Spillovers through Multimarket Firms: The Uniform Product Replacement Channel

Appendix: For Online Publication

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A Implications

A.1 Firm-level Returns to Scale

The reduced-form spillover results suggest that most domestic CPG firms feature short-run increasing returns to scale at the firm level conditional on regional shocks, a first-order building block in studying regional shock transmissions.

In particular, previous papers in the trade literature have studied the response of exporters' sales in one market to shocks in other markets, to infer firm-level returns to scale and shock transmission mechanisms. (e.g., Vannoorenberghe 2012; Blum et al. 2013; Berman et al. 2015; Ahn and McQuoid 2017; Kramarz et al. 2020; Almunia et al. 2021). These studies are often motivated by the observation that the workhorse model in trade with firm heterogeneity features constant marginal cost (Melitz, 2003), which does not generate within-firm transmission of regional shocks.

Complementing the aforementioned studies on exporters' returns to scale, our analyses identify the underlying mechanism that generates short-run increasing returns to scale in intranational multimarket firms, thanks to the detailed barcode-level data. We find that negative regional shocks lead firms to significantly decrease their total firm-level sales, as they reduce sales even in unaffected areas. The underlying uniform product replacement can only be identified when we define products at the barcode level, but not under coarser product definitions (Appendix D.5). These findings suggest the need for a richer production function that integrates multi-product firms in studying regional shock transmissions, as well as more granular data to identify the within-firm mechanisms.

A.2 Intrafirm Spillover Mechanisms

The identified uniform product replacement mechanism is a new intrafirm network effect, which is different from the multiplant network effect. This effect could arise in the frictionless economy but generates a persistent spillover effect on local firm sales.

Previous analyses in finance literature have emphasized financial frictions in generating within-entity spillovers (Giroud and Mueller, 2019; Cetorelli and Goldberg, 2012; Gilje et al., 2016; Cortés and Strahan, 2017). Considering within-firm spillovers, these frictions prevent them from making product supply decisions optimally across locations when they face regional shocks, making them decrease their local sales in unaffected regions. On the other hand, our analyses show that such spillover can occur even in a frictionless economy, as shown in Appendix F.2. If the costs of producing and penetrating different products to different markets are high and outweigh the revenue gains from tailoring each product to each market, it is optimal for firms to provide uniform products across markets. In this environment, within-firm spillovers could occur even in the absence of financial frictions. These characteristics heavily rely on the fact that these firms sell their products to multiple markets, not that they produce their products in multiple locations; for example, Giroud and Mueller (2019), who identify within-entity spillovers in multiplant firms, model these spillovers as arising from the difficulty of input allocation across plants due to financial frictions. As in previous studies that distinguish between multiplant and multimarket firms (e.g., Amiti and Heise 2021), our analysis underscores the importance of differentiating among firm types to better understand intrafirm spillover effects: we find no evidence of spillovers through multiplant CPG firms (Appendix E.4), and the identified effect does not arise from within-firm plant networks (Appendix E.7).

Note that the new spillover effect arising from uniform product replacement may generate a more persistent impact on local sales than other channels mediated by local price changes or alternative spillover mechanisms, as it reflects a firm-wide product market decision that cannot easily be reversed due to the high costs of market penetration. Consistent with this intuition, Appendix D.3 shows a stronger long-run spillover effect operating through uniform product replacement, relative to the local effect. This finding suggests that the scarring effect identified at the local level in Bhattarai et al. (2021) may be even stronger when accounting for this spillover channel.

A.3 Regional Household Consumption

A comprehensive understanding of the regional consequences of local shocks requires studying manufacturers (producers) in addition to retailers (distributors). The spillover effects of manufacturers are strong and were larger than conventional local effects during the Great Recession.

Many influential papers pioneered the study of retailer behavior using scanner data and explored its implications for understanding regional household consumption effects (e.g., Cavallo 2017, 2018; DellaVigna and Gentzkow 2019; Adams and Williams 2019; Garcia-Lembergman 2022; Butters et al. 2022; Daruich and Kozlowski 2023). In studying their behavior, producers are typically abstracted away; for example, DellaVigna and Gentzkow (2019) use product fixed effect, which absorbs all the producer-variation, in identifying the retailers' uniform pricing behavior. While retailers are essential in understanding local consumption, Section 3.1 shows that manufacturers could be equally important in the context of generating spillover effects, and Figure OA.6 further highlights that manufacturers (i.e., producers) are more important than retailers in explaining county-by-firm-by-retailer-level sales variations. At the same time, the spillover effect through CPG manufacturers are independent of that of retailers (Section 3.1 and Appendix 3.1).

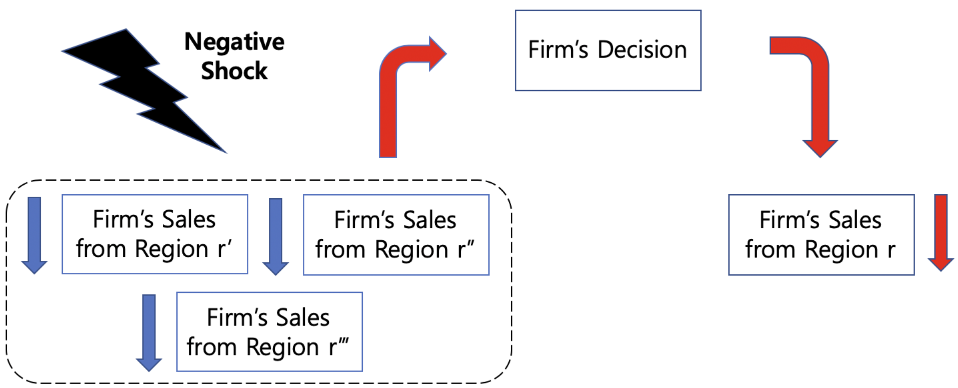
The importance of manufacturers was particularly pronounced during the housing market crisis of the Great Recession. While a large body of literature examines local variations in housing prices during this period (e.g., Mian et al. 2013; Mian and Sufi 2014; Kaplan et al. 2020; Stroebel and Vavra 2019; Giroud and Mueller 2017; Guren et al. 2021), we show that the spillover effect is as large as the local effect identified in previous studies, underscoring the important role of multimarket firms (Table 2). Appendix F.3 further provides a back-of-the-envelope calculation using a model, demonstrating that the spillover effect had a non-trivial impact on regional household consumption during this period.

B Additional Illustrations

B.1 Illustration of the Empirical Results

Figure OA.1: Illustration of the Empirical Results

(a) Reduced-form



(b) Mechanism

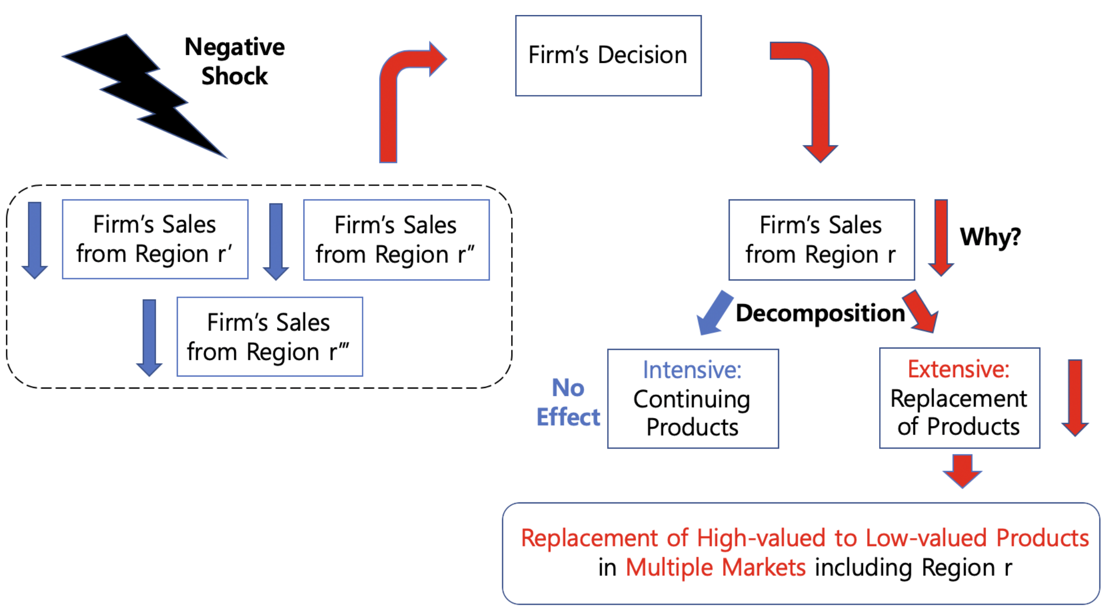


Figure OA.1a illustrates the main reduced-form finding in this paper. Consider a specific multimarket firm that initially sold its products in the local market (region) r and three other markets:

r', r'', and r'''. This paper studies how a negative regional shock, which jointly lowers sales in the three nonlocal markets (r', r'', and r'''), affects local firm sales in region r. Our main findings highlight that a negative demand shock in the nonlocal markets not only lowers firm sales in those markets (r', r'', and r''') but also decreases this firm's local market r sales through its firm-level decision.

Having established the reduced-form spillover effect, we further analyze the mechanism behind the spillover effect. Figure OA.1b illustrates the exact decomposition exercise using the granular barcode data. Our finding highlights that all the spillover effects work through product replacement rather than continuing products. In particular, these products are uniformly replaced across multiple markets, and the entering products have higher values—sales per UPC, price, and organic share—than existing products. These results, along with other results reported in the main body of the paper, support the uniform product replacement mechanism.

B.2 An Example: Kraft Company

(a) Organic Cheese

(b) Nonorganic Cheese

This section provides a concrete example of a multimarket company and its products in our data to illustrate the uniform product replacement channel. Consider Kraft, an American food manufacturing and processing company famous for its cheese products. Our sample shows that it sold two nearly identical products but one with an organic label and the other with a nonorganic label, over the period 2007-2009. In 2007, it sold high-quality, organic, shredded, low-moisture, part-skim mozzarella cheese, which is described in Figure OA.2a. It sold this product at $3.7 on average in 14 states andca 119 counties, including Philadelphia County in Pennsylvania, where housing prices were relatively stable during the crisis, as well as other counties that faced dramatic declines in housing prices, such as Coos County in New Hampshire and Stafford County in Virginia. In 2009, Kraft withdrew this organic cheese in all 119 counties and instead introduced a new lower quality, nonorganic cheese with the same features (shredded, low-moisture, part-skim, mozzarella), which is pictured in Figure OA.2b. It sold this new product at a lower price ($2.4 on average) in all 119 counties, including Philadelphia. As a result, Kraft generated lower sales in Philadelphia than its counterparts that did not lower their product values.

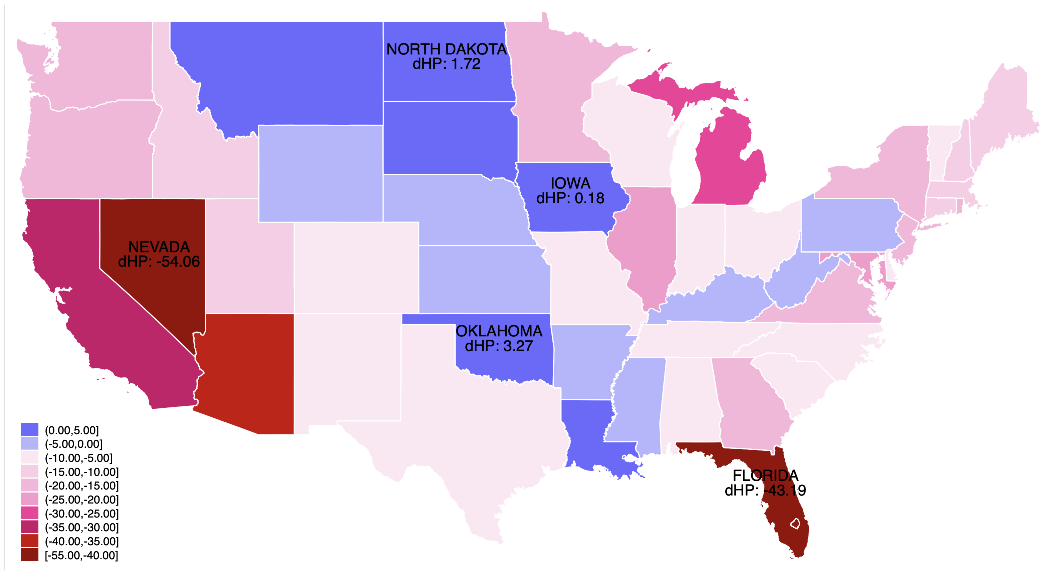
The statement written in its 2009 10-K filing is consistent with what we observe in the data:

> "*Our brands may be challenged to compete against lower-priced private label products, particularly in times of economic downturns. ... Consumers' willingness to purchase our products will depend upon our ability to offer products that appeal to consumers at the right price. ... Furthermore, during periods of economic uncertainty, such as we are currently experiencing, consumers tend to purchase more private label or other economy brands, which could reduce sales volumes of our higher margin products or there could be a shift in our product mix to our lower margin offerings.*"

The Kraft statement indicates that the company faced an economic challenge as households preferred to purchase lower quality products during the Great Recession. In particular, the company indicates that demand conditions depend on its ability to supply the right products at the proper price (*"Consumers' willingness to purchase our products will depend upon our ability to offer products that appeal to consumers at the right price"*), suggesting that this company may lower their product price and quality to meet household demand in this period.

The narrative of the Kraft company suggests the existence of uniform product replacement behavior: Firms pay close attention to changing demand conditions and adjust their product mix to meet firm-level demand and supply conditions.

Figure OA.3: Differential Changes in Housing Prices



Note. Figure OA.3 plots housing price growth rate across states using the Zillow data.

