict}$ , by regressing  $\log \gamma_{rt}$  on  $\log I_{rt}$  to estimate  $\delta_1$  and  $\delta_2$  in the equation (E.3) and calculating  $\log \gamma_{rt}^{predict} = \hat{\delta}_1 + \hat{\delta}_2 \log I_r$ .

Table A.15 in Appendix A summarizes the estimation result. We use either the log average income or the log house price as a measure of  $\log I_{rt}$ . Broadly, we find a strong positive association between  $\log \gamma_{rt}$  and  $\log I_{rt}$  across different specifications, although directly measuring  $\log I_{rt}$  using the average income yields a clearer association. We use the simplest specification in column (1) as our benchmark, which is a pooled regression across state and year with the inclusion of year fixed effects. The  $\log \gamma_{rt}^{predict}$  obtained from column (1) serves as our measure of  $\log \gamma_{rt}$ , implying that  $\delta_2 = 0.166$ .<sup>41</sup>

## (2) Estimation of $\beta$ and $\xi$

With the measures of  $\gamma_r$  and  $\hat{\gamma}_r$ , we recover the average  $\Upsilon_r, \bar{\Upsilon}$ , by estimating the structural equation (5.11), which is the model counterpart of our reduced-form regression equation (3.1). We estimate the structural equation by instrumenting  $\sum_{r \in k_f} [\omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'}]$  with the indirect demand shock along with the state and industry fixed effects and other various state-firm level controls. Table A.16 in Appendix A presents the result. Column (1) use OLS with the 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. Column (2) use the indirect demand shock as an instrument, and the estimated coefficient is  $\bar{\Upsilon} = 0.618$ , which is our baseline measure.

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<sup>41</sup>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 discrepancy does not pose a problem in our estimation of the structural parameters (e.g.,  $\beta$  and  $\xi$ ) because we instrument  $\sum_{r' \in k_f} [\omega_{r'f,0} \hat{S}_{r'f} + \theta_{r'f,0} \hat{\gamma}_{r'}]$  using the indirect shock  $\tilde{\Delta}HP_{r,f}(\text{other})$ , which is constructed by using the house price growth.

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

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

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

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

which allows us to estimate  $\beta \xi$  by using the indirect demand shock as an instrumental variable, similar to the estimation of the average  $\Upsilon$ . Column (3) of Table A.16 reports an OLS estimate of  $\beta \xi$ , and Column (4) reports the IV estimate of  $\beta \xi = 0.317$ , which is our baseline measure.<sup>42</sup>

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

$$\xi = \frac{\sigma - 1}{\kappa + \sigma - 1} \bar{\gamma} \quad (\text{E.6})$$

obtained by rearranging  $\kappa \equiv \frac{\tilde{\Upsilon}}{\beta \xi} = \frac{\beta(\sigma-1)(\bar{\gamma}-\xi)}{\beta \xi}$ . Since we have values for  $\kappa$ ,  $\sigma$  and  $\bar{\gamma}$  (which is the average  $\gamma_r$  across states), we can recover  $\xi$ .  $\beta$  is recovered using  $\beta = \frac{\beta \xi}{\xi}$ .<sup>43</sup>

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<sup>42</sup>In Table A.18 in Appendix A, we show the estimation result under the assumption that  $\gamma_{rt} = \gamma$  for all  $r$  and  $t$ . This implies homogeneous utility function across regions with homothetic preferences. Under this assumption, (5.11) and (E.5) become  $\hat{S}_{rf} = \Upsilon \left( \sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right) + (\sigma - 1) \hat{a}_f + \hat{A}_r$  and  $\hat{p}_{rf} = \beta \xi \left( \sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right) - \hat{a}_f$ , respectively, where  $\Upsilon \equiv \beta(\sigma - 1)(\gamma - \xi)$  and  $\omega_{rf} \equiv \frac{S_{rf}}{\sum_{r' \in S_{r'f}} S_{r'f}}$  is the initial sales weight. The point estimates of  $\Upsilon$  and  $\beta \xi$  (as well as the precision) are very similar to those in Table A.16 reflecting small variations in  $\left( \sum_{r \in k_f} \theta_{rf} \hat{\gamma}_r \right)$  relative to  $\left( \sum_{r \in k_f} \omega_{rf} \hat{S}_{rf} \right)$  (i.e., the ratio of standard deviations of these variables across firms is .5:100, which partially reflects the fact that  $\hat{\gamma}_r$  does not vary across firms while  $\hat{S}_{rf}$  varies across firms). This implies that the nonhomotheticity plays a limited role under our estimation.

<sup>43</sup>Note that the calculation of the independent variable  $\sum_{r' \in k_f} \left[ \omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'} \right]$  requires knowledge of  $\xi$  because of  $\theta_{rf} \equiv \frac{S_{rf} \gamma_r}{\sum_{r' \in k_f} S_{r'f} (\gamma_{r'} - \xi)}$ . Thus, in practice, we start with a guess value of  $\xi$ , measure  $\sum_{r' \in k_f} \left[ \omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'} \right]$  and run the regression, and then check if (E.6) returns the same value of  $\xi$ .