B.3 Differential Changes in Housing Prices

Figure OA.3 visualizes a sharp differential decline in housing prices across regions in 2007-2009 in the United States, as documented in previous literature. States such as Nevada and Florida experienced a large decrease in housing prices, whereas states such as Oklahoma and North Dakota experienced a mild increase in housing prices. These large variations in housing price growth help identify the spillover effect through multimarket firms. This section utilizes housing price growth at the state level to visualize the variation compactly and to be consistent with the regional analyses documented in Appendix G.3. Note that our empirical results are robust to using state-level variation, as shown in Appendices E.3 and E.11.

B.4 Top 30 Sectors in the data

Table OA.1 lists the top 30 sectors in the final sample based on the major 4-digit SIC sector code associated with each firm. Since our data utilize the Nielsen Retail Scanner data, most firms in the sample mainly produce consumer packaged goods (CPG).

Table OA.1: Sector List (Top 30)

	SIC 4-digit	Description
1	2841	Soap and other detergents
2	2043	Cereal breakfast foods
3	2022	Cheese; natural and processed
4	2099	Food preparations, nec
5	2032	Canned specialties
6	2844	Toilet preparations
7	2842	Polishes and sanitation goods
8	2033	Canned fruits and specialties
9	2053	Frozen bakery products, except bread
10	2066	Chocolate and cocoa products
11	2086	Bottled and canned soft drinks
12	2026	Fluid milk
13	2011	Meat packing plants
14	2051	Bread, cake, and related products
15	2084	Wines, brandy, and brandy spirits
16	2082	Malt beverages
17	2621	Paper mills
18	2024	Ice cream and frozen deserts
19	2038	Frozen specialties, nec
20	2834	Pharmaceutical preparations
21	3634	Electric housewares and fans
22	2085	Distilled and blended liquors
23	5148	Fresh fruits and vegetables
24	3841	Surgical and medical instruments
25	5182	Wine and distilled beverages
26	5149	Groceries and related products, nec
27	2047	Dog and cat food
28	2035	Pickles, sauces, and salad dressings
29	2091	Canned and cured fish and seafoods
30	2013	Sausages and other prepared meats

Note. This table lists the top 30 4-digit SIC sectors. The ranking is based on the number of firms in each sector.

C Additional Data Description

C.1 Data and Merging Procedure

As described in Section 2, our dataset combines barcode-region-level prices and quantities from the ACNielsen Retail Scanner database augmented with GS1, firm- and establishment-level information from the National Establishment Time-Series (NETS) database, and house price information (at the county and state level) from the Zillow database. We describe each dataset and the merging procedure below.

ACNielsen Retail Scanner. The ACNielsen Retail Scanner database, which was made available by the Kilts Marketing Data Center at the University of Chicago Booth School of Business, consists of weekly pricing, volume, and store merchandising conditions generated by participating retail stores' point-of-sale systems in all US markets. The data contain approximately 2.6 million barcode-level product prices and quantities recorded weekly from approximately 35,000 participating grocery, drug, mass merchandise, convenience, and liquor stores in all US markets. A barcode is a unique universal product code (UPC) assigned to each product and is used to scan and store product information. Participating retail stores use point-of-sale systems that record information whenever product barcodes are scanned to be purchased.

The data begin in 2006 and end in 2015, covering the period of a collapse in house prices during the Great Recession. The dataset mainly includes consumer packaged goods (CPG), such as food, nonfood grocery items, health and beauty aids, and general merchandise. According to Nielsen, the Retail Scanner database covers more than half the total sales volume of US grocery and drug stores and more than 30 percent of all US mass merchandiser sales volume.

The data allow us to identify the location of each barcode purchase up to the 3-digit zip code level through the store location information. We use the county as the baseline definition of a local market. For each barcode in each county, we calculate the total sales, quantity, and price for each product purchased by households.

To identify the producer of each barcode, we integrate the prices and quantities of each product (UPC) using the GS1 US Data Hub. GS1 is the company that issues barcodes to producers.[1] GS1 records the producer name and address together with the producer identifier (gs1prefix) for each

[1] GS1 provides a business with up to 10 barcodes for a $250 initial membership fee and a $50 annual fee. There are significant discounts in the cost per barcode for firms purchasing larger quantities of barcodes (see http://www.gs1us.org/get-started/im-new-to-gs1-us).

barcode-level product. Using the producer identifier, we calculate county-producer level sales by aggregating county-barcode sales by each producer (i.e., firm). We use the gs1prefix as our baseline firm identifier. For further details on the ACNielsen database, refer to Broda and Weinstein (2010) and Hottman et al. (2016).

National Establishment Time-Series (NETS). We integrate the prices and quantities of each product with its producer's establishment-level information using the NETS database. NETS is a US establishment-level longitudinal database made available by Walls & Associates. The original source of the data is Dun and Bradstreet (D&B) archival data, which are collected primarily for marketing and credit scoring. The data contain annual establishment-level information, where each establishment has a unique identifier (duns). The data provide the domestic headquarters identifier (hqduns) for each establishment. We restrict the sample to establishments for which a headquarters existed in 2006.

The data provide establishment-level information such as location, primary industry code (SIC), and D&B credit and payment rating in 1990-2014.[2] We use this information to compare firms having the same primary industry code, investigate the mechanism behind the spillover results by analyzing heterogeneous treatment effects, and address concerns related to supply-side or collateral channels.[3] For a more detailed discussion of the NETS data, see, e.g., (Neumark et al., 2011), Barnatchez et al. (2017), Rossi-Hansberg et al. (2018), and Asquith et al. (2019).

Zillow. To measure county-level house prices, we use the end-of-period Zillow Home Value Index (ZHVI) from 2007 to 2009. These are available for 1,065 counties, covering 77% of the total US population. Similarly, state-level house prices are available for 51 states.[4] We supplement county-level house prices with housing supply elasticity from Saiz (2010) as well as various county-level demographic and industry composition information from Mian and Sufi (2014).

[2]Often, nonheadquarters establishments' credit ratings are missing, while headquarters' credit ratings are available. Thus, we use the headquarters' credit rating to measure a firm's credit rating. Similarly, we use the headquarters industry code to measure firms' primary industry code. The results are not sensitive to alternative ways of defining a firm's primary industry code, such as the SIC of the largest establishment within the firm.

[3]The data also contain information on establishment-level employment. However, according to Barnatchez et al. (2017), the NETS dataset is useful for studying cross-sectional business activities, while there are some limitations to studying business dynamics. Thus, we only use cross-sectional prerecession establishment location information, credit rating, and primary industry code for the analyses and abstain from exploiting the dynamic perspective of the data.

[4]See http://www.zillow.com/research/data for an overview of the ZHVI methodology and a comparison with the S&P/Case-Shiller Home Price Index.For references using the Zillow database, see, e.g., Giroud and Mueller (2017) and Giroud and Mueller (2019).

Linking GS1 and NETS. We use a company name, state, city, zip code, and additional address (e.g., street and building) to link GS1 and the NETS. We use gs1prefix and hqduns as firm identifiers of the GS1 and the NETS, respectively. We link gs1prefix and hqduns using the RECLINK2 command that performs probabilistic record linkage across datasets with no common identifier.[5] The application of RECLINK2 consists of two steps: (i) standardizing company names and addresses and (ii) matching. After standardizing company names and addresses, we match the two datasets based on the criteria below. In general, we choose a conservative procedure in an effort to minimize incorrect matches (i.e., reduce false positives) to be confident that the matched results are correct. Nevertheless, we confirm that the results are robust to using the total sample without NETS data, as shown in Appendix E.12.

1. If either the GS1 or the NETS does not provide any address-related information (including state, city, zip code, street/building), we match only based on the standardized company names (`stn_name`).

2. If address-related information is available, we use both name (`stn_name`) and addresses (`state`, `city`, `zipcode`, `add1`), where `add1` is the standardized address regarding street/building. The corresponding weights we use in the RECLINK2 command are WMATCH(10 1 2 5 8) and WNOMATCH(10 8 5 2 1).

    ⋆ During procedures 1 and 2, we require the match of the two datasets to have identical standardized company names (`stn_name`).

3. After combining the results of procedures 2 and 3, we require the link probability (`rlsc`) to exceed 0.8 and the match to have an identical standardized entity type (`entitytype`).

There are 25,618 firms (gs1prefix) that had positive sales in 2007, among which 24,876 have positive sales in counties where the house price variables are available. Of these, 22,317 are multimarket firms. Among these firms, 5,402 are matched with hqduns, and they cover approximately 40% of total ACNielsen sales.[6] Finally, by dropping singleton observations while running a fixed effect regression with industry-by-county fixed effects, the final sample contains 4,171 firms, 991 counties, and 840,681 observations as reported in Table OA.2.

[5]See Wasi and Flaaen (2015) for a detailed illustration of RECLINK2.

[6]The NETS data do not cover the universe of business in the US, and accordingly, a number of firms (especially very small firms) are dropped during the merging process.

C.2 Summary Statistics

Table OA.2 presents the mean and dispersion of the main variables in the final sample. In general, there is large variation in sales growth and housing price growth across counties and firms, ensuring the empirical investigation of the spillover effects. The variation in the indirect shock ($\tilde{\Delta}\text{HP}_{cf}$ (other)) arises from both substantial differences across firms in their initial sales share ($\omega_{cf,07}$) across counties, as illustrated in Figure 2, and the large dissimilarity in local house price growth ($\tilde{\Delta}\text{HP}_{c,07-09}$) across these counties. Note that the reported initial sales shares, which measure the importance of each market for a given firm, are small because these firms sell in many markets. The median value is less than 0.06%, and even at the 95% percentile, the sales share is less than 1.3%. The small local sales share, together with the large number of markets per firm presented in Table 1, suggests that local housing price growth is less likely to be important for firm-level decisions than the indirect shock.

The exact decomposition of sales growth supports the uniform product replacement pattern emphasized throughout this paper: When firms generate sales by replacing products, they do so across multiple markets. Decomposing the extensive margin of sales growth ($\tilde{\Delta}\text{S}^{\text{R}}_{cf}$) into those products that are replaced across multiple markets ($\tilde{\Delta}\text{S}^{\text{R,M}}_{cf}$) and in a single local market ($\tilde{\Delta}\text{S}^{\text{R,L}}_{cf}$), we find that almost all the sales growth is attributed to those products replaced across multiple markets. Further decomposing these margins into entry and exit shows a consistent empirical pattern. Comparing the mean values, more than 99.9% of the entering (15.691/15.693) or exiting (8.895/8.899) sales are generated from products that uniformly enter or exit across multiple markets, and a negligible number of products enter and exit in only one local market. Another fact from the exact sales decomposition of sales growth is that the sales of continuing products are much larger than the sales of entering and exiting products in general. For example, considering local-firm sales in 2007, approximately 86.4% of average sales (56.524/65.423) were generated from those products that continued in 2009, and only the remaining 13.6% of average sales (15.693/65.423) arose from those products that exited in 2009. Despite such a seemingly small role of the entering and exiting products, Section 3 shows that all the spillover effects work through uniform product replacement across markets. The empirical patterns reported in Table OA.2 are similar when the state is defined as the market, as shown in Appendix C.2. Appendix C.2 also reports the summary statistics of product value, quality, and variety changes across entering and exiting products, and Appendix B.4 reports the top 30 major sectors in the final sample.

Table OA.3 reports the summary statistics for the state-firm-level analyses and confirms the general empirical pattern documented in the main body of the paper. Similar to what is reported in

Table OA.2: Summary Statistics: Main Variables

Variable	Obs	Mean	Std. Dev.	P5	P50	P95
$\tilde{\Delta}\text{S}_{cf}$	840,681	-.041	.799	-1.633	.017	1.348
$\tilde{\Delta}\text{S}^{\text{C}}_{cf}$	840,681	-.061	.543	-1.039	-.037	.816
$\tilde{\Delta}\text{S}^{\text{R}}_{cf}$	840,681	.021	.53	-.96	0	.938
$\tilde{\Delta}\text{S}^{\text{R,M}}_{cf}$	840,681	.021	.529	-.959	0	.937
$\tilde{\Delta}\text{S}^{\text{R,L}}_{cf}$	840,681	0	.017	0	0	0
$\text{S}_{cf,07}$	840,681	65.423	739.854	.046	2.346	187.296
$\text{S}^{\text{cont}}_{cf,07}$	840,681	56.524	631.472	.026	1.639	162.015
$\text{S}^{\text{exit}}_{cf,07}$	840,681	8.899	129.795	0	.197	22.431
$\text{S}^{\text{exit,multiple}}_{cf,07}$	840681	8.895	129.774	0	.196	22.418
$\text{S}^{\text{exit,local}}_{cf,07}$	840681	.004	.544	0	0	0
$\text{S}_{cf,09}$	840,681	68.068	768.49	.024	2.347	198.201
$\text{S}^{\text{cont}}_{cf,09}$	840,681	52.375	528.692	.013	1.475	154.278
$\text{S}^{\text{enter}}_{cf,09}$	840,681	15.693	283.807	0	.216	39.505
$\text{S}^{\text{enter,multiple}}_{cf,09}$	840,681	15.691	283.805	0	.215	39.497
$\text{S}^{\text{enter,local}}_{cf,09}$	840,681	.002	.193	0	0	0
$\tilde{\Delta}\text{HP}_{cf}$ (other)	840,681	-.169	.042	-.239	-.17	-.104
$\text{elasticity}_{\text{cf}}$ (other)	452,162	1.713	.306	1.228	1.702	2.224
$\text{sensitivity}_{\text{cf}}$ (other)	592,176	.998	.122	.801	1.006	1.165
$\text{lending}_{\text{cf}}$ (other)	664,049	-.427	.026	-.47	-.427	-.387
$\omega_{cf,07}$ (in %)	840,681	.411	2.484	.002	.058	1.235
$\tilde{\Delta}\text{HP}_c$	991	-.092	.138	-.345	-.079	.105
$\tilde{\Delta}\text{HP}_f$	4,171	-.161	.087	-.329	-.156	-.03

Note. The subscript c denotes county and f denotes firm. S is sales, HP is housing price, and $\tilde{\Delta}$ stands for the Davis et al. (1996) growth rate from 2007 to 2009. $\tilde{\Delta}\text{HP}_c$ is the county-level housing price growth, $\tilde{\Delta}\text{HP}_f \equiv \sum_c \omega_{cf} \times \tilde{\Delta}\text{HP}_c$ is the firm-level housing price growth, which is the weighted average of county-level housing price growth, and $\tilde{\Delta}\text{HP}_{cf}$ (other) is the indirect shock defined in Equation (2.5). Sales growth ($\tilde{\Delta}\text{Sale}_{cf}$) is exactly decomposed into the growth in continuing products ($\tilde{\Delta}\text{Sale}^{\text{C}}_{cf}$) and the growth due to product replacement ($\tilde{\Delta}\text{Sale}^{\text{R}}_{cf}$), as shown in Equation (2.2). The growth due to product replacement is further decomposed into global product replacement ($\tilde{\Delta}\text{Sale}^{\text{R,M}}_{cf}$) and local product replacement ($\tilde{\Delta}\text{Sale}^{\text{R,L}}_{cf}$), as shown in Equation (2.3). Sales in 2007 ($\text{Sale}_{f,07}$) are decomposed into sales of products that are available in 2009 ($\text{S}^{\text{cont}}_{cf,07}$) and that exit in 2009 ($\text{S}^{\text{exit}}_{cf,07}$). Similarly, sales in 2009 ($\text{S}_{cf,09}$) are decomposed into sales of products that are available in 2007 ($\text{S}^{\text{cont}}_{cf,09}$) and that newly enter in 2009 ($\text{S}^{\text{enter}}_{cf,09}$). The $\text{elasticity}_{\text{cf}}$ (other), $\text{sensitivity}_{\text{cf}}$ (other), and $\text{lending}_{\text{cf}}$ (other) are the leave-one-out lagged share-weighted average of the regional Saiz (2010) elasticity, Guren et al. (2021) sensitivity estimates, and García (2018) nonlocal mortgage lending shock, respectively. All sales variables are in thousands of US dollars, and $\omega_{cf,07}$ is in percent.

Table OA.2 at the county-firm level, the exact decomposition of the sales growth shows that uniform product replacement across multiple states dominates extensive margin growth. Again, considering the mean, more than 99.9% of the entering (175.034/175.495) or exiting (57.903/58.273) sales are generated from products that uniformly enter or exit across multiple markets. Additionally, most of the sales are generated from the intensive margin, but the extensive margin still plays a critical role in generating the spillover, as reported in Appendix E.3. Lastly, we also observe large variations in sales growth and housing price growth. See Appendix B.3 for the visualization of the differential housing price growth across states.

Table OA.3: Summary Statistics: Main Variables, at the State-Firm level

Variable	Obs	Mean	Std. Dev.	P5	P50	P95
$\tilde{\Delta}S_{sf,07-09}$	83,610	-.142	.942	-1.923	-.016	1.521
$\tilde{\Delta}S^{C}_{sf,07-09}$	83,610	-.188	.696	-1.603	-.098	.913
$\tilde{\Delta}S^{R}_{sf,07-09}$	83,610	.046	.558	-1.006	0	1.043
$\tilde{\Delta}S^{R,M}_{sf,07-09}$	83,610	.047	.546	-.969	0	1.019
$\tilde{\Delta}S^{R,L}_{sf,07-09}$	83,610	-.001	.09	-.003	0	.002
$S_{sf,07}$	83,610	772.657	7263.43	.104	19.302	2265.452
$S^{cont}_{sf,07}$	83,610	714.384	6683.584	.059	14.906	2096.945
$S^{exit}_{sf,07}$	83,610	58.273	702.309	0	.464	146.443
$S^{exit,multiple}_{sf,07}$	83,610	57.903	701.34	0	.408	145.044
$S^{exit,local}_{sf,07}$	83,610	.37	13.617	0	0	.228
$S_{sf,09}$	83,610	808.711	7552.271	.018	18.027	2410.263
$S^{cont}_{sf,09}$	83,610	633.216	5295.794	.01	10.895	1936.866
$S^{enter}_{sf,09}$	83,610	175.495	2634.26	0	.661	436.943
$S^{enter,multiple}_{sf,09}$	83,610	175.034	2633.954	0	.591	434.662
$S^{enter,local}_{sf,09}$	83,610	.461	13.497	0	0	.143
$\tilde{\Delta}HP_{sf,07-09}$ (other)	83,610	-.168	.05	-.255	-.169	-.088
$\omega_{sf,07}$ (in %)	83,610	4.553	11.764	.04	1.232	18.312
$\tilde{\Delta}HP_{f,07-09}$	3,893	-.162	.076	-.308	-.16	-.05
$\tilde{\Delta}HP_{s,07-09}$	49	-.117	.117	-.381	-.084	.013

Note. Table OA.3 replicates Table OA.2 by using the state-firm level data instead of county-firm level data. All sales variables are in millions of US dollars.

Finally, Table OA.4 reports the changes in barcode-level product price, quality, and variety used in Table 5. In general, there is a large change in these margins across firms and counties.

Table OA.4: Summary Statistics: Changes in Price, Quality, Variety

Variable	Obs	Mean	Std. Dev.	P5	P50	P95
$\tilde{\Delta}$ S per UPC	486,765	.112	.379	-.474	.096	.749
$\tilde{\Delta}$ Price (simple)	484,200	.222	1.169	-1.246	.176	1.771
$\tilde{\Delta}$ Price (weight)	484,200	.162	1.218	-1.414	.127	1.807
$\tilde{\Delta}$ Price (weight, d)	484,200	.106	.823	-1.039	.082	1.296
$\tilde{\Delta}$ Organic (sale)	38,169	-.105	1.222	-2	0	2
$\tilde{\Delta}$ Organic (number)	38,169	-.118	1.211	-2	0	2
$\tilde{\Delta}$ N_{cf}	840,681	-.046	.527	-1	0	.857

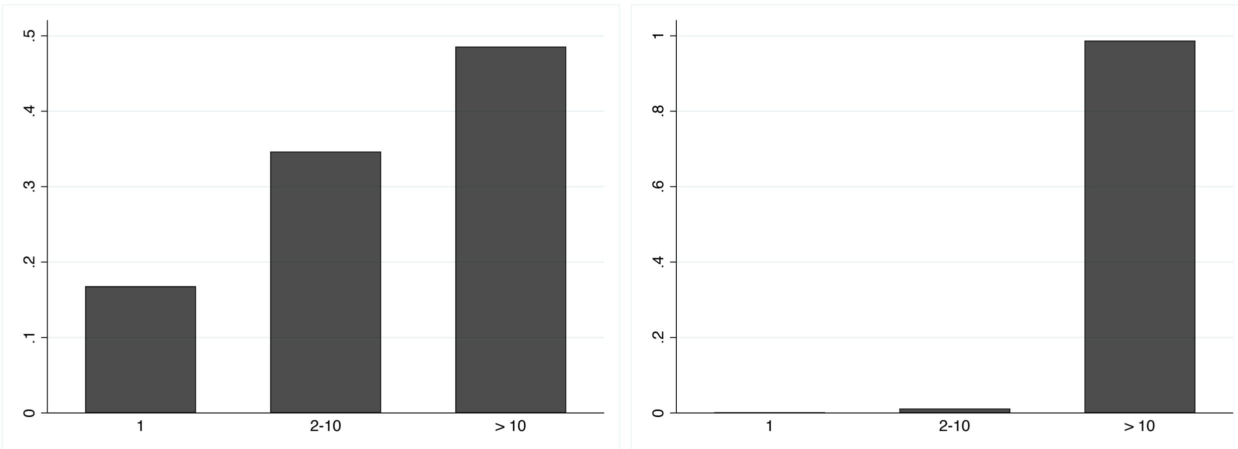
Note. Table OA.4 provides summary statistics of changes in price, quality, variety across entering and exiting products used in Table 5.

C.3 The Prevalence and Importance of Multi-market Firms

Figure OA.4 confirms the importance and prevalence of multimarket firms when the market is defined with a state. Regardless of using a broader definition of the market, multimarket firms account for more than 90% of the total number of firms and total sales. Appendix E.3 confirms that the spillover results are robust to using a state as the definition of a market.

Similarly, Figure OA.5 confirms the importance and prevalence of multimarket firms by using the Nielsen and GS1 combined sample. Even in this broader sample, we still observe that multimarket firms account for more than 90% of the total sales and the total number of firms. Appendix E.12 confirms that the spillover results are robust to using a Nielsen and GS1 combined sample.

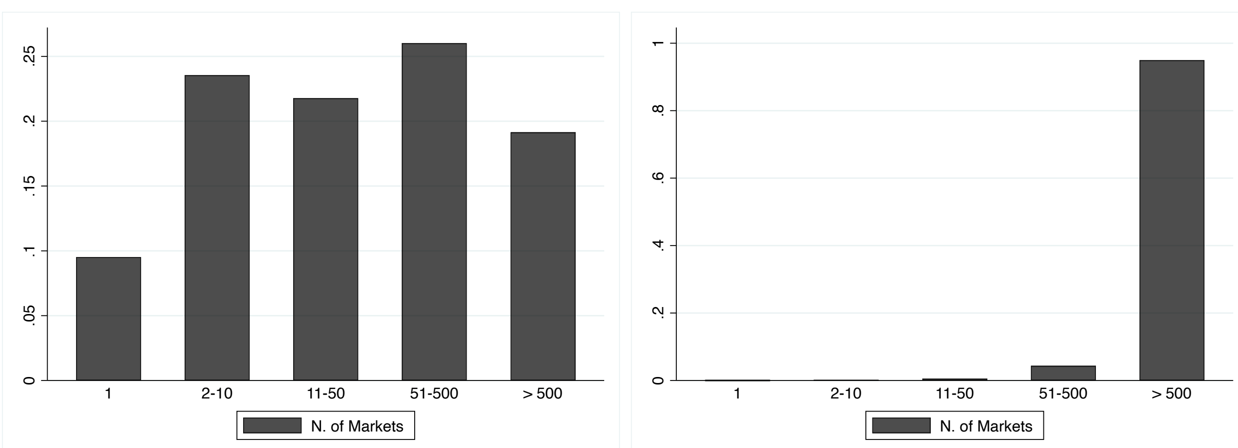
Figure OA.4: Extensive Margin: Market defined as State



(a) Number of Firms (share, %) **(b)** Sales of Firms (share, %)

Note. Figure OA.4 plots the distribution of 5,597 firms that have nonmissing sales and number of plants information in the ACNielsen and NETS combined data. We categorize these firms into three different groups based on the number of markets (states). "1" on the X-axis denotes a single market firm, "2-10" denotes firms that sell to 2 to 10 markets, and "> 10" denotes firms that sell to 11 to 49 markets. Note that the largest number of markets (states) in this sample is 49 since we do not have Alaska and Hawaii and include the District of Columbia as a separate market. Figure 1a shows the ratio of the number of firms in each group to the total number of firms in the sample, and Figure 1b shows the sales share of the firms in each group.

Figure OA.5: Extensive Margin: Using ACNielsen + GS1 Sample



(a) Number of Firms (share, %) **(b)** Sales of Firms (share, %)

Note. Figure OA.5 replicates Figure 1 by using 25,618 firms that have nonmissing sales information in the ACNielsen + GS1 combined data.

D Additional Empirical Analyses

D.1 Instrumental Variables: First-Stage Regression

Table OA.5 presents the first-stage regression results for the three instrumental variables—housing supply elasticity, housing sensitivity estimate, and nonlocal lender shock—used in Section 3. Regardless of including or excluding control variables, all three instrumental variables are highly relevant for the main independent variable used in the paper. This analysis confirms previous studies, which use these instruments and document similar relationships in the shift-share regression setup.

Table OA.5: First-Stage Regression Results

	$\tilde{\Delta}\text{HP}_{cf}$ (other)					
	(1)	(2)	(3)	(4)	(5)	(6)
elasticity_{cf} (other)	0.098***	0.096***				
	(0.008)	(0.004)				
sensitivity_{cf} (other)			-0.218***	-0.214***		
			(0.019)	(0.014)		
lending_{cf} (other)					1.423***	1.383***
					(0.082)	(0.060)
County-Firm Controls		✓		✓		✓
County x Sector 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 elasticity_{cf} (other), sensitivity_{cf} (other), and lending_{cf} (other) are the leave-one-out lagged share-weighted average of the regional Saiz (2010) elasticity, Guren et al. (2021) sensitivity estimates, and García (2018) nonlocal mortgage lending shock, respectively. Sector is the 4-digit SIC code. County-firm controls are the initial log of county-firm sales, firm sales, and a firm's number of markets and product groups. $\tilde{\Delta}\text{HP}_{cf}$ (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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 Venting Out Surplus Mechanism

Our reduced-form results may look surprising given the recent influential paper by Almunia et al. (2021). They show that Spanish exporters facing a negative demand shock from Spain during the crisis *increase* their sales in their foreign markets by venting out their surplus, in contrast to our reduced-form empirical results. The uniform product replacement channel emphasized in our paper explains why we find the opposite results. For the multimarket firms to spill over the shocks through product replacement, they must initially sell the same barcode-level products across multiple markets; in our analyses, all the spillover effects arise from the products that are sold in multiple markets. Although we expect our results to apply to a set of countries that likely share many of the same barcode-level products, such as the North American Free Trade Agreement (NAFTA), we don't expect firms to sell the same barcode-level products across countries in general. Due to the vastly different customer characteristics, our model in Section F anticipates most of the international firms to tailor their products to each country since the resulting revenue gains would be larger than the costs of offering different products across countries. Evidence reported in Table 6 panel A columns (7) and (8) provides empirical support for this reasoning.

Without uniform products across markets, exporters would only be able to spill over the shock by changing the quantity of continuing products, which depends on their short-run returns to scale on quantity production. With short-run decreasing returns to scale technology, exporters that face a negative demand shock in one market raise their sales in the other market through the continuing products, consistent with the venting out surplus mechanism. One way to test the short-run decreasing returns to quantity for exporters is to extract exporters in our sample and test whether these firms *raise* their continuing product sales when they face the negative indirect demand shock. Correspondingly, we divide the sample of firms into exporters and nonexporters. For each sample of firms, we conduct the same spillover regression analyses and the corresponding decomposition exercise reported in Tables 2 and 4. This analysis uses the most conservative specification where we allow county times sector fixed effects.

Table OA.6 presents the results. Columns (1)-(3) replicate the main analyses, and the other columns do the same analyses by dividing the sample into exporters and nonexporters. The spillover effect becomes weaker for exporters based on column (4), and this is because the positive sales growth due to product replacement is partially canceled out by the negative sales growth arising from continuing products. The result focusing on the continuing products reported in column (5) is fully consistent with the venting-out surplus mechanism, which theoretically arises from the decreasing returns firms face in producing larger quantities per given product. On the other hand, the results based on nonexporters, reported in columns (7)-(9), show a similar empirical pattern as in our main results reported in columns (1)-(3). These purely domestic firms still spill over the demand changes by replacing products, and there is no significant effect arising from the continuing products at the conventional level of statistical significance.[7]

[7]There is a question of why domestic firms do not vent out their surplus like exporters. These domestic firms are not

Table OA.6: Exporters vs. Nonexporters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total			Exporter			Non-exporter		
	$\tilde{\Delta}S_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$	$\tilde{\Delta}S_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$	$\tilde{\Delta}S_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$
$\tilde{\Delta}HP_{cf}$ (other)	0.40***	-0.02	0.42***	0.15	-0.25***	0.41***	0.52***	0.13	0.38***
	(0.10)	(0.05)	(0.10)	(0.14)	(0.07)	(0.15)	(0.17)	(0.11)	(0.04)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.39	0.43	0.41	0.47	0.47	0.46	0.44	0.51	0.47
Observations	840,681	840,681	840,681	314,993	314,993	314,993	481,946	481,946	481946

Note. Table OA.6 columns (1)-(3) replicates Table 2 column (4) and Table 4 columns (4) and (5), respectively. Table OA.6 columns (4)-(6) and columns (7)-(9) replicates columns (1)-(3) by using exporters and nonexporters, respectively. All other regression specifications are identical to Table 2 column (4) and Table 4 columns (4) and (5).

Overall, our results highlight that exporters face short-run decreasing returns to scale in quantity and are likely to vent out their surplus through continuing products. Moreover, these exporters are unlikely to spill over the shock through uniform product replacement at the international level because they are likely to offer different products in international markets. These results are consistent with the global venting our surplus results documented in Almunia et al. (2021). Appendix E.8 also documents some evidence on the venting-out surplus mechanism at a more aggregate level by using the NBER commodity flow survey data.

D.3 Long-run Implications

This section studies the long-term implications of the spillover effect by using the dependent variable covering 2007-2013 instead of 2007-09. In this way, the coefficient estimates report the 6-year response to the shocks spanning both during and after the Great Recession.

Table OA.7 shows the results with the empirical specifications identical to those reported in the paper except for the period for the dependent variable. In general, we see a persistent effect of both direct and indirect shocks on local sales, generally consistent with the previous literature emphasizing the local scarring effect of the housing bust in 2007-09 (Bhattarai et al. 2021). Considering column (1), the direct effect is about two times larger and the indirect effect is about three times larger than those using the 2007-09 sales growth. These effects are generally similar across different columns except columns (5) and (6); the indirect effect is even larger when housing elasticity and sensitivity

likely to face short-run diseconomies of scale (or scope in terms of markets) that exporting firms face in selling to many heterogeneous markets.

Table OA.7: The Direct and Indirect Effects of the Housing Market Disruptions: Long-term Effect

	$\tilde{\Delta}\text{S}_{cf}$, 2007-2013							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ordinary Least Squares				IV Estimation Using			
					elasticity	sensitivity	lending	all
$\tilde{\Delta}\text{HP}_{c,07-09}$	0.10**	0.10**						
	(0.04)	(0.05)						
$\tilde{\Delta}\text{HP}_{cf,07-09}$ (other)	0.97***		0.99***	0.95***	1.33***	1.26***	0.98*	0.97*
	(0.34)		(0.34)	(0.34)	(0.24)	(0.42)	(0.53)	(0.57)
Region-Firm Controls	✓		✓	✓	✓	✓	✓	✓
Region Controls		✓						
Firm FE		✓						
Sector FE	✓		✓					
Region FE			✓					
Sector x Region FE				✓	✓	✓	✓	✓
First-stage F statistics					574.60	199.70	572.80	292.00
Hansen's J-stat p-value								.
R^2	0.30	0.71	0.37	0.49	0.03	0.03	0.03	0.00
$E[\tilde{\Delta}\ \text{S}_{\text{cf}}:\tilde{\Delta}\text{HP}_{\text{p95}}-\tilde{\Delta}\text{HP}_{\text{p5}}]$	.048	.044						
$E[\tilde{\Delta}\ \text{S}_{\text{cf}}:\tilde{\Delta}\text{HP}_{\text{p95,other}}-\tilde{\Delta}\text{HP}_{\text{p5,other}}]$	.085		.087	.084	.115	.108	.084	.085
Observations	680496	680288	680496	666381	365308	478769	537660	340724

Note. The empirical specifications are identical to what are in the main table in the main draft except that the dependent variable is sales growth in 2007-13 instead of 2007-09. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are used as instrumental variables.

D.4 Price and Quantity Decomposition

Local-firm price and quantity index for the continuing products. Observing product prices at the product-county-time level, we aggregate across products within county, firm, and product group by using the chain-weighted price index for continuing products. We then further aggregate across product groups within the firm and time, again using the chain-weighted price index.

Specifically, consider the change in price index at the county-firm-group-level:

$$\Phi^k_{cfgt} = \frac{\prod_{cp\in\Omega_{cfgt,t-1}} (P_{cpt})^{s^k_{cp,t-1}}}{\prod_{cp\in\Omega_{cfgt,t-1}} (P_{cp,t-1})^{s^k_{pcfgt,t-1}}} \tag{D.1}$$

where the the superscript k $\in$ {Tornqvist, Passche, Laspyres} denotes three different chain-weighted index we used, the subscript p is product (UPC), c is county, f is firm, g is product group, and t is time. The county-firm-specific price index change is then:

$$\Phi_{cft}^{k} = \frac{\prod_{cg \in \Omega_{cft,t-1}} (P_{cfgt})^{s_{cfgt,t-1}^{k}}}{\prod_{cg \in \Omega_{cft,t-1}} (P_{cfgt,t-1})^{s_{cfgt,t-1}^{k}}} \tag{D.2}$$

and the price growth index is $\ln \Phi_{cft}^{k}$ and the quantity growth index is the sales growth index minus the price growth index ($\ln \text{Sales}_{cft} - \ln \Phi_{cft}^{k}$).

Table OA.8: Price and Quantity, Continuing Products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Tonqvist		Laspeyres		Paasche	
	S		P	Q	P	Q	P	Q
$\tilde{\Delta}\text{HP}_c$	0.06***	0.06***	0.01**	0.05**	0.01	0.05**	0.01**	0.05**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
$\tilde{\Delta}\text{HP}_{cf}$ (other)	-0.05							
	(0.08)							
Region-Firm Controls	✓							
Region Controls		✓	✓	✓	✓	✓	✓	✓
Firm FE		✓	✓	✓	✓	✓	✓	✓
Sector FE	✓							
R^2	0.27	0.65	0.68	0.63	0.65	0.62	0.67	0.63
$E[\tilde{\Delta}\ \text{S}_{\text{cf}}\text{:}\tilde{\Delta}\text{HP}_{\text{p95}}\text{-}\tilde{\Delta}\text{HP}_{\text{p5}}]$	.029	.027	.005	.022	.005	.023	.006	.022
$E[\tilde{\Delta}\ \text{S}_{\text{cf}}\text{:}\tilde{\Delta}\text{HP}_{\text{p95,other}}\text{-}\tilde{\Delta}\text{HP}_{\text{p5,other}}]$	-.004							
Observations	839096	839093	839093	839093	839093	839093	839093	839093

Note. The empirical specifications are identical to what are reported in the main table in the main draft except that we use different dependent variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.8 shows the results using the local-firm price and quantity indexes. The first column shows that consistent with the main result, the local effect is positive, but the spillover effect is not statistically different from zero, especially looking at the 95th-5th percentile difference.[8] Column (2) includes firm fixed effect as a tighter specification, and columns (3)-(8) decompose the local sale effect into price and quantity using different indexes. The effect on price is consistent with those reported in Stroebel and Vavra (2019).

Note that the direct effects on price and quantity are 0.01 and 0.05, respectively, regardless of using different indexes. That is:

[8]Note that the results are almost but not exactly the same as the main specification because of two reasons. First, there is a small sample decrease because we exclude products without the product group information. Second, the sales growth is slightly different because the denominator is based on the continuing product sales instead of the total product sales in 2007 and 2009.

$$\frac{\partial \Delta \ln p_{cf}}{\partial \Delta \ln hp_{cf}} = 0.01 \tag{D.3}$$

$$\frac{\partial \Delta \ln q_{cf}}{\partial \Delta \ln hp_{cf}} = 0.05 \tag{D.4}$$

These two numbers suggest that the demand elasticity is:

$$\varepsilon = -\frac{\partial \ln q_{cf}}{\partial \ln p_{cf}} = -0.054/0.011 \approx -5 \tag{D.5}$$

Note that the inferred demand elasticity is comparable to those reported in the previous literature. For example, Hottman et al. (2016) shows that the median demand elasticity across firms within the product group is 3.9 across all years. We find a somewhat more elastic demand, potentially because of the focus on the period of the Great Recession when the demand is more likely to be elastic (Stroebel and Vavra 2019).

Local-firm price and quantity index for the product replacement. It is extremely difficult to define the price and quantity index across product entry and exit without putting additional structure because we can no longer compare the product prices for the same products. Just for the specific purpose of understanding whether firms change the price markup or quality by the product replacement, we define the quantity index for the product replacement. For the entering and exiting products within each firm and county, we make the quantity index by dividing total sales by the price index.[9] Using the quantity index, we aim to separate two different mechanisms conditional on the product replacement with respect to the indirect shock. First, as we propose in the paper, firms can lower quality and revenue conditional on the negative spillover shock by replacing high-quality products with low-quality products. Second, firms can lower price markup conditional on the negative spillover shock by replacing high-markup products with low-markup products to boost revenue. In this case, conditional on the negative spillover shock, firms must generate a larger quantity and revenue. The fact that revenue increased is consistent with the former hypothesis on product quality. We further analyze the quantity index to distinguish these two different mechanisms better.

The first three columns replicate the previous results we documented: the firms replace high-

[9] Note that we cannot define the price index using the chain-weighted index because these products are entering and exiting products.

Table OA.9: Changes in Barcode-level Product Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					$\tilde{\Delta} v_{cf}$				
v_{cf} is	Price			Quantity					
	Simple	Weight	Weight (d)	Simple	Weight	Weight (d)	Simple	Weight	Weight (d)
$\tilde{\Delta}\text{HP}_{rf}$ (other)	0.73**	0.92**	0.70**	0.75	0.63	0.65	0.76	0.65	0.68
	(0.27)	(0.44)	(0.33)	(0.52)	(0.47)	(0.47)	(0.69)	(0.55)	(0.56)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE							✓	✓	✓
Region FE							✓	✓	✓
Sector x Region FE	✓	✓	✓	✓	✓	✓			
R^2	0.51	0.41	0.42	0.40	0.40	0.40	0.25	0.26	0.26
Observations	461672	461672	461672	461672	461672	461672	484198	484198	484198

Note. The regression specifications are the same as that in Table 2 column (4). * p < 0.10, ** p < 0.05, *** p < 0.01.

priced products with low-priced products conditional on the indirect shock. The next six columns use the quantity index, which is defined by sales of entering and exiting products divided by the corresponding price index. The quantity effect is not statistically significant. If anything, the effect is positive conditional on the indirect shock, consistent with the quality downgrading but inconsistent with the markup adjustment.

D.5 Alternative Definitions of Products

Our main analyses define products at the UPC level, which is likely the most granular definition of a product. Previous studies have often considered more aggregate definitions of products, such as product brand-module (Faber and Fally (2021)), HS 10 digit (Broda and Weinstein (2006)), and SIC 5-digit (Bernard et al. (2010)). This is especially the case in the international context because UPC-level information is mostly unavailable in the global firm-level data.

This section shows that the granular definition of a product at the UPC level is essential in identifying the uniform product replacement channel. We consider broader definitions of products at the product group-, module-, and brand-level, and perform the same analyses as in Table 2 columns (1) and Table 2 columns (4). For example, there are multiple UPCs within the product brand "Schultz Garden Safe", which is included in the product module "Lawn and Soil Fertilizer and Treatment", which is again included in the product group "Floral, Gardening". Other examples of product group are "Baby food", "Beer", "Cosmetics", "Glassware", "Laundry supplies", and "Paper products". These aggregated product definitions are comparable to the definitions of products used in previous studies. For instance, a concordance created by Bai and Stumpner (2019) shows that 1,147 product modules in the Nielsen data can be mapped to 878 HS 6-digit commodities.

Table OA.10 shows that the indirect effect works through continuing products with a broader definition of the product. Only by defining a product at the barcode level do we observe that the indirect demand effect works through product replacement. The results are consistent with the Kraft example presented in Appendix B.2, where the firm introduced a new nonorganic product and withdrew its existing organic products under the same brand, module, and group. This result is intuitive given that establishing a new brand or broader product category incurs a much higher fixed cost than replacing a UPC; replacing a UPC would likely be a more cost-efficient way to change the product quality of firms.

Table OA.10: The Exact Decomposition with Alternative Product Definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\tilde{\Delta}\mathrm{S}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{C}}_{cf}$	$\tilde{\Delta}\mathrm{S}^{\mathrm{R}}_{cf}$
Product defined as		Group		Module		Brand		UPC	
Panel A: With Sector FE									
$\tilde{\Delta}\mathrm{HP}_c$	0.06**	0.06**	-0.00***	0.06**	-0.00	0.06**	0.00	0.05***	0.01
	(0.03)	(0.03)	(0.00)	(0.03)	(0.00)	(0.03)	(0.00)	(0.02)	(0.01)
$\tilde{\Delta}\mathrm{HP}_{cf}$ (other)	0.35***	0.39***	-0.05**	0.32***	0.02	0.33***	0.02	0.03	0.32***
	(0.11)	(0.10)	(0.02)	(0.07)	(0.05)	(0.08)	(0.08)	(0.06)	(0.09)
R^2	0.20	0.21	0.04	0.21	0.10	0.21	0.14	0.22	0.28
Panel B: With County × Sector FE									
$\tilde{\Delta}\mathrm{HP}_{cf}$ (other)	0.40***	0.47***	-0.07***	0.36***	0.04	0.40***	0.00	-0.02	0.42***
	(0.10)	(0.09)	(0.02)	(0.06)	(0.06)	(0.08)	(0.10)	(0.05)	(0.10)
R^2	0.39	0.40	0.17	0.41	0.21	0.41	0.26	0.43	0.41

Note. Observations = 840,681. The Panel A regression specifications are the same as those in Table 2 column (1), and the Panel B regression specifications are the same as those in Table 2 column (4). * p < 0.10, ** p < 0.05, *** p < 0.01.

D.6 Structural Regression

This section estimates the model-predicted intrafirm interdependence equation, which is similar to the main reduced-form Equation (3.1). In doing so, we use the weight identical to the reduced-form equation and estimate Equation (F.12), but estimating Equation (F.11) yields similar results. In this way, the regression specification is identical to Equation (3.1) except that we use county-firm sales growth as the change in product demand instead of housing price growth. Appendix G.3.1 presents a similar analysis with the extended model as well as the comparison of direct and indirect effects in using the actual and the model-generated data.

Table OA.11: Estimation of the Structural Equation

	$\tilde{\Delta}S_{kf}$, 2007-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Geographic Unit (subscript k):	County					State	
	OLS	IV using				OLS	IV using
		HP	elasticity	sensitivity	lending		HP
$\tilde{\Delta}S_{kf,07-09}$ (other)	1.00***	0.86***	0.97***	1.02***	0.85***	0.88***	0.71***
	(0.01)	(0.09)	(0.10)	(0.12)	(0.08)	(0.05)	(0.15)
Geo.Unit-Firm Controls	✓	✓	✓	✓	✓	✓	✓
Geo.Unit FE							
Sector x Geo.Unit FE	✓	✓	✓	✓	✓	✓	✓
First-stage F statistics		18.00	14.00	9.10	4.20		35.40
R^2	0.76	0.61	0.64	0.63	0.62	0.74	0.59
Observations	840,681	840,681	448,604	587,436	658,607	83,309	83,309

Note. Table OA.11 estimates Equation (F.12), where $\tilde{\Delta}S_{kf,07-09}$ (other) $\equiv \sum_{r'\neq r}\left(\frac{\omega_{r'f}}{1-\omega_{rf}}\right)\hat{S}_{r'f}$. Geo.Unit Stands for the geographic unit (market). Columns (1)-(5) define a county as a market, and columns (6)-(7) define a state as a market. The regression specification is the same as that in Table 2 column (4)-(7) except that the sales growth rate at the geographic unit-firm level ($\hat{S}_{kf}$) is used as the demand change in the indirect demand shock instead of house price growth at the county level. The HP, elasticity, sensitivity, and lending are the leave-one-out weighted average of the regional housing price growth ($\tilde{\Delta}HP_{kf,07-09}$ (other)), Saiz (2010) housing supply elasticity, Guren et al. (2021) housing price sensitivity, and García (2018) nonlocal mortgage lending shock, respectively. * p < 0.10, ** p < 0.05, *** p < 0.01.

Using various regression specifications, Table OA.11 confirms the positive spillover effect (Υ>0) with the model-predicted equation. Column (1) utilizes the sales growth as it is, and columns (2)-(5) utilize four different measures used in the main reduced-form analyses as instrumental variables. Columns (6) and (7) show that the results are robust to using the state as the definition of a market.

E Robustness

E.1 Retail Margin

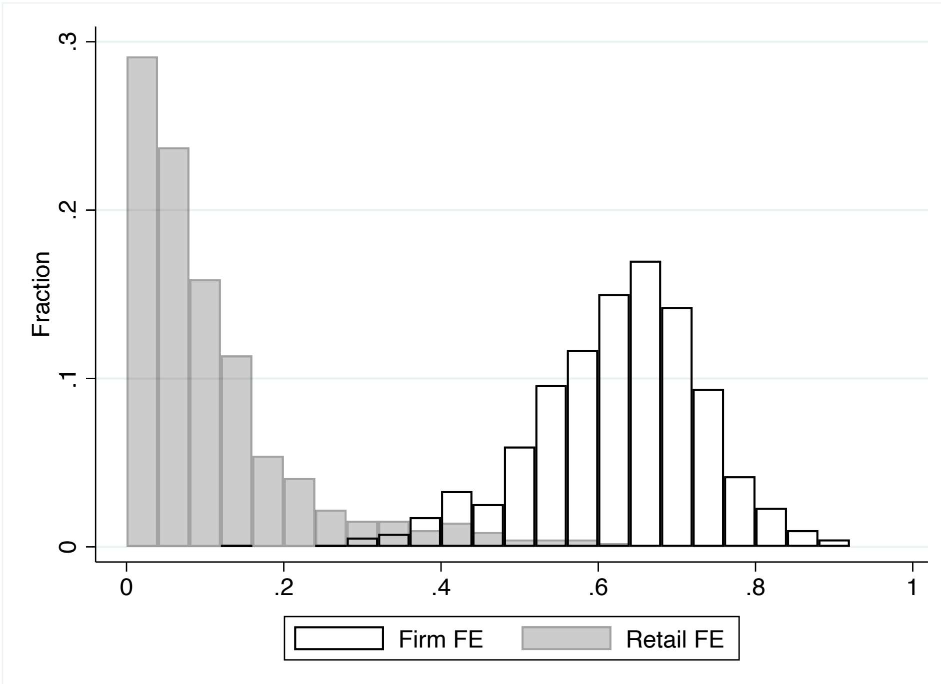
By combining the Nielsen Retail Scanner data and the GS1 and NETS data, we study firms such as Kraft and Coca-Cola that mainly generate intrafirm networks by selling their products in many markets (multimarket firms), rather than Target or Whole Foods that simultaneously produce and sell in multiple markets (multiplant firms). This distinction is well-documented at the international level: exporters (multimarket firms) and multinationals (multiplant firms).

One concern in using the combined data to study multimarket firm behavior is that the sales information is recorded at the retail level. In contrast, our work focuses on nonretailers, mainly manufacturers in the economy. Although our main analyses aggregate retail dimensions within multimarket firms and compare total sales generated from these firms across retailers, there may be a confounding factor associated with retail characteristics that vary across the aggregated sample. For example, if large retailers contract with large manufacturers, retail size may appear as an omitted variable in the regression. As another example, the seminal paper by DellaVigna and Gentzkow (2019) shows that retailers choose a uniform price across regions. In this case, retailers may spill over regional shocks by choosing a uniform price across markets, and this within-retail network may confound the multimarket firm network in our regression analyses.

Given the concerns regarding retail characteristics and behavior, we explicitly include the retail dimension in the data and conduct exercises separately, investigate the importance of retail variation in our sample, and bring in new data that directly report producer price information and conduct the robustness exercise. The county-firm-retail-level regression analyses are conducted in Section 3, and the other two exercises are reported in this Appendix.

We regress county-retail-firm-level sales growth on either retail or firm fixed effects for each county and plot the associated R^2 across counties. Figure OA.6 presents the R^2 associated with the retailer and manufacturer fixed effects. Producers explain more variation in county-retail-firm sales growth than retailers. The median R^2 associated with the retailer fixed effect is .07, and the R^2 associated with the firm (producer) is .63. This result is not surprising given the nature of the data. Our sample excludes the private-label products made by retailers, which are important for retail sales share because they are masked in Nielsen Retailer Scanner data in merging them with the GS1 data. Moreover, there are not many retail chains in each county. The median number of firms in a given county is 1,065, whereas the median number of retailers is only seven. The relatively unimportant variation across retailers suggests that different characteristics across retailers

Figure OA.6: Local Sales Variation Decomposition: Firms (Producers) vs. Retailers



Note. For each county, Figure OA.6 plots the R^2 acquired by regressing county-retail-firm-level sales growth, $\tilde{\Delta}\text{S}_{crf}$, on either retail fixed effects or firm fixed effects.

are unlikely to invalidate the multimarket firm analyses in our sample.

Moreover, we brought new data that directly records the producer price information from the major wholesaler's cost information (Promodata) and still found empirical support for the main uniform product replacement mechanism. Table OA.12 replicates Table 5 columns (2) and (4). The results show that even using the directly observed producer price information, the replaced product prices are higher conditional on the indirect shock, consistent with the results reported in Table 5 columns (2)-(4).

E.2 Distance to the Local Market

In studying the spillover effect, various potential confounding factors can be captured by measuring the distance to the local market. For example, one of the most critical concerns in studying the spillover effect is a common shock that affects clustered markets simultaneously. If clustered shocks exist, they will generate a correlation of local sales growth across nearby markets and may invalidate the spillover effect if multimarket firms initially sold specifically to these clustered areas. Other

Table OA.12: Spillover Effects using Promodata

	Change in Product Value					
	Average Price				Demeaned Price	
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\Delta}\text{HP}_{rf}$ (other)	3.14**	3.25**	3.23**	3.37**	3.75**	3.80**
	(1.40)	(1.48)	(1.58)	(1.60)	(1.55)	(1.60)
Firm Controls		✓		✓		✓
Sector x Region FE	✓	✓	✓	✓	✓	✓
R^2	0.20	0.23	0.20	0.23	0.20	0.22
Observations	348	348	324	324	324	324

Note. The dependent variables in columns (1)-(4) and (5)-(6) replicate Table 5 columns (2) and (4), respectively, using the Promodata. Columns (1)-(4) use the average price, and columns (5) and (6) additionally demean the price by using the group-level price index. Columns (1) and (2) use all the samples available in the Promodata, whereas columns (3)-(6) use only those products that can be matched to the Retail scanner data with the product group information. The location is defined at the state level. Firm controls are total firm sales, number of counties, and the number of product groups identified from the GS1 matched to the Retail Scanner data. The sector is defined by the 2-digit SIC code from NETs data. The dependent and independent variables are winsorized by top and bottom 5%. * p < 0.10, ** p < 0.05, *** p < 0.01.

types of potentially concerning spatial networks—such as (i) the local bank network in which banks prefer to lend to closely located customers, (ii) the trade network that is governed by the gravity equation, and (iii) the customer network due to their trips to nearby counties for purchasing grocery goods—would also be closely related to the distance to the local market. If such channels exist, the spillover effect may disappear as we control for distance or exclude counties near the local market of interest.

As the distance to the local market can proxy for various factors that may confound the spillover effect, this section measures the distance from the local market of interest to other markets and explicitly addresses related channels associated with distance. By using the distance measure in the NBER county distance database, we address the distance-related concerns in two different ways. First, we measure and control variables related to distance to the local market. Second, we remeasure the indirect demand shock by excluding nearby markets.[10]

Considering the distance-related measures, we construct and include two variables in the regression, similar to the measures of the trade networks used in Appendix E.8. First, given the log of distance to the local market from each of other markets, we take a weighted average across all

[10]The 2000 Census county distance data, which are available at https://www.nber.org/research/data/county-distance-database, are used in this analysis.

counties within each firm except the local market of interest, where the weight is the initial sales share. This variable may confound the spillover effect if housing price changes within the network of multimarket firms are related to the distance to the local market of interest. Second, given the housing price growth, we use the initial inverse distance as a weight to measure the indirect demand shock. Including this variable in the regression is intended to estimate the effect of nearby housing price changes on the local county firm sales. If the inverse-distance measure is highly correlated with the initial sales share of multimarket firms, the indirect effect may disappear with this control variable. Regarding the exclusion of nearby markets, we consider five different specifications. We exclude markets that are located within a radius of 50 miles, 100 miles, 150 miles, and 1000 miles. Additionally, we exclude all counties that are located within the same state. In constructing these variables, we assign zero weights to these nearby counties and renormalize the remaining weights to be one. Furthermore, we control for the total initial sales share of the excluded nearby counties in the regression following what is suggested in Borusyak et al. (2022).

Table OA.13 shows the results. Columns (2) and (3) control for the distance-related measures. Although the distance-related measures affect local firm sales, the effect is weak and does not alter the main spillover effect through multimarket firms. Columns (4)-(8) consider the indirect demand shock that excludes nearby counties. While the spillover coefficients become smaller as we exclude more nearby counties, the effect becomes stable once we exclude those counties that are located within a radius of 150 miles.[11] These results highlight that other potential channels related to distance are unlikely to confound the main spillover effect through multimarket firms, consistent with the other robustness exercises that use a broader definition of markets (Appendices E.3 and E.11).

E.3 Alternative Market Definition

Following the previous literature (Hanner et al. 2015; Hottman 2021), the baseline analyses use the county as a definition of a market. This section considers alternative definitions of markets. The Retail Scanner data have two other broader geographical units: state and 3-digit zip code. Using a broader definition of the market helps address clustered shocks, which affect multiple counties

[11] The smaller effect from excluding nearby counties is consistent with the multiplant firm results on local employment documented in Giroud and Mueller (2017). The effect is likely to be smaller due to a larger measurement error associated with excluding counties that affected local firm sales through the multimarket firm network. Alternatively, the smaller effect may arise from other reasons, such as firms' product replacement behavior within clustered markets, as shown in G.2.4. The stability and magnitude of the coefficient after excluding counties within a radius of 150 miles ensures that the main spillover effect is unlikely to be driven by other confounding factors.

Table OA.13: Addressing Concerns related to the Distance

	$\tilde{\Delta}S_{cf}$, 2007-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Adding controls			Nearby counties are defined as:				
				≤50mi	≤100mi	≤150mi	≤1000mi	Same State
$\tilde{\Delta}HP_{cf}$ (other)	0.40***	0.46***	0.43***					
	(0.10)	(0.10)	(0.08)					
ln $dist_{cf}$ (other)		-0.27	-0.27					
		(0.22)	(0.21)					
$\tilde{\Delta}HP_{cf}$ (other, inv-dist-weighted)			-0.05***					
			(0.01)					
$\tilde{\Delta}HP_{cf}$ (other, exclude nearby counties)				0.34***	0.31***	0.27***	0.27***	0.30***
				(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
ω_{cf} (nearby counties)				0.07*	0.02	0.01	-0.03	0.12**
				(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.39	0.39	0.39	0.39	0.39	0.39	0.40	0.39
Observations	840,681	840,681	840,681	840,235	839,548	838,641	813,736	838,812

Note. The regression specification is the same as that in Table 2 column (4); Table OA.21 column (1) is identical to Table 2 column (4). Columns (2) and (3) include two different distance-related measures. "ln $dist_{sf}$ (other)" is the initial sales-weighted average of the distance to the local market of interest across counties within all markets of firm. "$\tilde{\Delta}HP_{sf}$ (other, inv-dist-weighted)" is the inverse distance weighted average of housing price changes of the other markets. Columns (4)-(8) consider the indirect demand shock that excludes the nearby located markets, where the definition of nearby counties is based on 50 miles, 100 miles, 150 miles, 1000 miles, and same state. "ω_{cf} (nearby counties)" is total initial sales share of excluded nearby counties. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

within this broader market. Section E.11 considers other definitions of markets using the Homescan Panel data. The indirect demand shock is constructed based on the different definitions of markets.

Table OA.14 shows that the spillover results are robust to using other definitions of markets. Columns (1) and (2) utilize state, still estimating a positive spillover coefficient. Since Zillow housing price information is not available at the 3-digit zip code level, we use Federal Housing Finance Agency (FHFA) data, which has housing price information at the 3-digit zip code level. Columns (3) and (4) confirm that the spillover effect is robust to using the 3-digit zip code as the definition of a market, and columns (5) and (6) reassure that using FHFA data does not change the spillover results we observe at the county level.

Table OA.14: Alternative Geographic Units

	$\tilde{\Delta}\mathrm{S}_{kf}$, 2007-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
Housing Price Data Source:	Zillow		FHFA			
Geographic Unit (subscript k):	State		3-digit Zip		County	
$\tilde{\Delta}\mathrm{HP}_{kf}$ (other)	0.25***	0.30**	0.32***	0.37***	0.30***	0.35***
	(0.09)	(0.11)	(0.10)	(0.09)	(0.10)	(0.09)
Geo.Unit-Firm Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓		✓		✓	
Geo.Unit FE	✓		✓		✓	
Sector x Geo.Unit FE		✓		✓		✓
N of Geo.Units	49	49	868	868	983	983
N of Firms	4,281	4,281	4,440	4,440	4,171	4,171
R^2	0.23	0.36	0.23	0.39	0.24	0.39
Observations	83,296	83,296	941,418	941,418	839,300	839,300

Note. The subscript k is a geographic unit, and f is a firm, which is defined to be a producer. The sector is based on 4-digit SIC. Geo.Unit stands for the geographic unit. All the regression specifications are the same as those in Table 2 columns (2) and (3), except for using different geographic units or house price measures. * p < 0.10, ** p < 0.05, *** p < 0.01.

E.4 Placebo Tests

One of the most important concerns in studying the spillover through the network is the alternative networks that may similarly spill over the shock. Specifically, the multimarket firm network is defined based on how much these firms sell in each market, the local initial sales share of firms $\omega_{c'f}$. One concern is that this network may proxy for another network in the economy, and the effect may be generated from the other hidden network.

This section explicitly considers a potential network that may spill over the regional housing price changes by constructing a placebo network. Consider the following construction of the indirect demand shock using the placebo network, which replaces initial sales share in Equation (2.5) with alternative placebo weights:

$$\tilde{\Delta}\mathrm{HP}_{cf}^{\mathrm{Placebo}}\,(\mathrm{other}) \equiv \sum_{c'\neq c} \omega_{c'f}^{\mathrm{Placebo}} \times \tilde{\Delta}\mathrm{HP}_{c'} \tag{E.1}$$

where $\omega_{c'f}^{\mathrm{Placebo}}$ is the initial placebo share measuring the alternative network. Within the markets in which firms operate, we consider weights of equal share, household population, household median income, and household debt-to-income ratio. We also use the initial share of entrants to explore firms' potential selection into the exposed counties and use the establishment network to investigate the supply-side effect arising from land collateral or a productivity shock.

Table OA.15: Placebo Tests

	$\tilde{\Delta}$ S$_{cf}$, 2007-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
	Alternative measures of $\tilde{\Delta}$HP$_{cf}$ (other) using					
	equal	pop.	inc.	debt	entry	plant
$\tilde{\Delta}$HP$^{\text{Placebo}}_{cf}$ (other)	0.13	0.03	0.11	0.07	-0.03	-0.06
	(0.21)	(0.18)	(0.18)	(0.20)	(0.11)	(0.18)
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓
Observations	840,681	840,681	840,681	835,778	833,290	704,809

Note. The regression specification is the same as that in Table 2 column (4) except the initial weight used in measuring the independent variable, $\tilde{\Delta}$HP$_{rf}$. We consider six alternative weights in constructing the indirect demand shock: "equal" is equal weight, "pop." is population weight, "inc." is household median income weight, and "debt" is the household debt-to-income weight. "entry" is the weight that still uses 2007 sales but replaces the value with zero if the 2006 sales are nonzero, and the "plant" is based on the firms' spatial plant network. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.5 Idiosyncratic Shocks

One concern about the interpretation of the spatial spillover effect is that the results may be driven by global shocks and do not arise from the spillover. In addition to other robustness exercises to address this concern, this section conducts two supplementary exercises. First, we only consider counties that experienced negative housing price changes in this period in constructing the indirect shock and study how they affect counties experiencing positive housing price changes. This specification allows us to study only those counties experiencing the housing price boom and investigate how negatively affected areas can have spatial spillover effects on these counties. Second, again, in constructing the indirect shocks, we only consider a specific region that is well-known for experiencing a significant housing market collapse: the Pacific Census Division (West Coast). Then, we study how the shocks that originated in the Pacific region affect the other counties in the United States.

Table OA.16 presents the results. Columns (1)-(3) show the spatial spillover effect from counties with housing bust to counties with housing boom through multimarket firms, and columns (4)-(6) show the spatial spillover effect from the Pacific Division to other areas in the United States.

In both exercises, we find that the negative indirect shock leads to a decline in firms' local sales, primarily through the extensive margin of product replacement.

Table OA.16: Spillover Effects from
(i) Counties with Negative Shocks and (ii) Pacific Census Division

	(1) $\tilde{\Delta}S_{cf}$	(2) $\tilde{\Delta}S^{C}_{cf}$	(3) $\tilde{\Delta}S^{R}_{cf}$	(4) $\tilde{\Delta}S_{cf}$	(5) $\tilde{\Delta}S^{C}_{cf}$	(6) $\tilde{\Delta}S^{R}_{cf}$
	Only-Negative-Shocks			Shocks from Pacific Div.		
$\tilde{\Delta}HP_f$ (other, < 0)	1.02***	-0.20	1.22***			
	(0.26)	(0.23)	(0.24)			
$\tilde{\Delta}HP_f$ (other, Pacific Div.)				0.32*	-0.43***	0.75***
				(0.16)	(0.12)	(0.12)
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓
R^2	0.44	0.45	0.43	0.42	0.45	0.43
Observations	132238	132238	132238	661241	661241	661241

Note. This table shows the impact of the indirect shock on firm-county-level sales growth, where the indirect shock is measured by calculating the weighted average house price growth that each firm faces (i) from counties that experienced negative house price growth (Columns (1)-(3)) and (ii) from counties located in Pacific Census Division (Columns (4)-(6). To capture the spillover effect, we drop counties of shock origination. That is, we drop counties with negative house price growth and only consider those that experienced positive house price growth in Columns (1)-(3), and we drop counties in the Pacific Census Division in Columns (4)-(6). Columns (1) and (4) reproduce Column (4) in Table 2 and Columns (2)-(3) and Columns (5)-(6) reproduce Columns (4)-(5) in Table 4, respectively. We additionally control for the firm's sales share from the dropped counties. We two-way cluster the standard errors in Columns (1)-(3) by county and sector (instead of state and sector) to account for the small number of states in the sample.

E.6 County-Firm-Group-Level Analyses

For simplicity, our baseline analyses do not consider a detailed product group as a separate dimension of the data. The examples of product group are "Floral, Gardening", "Baby food", "Beer", "Cosmetics", "Glassware", "Laundry supplies", and "Paper products". In comparing firm sales, while we group firms based on their major sectors by including sector fixed effects, we do not compare firm sales within detailed product group categories. This choice is motivated by the empirical fact that a typical firm does not sell many detailed product group categories, as documented in Table 1. Nevertheless, there may be a confounding hidden correlation structure across product groups and markets.

This section explicitly includes the product group dimension in the regression analysis in addition to the firm and county dimensions and incorporates product group fixed effects that absorb all the sales growth variation across product groups. Specifically, we use the following regression specification, which extends Equation (3.1):

$$\tilde{\Delta}\mathrm{S}_{cgf} = \delta_0 + \lambda_{cg} + \delta_1 \tilde{\Delta}\mathrm{HP}_{cf}\ (\text{other}) + \boldsymbol{X'_{cgf}}\boldsymbol{\delta_2} + \varepsilon_{crf} \tag{E.2}$$

where λ_{cg} is county times group fixed effect. The county times group fixed effect not only accounts for the difference in product group characteristics but also addresses potential firm competition. Although our baseline model abstracts away from strategic competition by assuming monopolistic competition, which is reasonable for most of the firms in the Nielsen data, strategic product market competition may arise. Under the nested CES demand system, such competition works through the product group price index (Atkeson and Burstein 2008; Hottman et al. 2016). With the product group times county fixed effect, we absorb all such variation in county-group-level prices in our setup and shut down the competition channel. Additionally, we reconstruct the price index by entering and exiting products and reestimate the price regression reported in Table 5 columns (2)-(4). We revisit this analysis because the price index is more precise with the product group dimension.

Table OA.17: County-Firm-Group-level Regression Analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\tilde{\Delta}S_{cgf}$	$\tilde{\Delta}S^{\mathrm{R}}_{cgf}$	$\tilde{\Delta}S^{\mathrm{C}}_{cgf}$	$\tilde{\Delta}$ Price Index$_{cgf}$			
				Simple	Weight	Weight (d)	Weight (d,s)
$\tilde{\Delta}$HP$_{cf}$ (other)	0.17**	0.31***	-0.13	1.48***	1.51***	0.84***	0.96**
	(0.07)	(0.05)	(0.10)	(0.22)	(0.51)	(0.21)	(0.41)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓
County x Sector FE	✓	✓	✓	✓	✓	✓	✓
County x Group FE	✓	✓	✓	✓	✓	✓	✓
R^2	0.42	0.49	0.48	0.57	0.55	0.61	0.63
Observations	1,592,287	1,592,287	1,592,287	704,750	704,750	704,750	704,750

Note. The subscript c is a county, g is a product group classification, and f is a firm. The sector is based on 4-digit SIC. $\tilde{\Delta}$S$_{rgf}$ is county-group-firm-specific sales growth, and $\tilde{\Delta}$S$^{\mathrm{R}}_{rgf}$ and $\tilde{\Delta}$S$^{\mathrm{C}}_{rgf}$ decompose $\tilde{\Delta}$S$_{rgf}$ into net creation and continuing product sales growth. $\tilde{\Delta}$HP$_{rf}$ (other) is the indirect demand shock defined in Section 2, which is the initial county-firm-specific sales-weighted local house price growth excluding region r housing price growth. The simple and weighted price indexes in columns (4) and (5) are the simple and the sales-weighted geometric price across UPCs within the product group and firm. The simple index is the conventional price index component of the nested CES demand system in Hottman et al. (2016), and the weighted index is used to adjust for the importance of each UPC, as in the Cobb-Douglas utility function. The weighted and demeaned price index in column (6) additionally subtracts the average product module price index, similar to the quality index used in Argente et al. (2018). The weighted, demeaned, and size-adjusted price index in column (7) additionally adjusts the product size for each UPC. County-firm controls are the initial log of the following variables: county-group-firm sales, firm sales, and the firm's number of markets and product groups. The regression is weighted by initial county-group-firm sales; standard errors are three-way clustered by state, sector, and product group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.17 columns (1)-(3) present the spillover effect and its decomposition with the product group fixed effect. Regardless of including the county times group fixed effect, we still find a positive spillover effect, mainly from product replacement. Columns (4)-(6) revisit the price regression and confirm that firms spill over the negative housing price changes by replacing high-priced products with lower-priced products. In particular, column (7) additionally adjusts for the unit product price, showing that the price change is not coming from the change in product units. Note that while we show product unit is not relevant, a change in product unit can be interpreted as a change in product quality offered by firms in our framework because this change decreases firm sales while holding the output price fixed.

E.7 Supply-side Concerns

One potential concern related to the main analyses is that the decline in housing prices may affect not only local consumers and their product demand but also locally operating firms and their product supply decisions. For example, a large decrease in housing prices (or land prices) in a given county is likely to directly affect those firms that have their plants or establishments in the same county. Specifically, suppose that these firms finance their spending by using their plants as collateral. In that case, the decrease in the value of their collateral may negatively affect these firms' production and local sales, leading to a uniform decrease in product sales across markets within firms. Butters et al. (2022) show that such a cost-side shock only affects local sales for retailers, but it is unclear how manufacturers respond to such a shock.

This section explicitly considers the supply-side channel. In constructing the indirect demand shock, we exclude all counties where firms initially have their plants to separate all the supply-side effects. We renormalize weights such that they sum to one. In this way, we rule out any regional shocks that affect firm plants and potentially confound the spillover effect, similar to the identification strategy employed in Baker et al. (2020). Since most firms have one or two plants, as reported in Table 1, excluding these counties does not make a substantial difference in the measure of the indirect demand shock. Similar to Appendix E.2 Table OA.13 columns (4)-(8), we control for the total sales share of the excluded counties.

Table OA.18 shows that the spillover effects are robust to the supply-side concerns. Columns (1)-(3) consider the counties where firms have plants in 2007, the initial baseline year. Columns (4)-(6) consider the counties where firms have plants in 2006 in case it better proxies for the large decline in housing prices initiated in 2006. Regardless of using different initial years or including sector times region fixed effects, the estimated coefficients are statistically significant at the conventional level and are similar to those reported in Table 2. These results are also consistent with the placebo results reported in Appendix E.4 Table OA.15 column (6), which shows that the decline in housing prices does not affect firm local sales for the CPG sector.

These results are consistent with the view that the regional spillover we identify reflects the firm's local market response, driven by its supply-side actions (i.e., uniform product replacement at the firm level), to demand shocks originating in other regions. Note that the only part we rule out is that the shock itself initially affects the supply condition of firms that arises from the fall in the establishment values of firms instead of the demand condition (sales) of firms.

E.8 Trade Channel

In studying the spillover effect across markets, one of the most critical networks across markets is a trade network. This section considers both intranational and international trade networks as a

Table OA.18: Excluding Counties where Firms have Plants

	Excluding 2007 Plants			Excluding 2006 Plants		
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\Delta}\text{HP}_{r,07-09}$	0.06**			0.06**		
	(0.02)			(0.02)		
$\tilde{\Delta}\text{HP}_{rf,07-09}$ (other, exclude counties, 07)	0.27**	0.41***	0.49***			
	(0.11)	(0.07)	(0.08)			
$\tilde{\Delta}\text{HP}_{rf,07-09}$ (other, exclude counties, 06)				0.28**	0.41***	0.48***
				(0.11)	(0.07)	(0.08)
ω_{cf} (excluded counties)	-0.04	0.16**	0.15**	-0.04	0.16**	0.14**
	(0.05)	(0.06)	(0.07)	(0.05)	(0.06)	(0.07)
Region-Firm Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓		✓	✓	
Region FE		✓			✓	
Sector x Region FE			✓			✓
R^2	0.19	0.23	0.40	0.19	0.23	0.40
Observations	821602	821602	821602	821503	821503	821503

Note. Table OA.18 columns (1)-(3) (and (4)-(6)) replicate Table 2 columns (1), (3), and (4) except the indirect demand shock. The indirect demand shock is constructed by excluding counties where firms have their plants. Columns (1)-(3) exclude counties where firms had their plants in 2007, and columns (4)-(6) exclude counties where firms had their plants in 2006. "ω_{cf} (excluded counties)" is total initial sales share of excluded counties where firms have their plants. * p < 0.10, ** p < 0.05, *** p < 0.01.

robustness exercise.

First, consider the intranational trade network. One potential concern is that the multimarket firm network may be confounded with the intranational trade network (see, e.g., Stumpner (2019)). For example, firms that face a large negative demand shock and spill over the housing price growth may operate in markets where intranational trade is prevalent. In this case, a positive correlation of sales across markets within firms may be attributed to the intranational trade network rather than the spatial network of multimarket firms. Given that the placebo analyses with the equal weight in Section E.4 reveal the importance of initial local sales share weight in generating the spillover effect, this concern is unlikely to be true. Nevertheless, we explicitly measure the trade network and control for it in the regression analyses.

We utilize the NBER commodity flow survey data to construct the intranational trade network.[12]

[12]We downloaded the data from https://www.nber.org/research/data/transportation-economics-21st-century-commodity-flow-survey-data.

The data provide both state-to-state 2002 commodity flow and state-to-state 2002 commodity flow by 3-digit 2007 NAICS industry.[13] Correspondingly, we use the state-level data, as in Appendix E.3. The NBER flow commodity survey data provide three different units for trade: value, tons, and tons per mile. We use all three units for our analyses.

We measure two different trade networks using the NBER commodity flow survey data. First, given the log trade, we take a weighted average across all states within each firm except the local market of interest, where the weight is the initial sales share. If different levels of initial trade are somehow related to housing price changes within the network of multimarket firms, this variable may confound the indirect demand effect. Second, given the housing price growth, we use the initial volume of trade as a weight to measure the indirect demand shock. This measure captures the idea that a state that faces a large negative demand shock may trade its surplus to other partnering states it used to trade with. If the trade network is highly correlated with the initial sales share weight, the indirect effect may disappear with this control.

Table OA.19 shows that the spillover effect through multimarket firms is robust to controlling for the intranational trade-related network. Panel A considers state-to-state trade. Columns (1)-(3) show that regardless of using different units of trade, the effect of initial trade in the other markets on local firm sales growth is negligible within the multimarket firm network. Columns (4)-(6) consider the effect of a trade-weighted indirect demand shock. We find some evidence of venting-out surplus happening at the aggregate level: When a state experiences a negative housing price growth, it sells the surplus to the other partnering state and generates the negative correlations. However, we still find a positive effect that works through the multimarket firm network, showing that two different effects coexist. Panel B considers state-to-state trade by industry, and the main spillover effects are largely robust to using these alternative control variables.

Second, we are also concerned about the international trade network. A potential concern is that exporters may primarily focus on the international market, and as a result, nonexporters might have faced a larger negative impact during the US housing crisis. Furthermore, if nonexporters change their local sales more than exporters due to their innate characteristics, exporting status may be an omitted variable that confounds the spillover effect. To address this concern, we define an indicator variable equal to one if firms are exporters and 0 otherwise. We explicitly control for exporting status in our analyses.

Table OA.20 columns (1) and (2) show that the multimarket firm spillover effect is robust to

[13]We concord 2007 NAICS code to NAICS 2012 in merging the data with the sector code available in the NETS data. There are three sectors that have two duplicates per 3-digit 2012 NAICS code (a total of six observations). We give equal weight to these sectors in distributing to the 2012 NAICS code.

Table OA.19: Trade Channel: Within US

	$\tilde{\Delta}S_{sf}$, 2007-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
Trade defined as:	Value	Ton	Ton/mile	Value	Ton	Ton/mile
Panel A: State-to-State						
$\tilde{\Delta}HP_{sf}$ (other)	0.29**	0.29**	0.29**	0.47***	0.42***	0.43***
	(0.12)	(0.12)	(0.12)	(0.10)	(0.10)	(0.10)
ln $Trade_{sf}$ (other)	0.02	0.02	0.02			
	(0.02)	(0.01)	(0.02)			
$\tilde{\Delta}HP_{sf}$ (other, trade-weighted)				-1.22***	-0.90***	-1.03***
				(0.18)	(0.16)	(0.18)
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓
R^2	0.36	0.36	0.36	0.36	0.36	0.36
Observations	83,296	83,296	83,296	83,296	83,296	83,296
Panel B: State-to-State by Industry						
$\tilde{\Delta}HP_{sf}$ (other)	0.40**	0.39**	0.40**	0.57***	0.57***	0.57***
	(0.17)	(0.17)	(0.16)	(0.20)	(0.19)	(0.19)
ln $Trade_{sf}$ (other)	0.01	0.02	-0.00			
	(0.02)	(0.02)	(0.03)			
$\tilde{\Delta}HP_{sf}$ (other, trade-weighted)				-1.08**	-0.95**	-1.05**
				(0.53)	(0.43)	(0.47)
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓
R^2	0.31	0.31	0.31	0.31	0.31	0.31
Observations	75,587	75,587	75,587	75,587	75,587	75,587

Note. ln $Trade_{sf}$ (other) is the weighted average of the initial log trade excluding the local market of interest, where the weight is the initial sales share. $\tilde{\Delta}HP_{sf}$ (other) is the weighted average of housing price growth excluding the local market of interest, where the weight is the log of the initial trade. Panel A considers state-to-state trade, and Panel B considers state-to-state trade by industry, where the industry is a 3-digit NAICS code. Columns (1) and (4) use the value of trade, columns (2) and (5) use tons of trade, and columns (3) and (6) use miles per ton of trade. The standard errors are two-way clustered by state and sector. While Panel A uses a 2-digit SIC code for clustering, Panel B uses a 3-digit SIC code for clustering because only 27 2-digit SIC codes are available in this analysis. All other regression specifications are the same as those in Table OA.14 column (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

exporter status. Including an indicator variable for exporter status makes a negligible difference in the spillover effect. Columns (3) and (4) group all international firms, both exporters and importers,

Table OA.20: Trade Channel: To Other Countries

	$\tilde{\Delta}S_{cf}$, 2007-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\Delta}HP_{cf}$ (other)	0.34***	0.40***	0.34***	0.41***	0.52***	0.50***
	(0.11)	(0.10)	(0.12)	(0.11)	(0.17)	(0.17)
$I(Export=1)_f$	-0.01	-0.02				
	(0.03)	(0.03)				
$I(International=1)_f$			-0.03	-0.04		
			(0.02)	(0.03)		
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓		✓			
County FE	✓		✓			
Sector x County FE		✓		✓	✓	✓
Non-exporters					✓	
Domestic Firms						✓
R^2	0.24	0.39	0.24	0.39	0.44	0.56
Observations	840681	840681	840681	840681	481946	197631

Note. The regression specification is the same as that in Table 2 column (4). $I(Export=1)_f$ is 1 if firms export to other countries and 0 otherwise. $I(International=1)_f$ is 1 if firms export to (or import from) other countries and 0 otherwise. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and compare the sales growth within international and domestic firms separately. The spillover effect persists in these alternative specifications. Columns (5) and (6) consider only nonexporters and domestic firms (noninternational firms), respectively. The spillover effect is stronger, consistent with the evidence documented in Appendix D.2.

Overall, we conclude that the spillover effect through multimarket firms is robust to the concerns related to the trade network. Appendix E.2 considers the distance between markets, which can be interpreted as a proxy variable for intranational trade. The spillover effects are robust to the distance-related controls.

E.9 Adding Additional Control Variables

This section addresses other potential confounding factors by including more observed firm characteristics. The baseline analyses only allow the essential variables available in the Nielsen data, but we also bring in information from the NETS data and other county x firm characteristics to address other potential concerns. Note that some NETS variables have missing observations, and we lose a small number of firms in using these variables.

Table OA.21: Adding Additional Control Variables

	$\tilde{\Delta}S_{cf}$, 2007-2009									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\tilde{\Delta}HP_{cf}$ (other)	0.40***	0.44***	0.47***	0.47***	0.52**	0.64**	0.59***	0.41***	0.77***	0.70**
	(0.10)	(0.08)	(0.12)	(0.12)	(0.20)	(0.26)	(0.10)	(0.10)	(0.22)	(0.29)
N_f^{Plants}		-0.00	-0.00	-0.00					-0.00	-0.00
		(0.00)	(0.00)	(0.00)					(0.00)	(0.01)
N_f^{UPCs}		-0.05***	-0.05***	-0.05***					-0.05***	-0.05***
		(0.01)	(0.01)	(0.01)					(0.02)	(0.01)
$paydex_f$			-0.15**	-0.15**					-0.13*	-0.09
			(0.07)	(0.07)					(0.07)	(0.06)
$D\&B_f$			-0.02	-0.02					-0.02	-0.05*
			(0.02)	(0.02)					(0.02)	(0.03)
Age_f				0.01					0.01	0.00
				(0.01)					(0.01)	(0.02)
$Income_{cf}$ (other)					0.00	-0.00			-0.00	-0.00
					(0.00)	(0.00)			(0.00)	(0.00)
$Owner_{cf}$ (other)					-0.00	0.00			-0.00	0.01
					(0.01)	(0.00)			(0.01)	(0.01)
$White_{cf}$ (other)						-0.00			0.00	-0.00
						(0.01)			(0.01)	(0.01)
$Educ_{cf}$ (other)						-0.02***			-0.01***	-0.01***
						(0.00)			(0.00)	(0.00)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Major State FE							✓		✓	
HQ State FE								✓		✓
R^2	0.39	0.41	0.41	0.41	0.39	0.39	0.40	0.42	0.41	0.44
Observations	840,681	758,227	650,634	650,622	840,681	840,681	840,681	835,492	650,622	645,751

Note. The regression specification is the same as that in Table 2 column (4); Table OA.21 column (1) is identical to Table 2 column (4). N_f^{UPCs} is the log initial number of UPCs per firm, N_f^{Plants} is the log initial number of plants per firm, $paydex_f$ is the 2002-2006 average numerical credit score given by Dun & Bradstreet, D&B is a dummy variable equal to 1 if the initial Dun & Bradstreet credit rating is limited or fair and equal to 0 if it is high or good, and Age_f is the log initial firm age. $paydex_f$ is measured as ln(100-paydex). $Income_{cf}$ (other), $Owner_{cf}$ (other), $White_{cf}$ (other), $Educ_{cf}$ (other) are the initial sales-weighted average of county-specific demographic variables across counties within firms, excluding the market of interest; it replaces county-specific housing price changes in $\tilde{\Delta}HP_{(07-09)}$ (other) with the initial customer demographic variables. Income is household median income, Owner is percentage owner-occupied houses, White is percentage white, and Educ is percentage with a high school diploma or less. Major State is the state where each firm generates the largest sales among all of the states in which it sells, and HQ State is the state where each firm has its headquarters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.21 presents various control variables. Column (1) replicates Table 2 column (4).

Column (2) adds characteristics associated with the economies of scope (number of plants and UPCs), column (3) includes financial constraint index (Paydex index and D&B rating), and column (4) includes firm age. Including these control variables only makes the spillover effect slightly larger, corroborating the main empirical results.[14]

Columns (5) and (6) consider a measure that proxies for the quality of products firms offer. In studying the spillover effect, firms that originally served low-income households may face a larger negative indirect demand shock. In this case, we may mistakenly attribute these firms' sales growth, which arises from their initial market characteristics, to the negative indirect demand shock. To explicitly address this concern, we include initial market characteristics. Similar to the measure of the indirect demand shock, we consider the initial sales share-weighted average of the initial market characteristics: household income, percentage homeowners, white, and education. Including these control variables only makes the spillover effect stronger.

Columns (7) and (8) group firms based on their major state and compare firm sales growth within these major states. One potential concern for the identification is that we may be comparing firms that sell to very different markets and fundamentally comparing firms with different characteristics. The placebo analyses using the equal weight reported in Table E.4 column (1) partially address this concern because the spillover effect cannot be identified by solely relying on the variation across different markets. In addition, we explicitly address this concern by defining the major state for each firm and comparing firm sales growth within those groups of firms that share the same major state. In defining the major state for each firm, we consider two alternative specifications. First, we select the state for each firm where this firm generates the largest amount of revenue initially. Second, we group firms based on their headquarters locations.[15] By including HQ state FE, we are comparing firms with the same destination (county or market) and the primary origination (HQ state). Including these major state or headquarters state fixed effects and comparing sales growth within each state makes the spillover effect stronger, as shown in columns (7) and (8).

Columns (9) and (10) include all the control variables included in columns (1)-(6) and separately consider two different types of state fixed effects. Again, the spillover effect is even stronger with all

[14]Note that Appendix E.10 shows that there is no statistically significant correlation between these variables and the indirect demand shock. In multivariate analyses with other controls and fixed effects, the change in coefficients indicates that there may be a small downward bias for the spillover effect, suggesting that the baseline specification in the main body of the paper presents a conservative estimate.

[15]Some firms generate the same largest revenue from multiple states and have multiple headquarters in multiple different states. We select the state that has the largest sales for the major market and the largest number headquarters employees. We drop a small number of firms that have the exact same sales (or employment) across two markets (or headquarters).

the control variables.

E.10 Balance Checks

This section presents one way to test the exogeneity of the indirect demand shock firms face. Observing that the indirect demand shock closely proxies for the average housing price changes firms face with a lower local sales share, we regress firm-level observed initial characteristics on the average housing price changes they face.[16] If there is selection on the indirect demand shock on firm characteristics, we must observe a high correlation between initial firm characteristics and the degree of housing price changes their customers face. We use initial firm characteristics that are known to be important in the literature, such as size (sales), economies of scope (number of UPCs, counties, groups, and plants), age, and financial constraints (Paydex index, D&B rating).

Table OA.22: Balance Checks

	(1) S_f	(2) N_f^{UPCs}	(3) N_f^{Counties}	(4) N_f^{Groups}	(5) N_f^{Plants}	(6) Age_f	(7) paydex_f	(8) $\text{D\&B}_f$
$\tilde{\Delta}\text{HP}_f$	-1.10	0.78	-0.58	1.40	1.48	0.99	-0.18	-0.16
	(1.53)	(1.12)	(0.92)	(0.97)	(2.17)	(0.72)	(0.15)	(0.50)
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.63	0.62	0.38	0.53	0.71	0.77	0.45	0.64
Observations	4,171	4,171	4,171	4,171	3,894	4,168	3,606	3,252

Note. This table reports coefficients from regressing firm-level initial characteristics on the firm-level average $\tilde{\Delta}\text{HP}$ (averaged across counties) and sector fixed effects (at the 4-digit SIC level). S_f is log initial firm-level sales, N_f^{UPCs} is the log initial number of UPCs per firm, N_f^{Counties} is the log initial number of counties per firm, N_f^{Groups} is the log initial number of product groups per firm, N_f^{Plants} is the log initial number of plants per firm, Age_f is the log initial firm age, paydex_f is the 2002-2006 average numerical credit score given by Dun & Bradstreet, and D&B is a dummy variable equal to 1 if the initial Dun & Bradstreet credit rating is limited or fair and equal to 0 if it is high or good. Paydex_f is measured as ln(100-paydex) to facilitate interpretation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.22 presents the regression results. Regardless of using different firm characteristics, we do not find any evidence that the average housing price changes are correlated with previously observed characteristics.

[16] Using the firm-level average housing price allows us to conduct this analysis at the firm level. The correlation between the indirect demand shock and the average housing price is 0.9983 at the county-firm level.

E.11 Homescan Panel Data

Our main analyses consider the Nielsen Retail Scanner data, which record price, quantity, and other product characteristics whenever customers shop at the sampled retail stores. One potential concern in using these data is that they mostly sample large retail stores and may not be fully representative.

This section considers alternative data provided by Nielsen, which is the Homescan Consumer Panel data. This data sample approximately 55,000 households annually on average and provide handhold scanners to these households so that they can scan the products whenever they purchase products that have a barcode. Thus, the data cover more product categories that are not available in retail stores but have barcodes, such as television and online purchases. Moreover, Nielsen assigns the household sample weight (projection factor) based on ten different demographic variables so that we can make a nationally representative sample at the scantrack market, census division, and national level. The scantrack market is another geographical code assigned by Nielsen. There is a total of 76 scantrack markets available in our final sample, and examples of the scantrack markets are Boston, Chicago, and Phoenix. The data starts in 2004, allowing us to explicitly control the preperiod sales growth.

With the Homescan Consumer Panel data, we consider four alternative geographical units (Geo.Unit) available in the data as a market definition: state, scantrack, 5-digit zip code, and census division. Since we want to utilize the fully representative nature of the Homescan Panel data, we do not further combine with the NETS data but only use Homescan Panel data combined with the GS1 data, which provides us with a firm boundary based on the gs1 prefix information.[17] In the absence of the NETS information, we define the firm-specific major sector code by using the product group code. We define the major sector code based on the top three largest sales-generating product groups. If one firm sells three product groups, we set these three as one sector index. If another firm sells the same two product groups but not the other one, then we set this firm to be in a different sector. We categorize firms into the same sector only when firms sell the same three top product groups. If a firm sells only two product groups, we set these two product groups as one sector. Note that there is a small number of observations that have the same largest initial sales across product groups. If more than 3 product groups have the same sales, we treat them as one separate sector for each firm.

The Zillow data do not report housing price information by scantrack market and census division. Thus, we construct the housing price information for these two markets by taking the 2000-population weighted average of housing prices. For the scantrack market, we use county-level

[17]Note that using the retailer scanner data that are not combined with the NETS data but only with the GS1 data generate similar results, as shown in Appendix E.12.

housing price and population, and for the census division, we use state-level housing price and population. The standard errors are two-way clustered by geographical unit and sector for all the analyses except when census division is used as the definition of a market because there are only nine census divisions in the United States. In using the census division, we cluster the standard errors by sector. Additionally, we use 2004 as the initial year for all our analyses to make our analyses more conservative: We use 2004 initial sales as a weight, 2004 firm controls, and 2004 sales as a weight in constructing the indirect demand shock. Panel A explicitly controls for the 2004-2006 sales growth, whereas Panel B does not include this control, consistent with the specification in the main body of the paper. We adjust sales by the coupon value to account for the potential confounding behavior of retailers.

Table OA.23 reruns the main analyses reported in Table 2 and presents the spillover results. Panel A adds the 2004-2006 sales growth as an additional control variable, and Panel B does not include it. Although statistical significance of some of the coefficients depends on specification due to the change in the sample and fixed effects, all the results show that firms that face a negative demand shock from other markets lower their local sales. Generally, adding the previous sales growth does not alter the results; including this control makes the coefficients more economically and statistically significant when the market is defined at the 5-digit zip code level.

Overall, we conclude that the spillover results are robust to using Homescan Panel data.

E.12 Broader Sample

This section considers a broader sample of the Nielsen retail scanner data. We consider two different samples and rerun the main regression analyses. First, we add 105 single-market firms that only sell to one market to our sample. These firms were originally dropped from our sample because the indirect demand shock is undefined for these firms. We set the indirect demand shock to be zero for these firms and included them in our sample. Second, instead of combining the retail scanner data with the GS1 data and the NETS data, we only combine them with the GS1 data to obtain the firm boundary so that we can have a maximum number of observations in the sample. Similar to what we did with the Homescan consumer panel data, we use the product group code to define the major sector for each firm.[18]

Table OA.24 reports the results when including the local firms. The spillover results are almost

[18] Since we have a large number of observations, we use five product groups per firm to define the major sector for each firm. For example, if one firm sells five product groups, we set these five as one sector index. Only if the other firm sells the same five product groups do we treat this firm to having the same major sector.

Table OA.23: Using Homescan Panel Data

	$\tilde{\Delta}S_{kf}$, 2007-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Geographic Unit (subscript k):	State		Scantrack		5-digit Zip		Census Division	
Panel A: With 2004-2006 Sales Growth								
$\tilde{\Delta}HP_{kf}$ (other)	0.67***	0.55**	0.56**	0.33	0.32*	0.29**	0.34	0.51**
	(0.21)	(0.27)	(0.26)	(0.22)	(0.18)	(0.11)	(0.23)	(0.25)
$\tilde{\Delta}S_{kf,\ 04\text{-}06}$	0.00	0.00	-0.03**	-0.04***	-0.12***	-0.12***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Geo.Unit-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓		✓		✓		✓	
Geo.Unit FE	✓		✓		✓		✓	
Sector x Geo.Unit FE		✓		✓		✓		✓
N of Geo.Units	49	49	76	76	6,196	6,196	9	9
N of Firms	10,298	10,298	9,945	9,945	3,712	3,712	10,486	10,486
R^2	0.17	0.38	0.13	0.41	0.37	0.74	0.27	0.37
Observations	120,485	120,485	169,316	169,316	218,520	218,520	49,029	49,029
Panel B: Without 2004-2006 Sales Growth								
$\tilde{\Delta}HP_{kf}$ (other)	0.67***	0.56**	0.53**	0.31	0.15	0.17**	0.35	0.54**
	(0.21)	(0.27)	(0.26)	(0.21)	(0.18)	(0.08)	(0.24)	(0.27)
Geo.Unit-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓		✓		✓		✓	
Geo.Unit FE	✓		✓		✓		✓	
Sector x Geo.Unit FE		✓		✓		✓		✓
N of Geo.Units	49	49	76	76	6,693	6,693	9	9
N of Firms	10,845	10,845	10,601	10,601	4,472	4,472	10,919	10,919
R^2	0.17	0.38	0.12	0.40	0.34	0.74	0.27	0.37
Observations	132,817	132,817	188,910	188,910	299,363	299,363	51,973	51,973

Note. Using the Homescan Panel data and different definitions of the market, Table OA.23 columns (1), (3), (5), and (7) replicate the results in Table 2 columns (3), and Table OA.23 columns (2), (4), (6), and (8) replicate the results in Table 2 columns (4). Panel A includes the 2004-2006 sales growth ($\tilde{\Delta}S_{kf,\ 04\text{-}06}$) as a control variable, whereas the Panel B does not include this variable. Geo.Unit stands for the geographic unit, which is a definition of a market. Standard errors are two-way clustered by geographic unit and sector except when census division is defined as a market, in which case standard errors are clustered by sector. Geo.Unit-Firm Controls are county-firm sales, firm sales, the firm's number of markets and product groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

identical to what are reported in Table 2. There is a relatively small number of single-market firms that sell in one market, and adding these firms does not change the main results. Table OA.25 columns (1)-(3) consider a sample that includes all multimarket firms with the definition of firm boundary in the retail scanner data, and columns (4)-(6) additionally include singe-market firms with $\tilde{\Delta}HP_{cf}$ (other) = 0. All the results show that firms that face a negative demand shock from other markets decrease their local market sales.

Based on the analyses in this section, we conclude that the spillover results are robust to using a broader sample of firms available in the retail scanner data.

Table OA.24: Integrating Local Firms

	$\tilde{\Delta}S_{cf}$, 2007-2009						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ordinary Least Squares			IV Estimation Using			
				elasticity	sensitivity	lending	all
$\tilde{\Delta}HP_c$	0.06**						
	(0.03)						
$\tilde{\Delta}HP_{cf}$ (other)	0.35***	0.34***	0.40***	0.60***	0.73***	0.42**	0.48**
	(0.11)	(0.11)	(0.10)	(0.14)	(0.24)	(0.19)	(0.19)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓
County Controls							
Sector FE	✓	✓					
County FE		✓					
Sector x County FE			✓	✓	✓	✓	✓
First-stage F statistics				548.20	223.10	546.00	250.30
Hansen's J-stat p-value							0.24
R^2	0.20	0.23	0.39				
Observations	841,105	841,105	841,105	448,821	587,696	658,882	418,083

Note. All the regression specifications are the same as those in Table 2 except that 105 local firms are added with $\tilde{\Delta}HP_{cf}$ (other) = 0. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.13 Excluding Extreme Values

In the baseline analyses, we seek to be agnostic on extreme values by including them but weight each observation by initial sales. However, Figure 3 and 4 suggest that the results may be different if we exclude the extreme values; we may be able to observe a negative relationship for continuing products and a stronger relationship for product replacement.

This section clarifies the role of the extreme values by revisiting the decomposition analysis in Table 4 by excluding outliers. Table OA.26 shows that the spillover effect becomes stronger once we exclude the extreme values. Although the spillover effect is negative for continuing products, the coefficient is not significant at the conventional level, as shown in column (2). On the other hand, column (3) shows that the spillover effect through product replacement effect is stronger, making the overall spillover effect a larger positive value. In general, the main spillover effect and the decomposition results reported in Table 4 are robust to excluding extreme values.

Table OA.25: All Firms in Nielsen Retail Scanner+GS1

	$\tilde{\Delta}S_{cf}$, 2007-2009					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline			Integrating Local Firms		
$\tilde{\Delta}HP_c$	0.06**			0.06**		
	(0.02)			(0.02)		
$\tilde{\Delta}HP_{cf}$ (other)	0.35**	0.37**	0.54**	0.35**	0.38**	0.54**
	(0.14)	(0.15)	(0.23)	(0.13)	(0.15)	(0.23)
County-Firm Controls	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓		✓	✓	
County FE		✓			✓	
Sector x CountyFE			✓			✓
R^2	0.26	0.28	0.40	0.26	0.28	0.40
Observations	1,943,319	1,943,319	1,943,319	1,943,959	1,943,959	1,943,959

Note. Table OA.25 columns (1)-(3) replicate Table 2 column (1), (3), and (4) by including all the multimarket firms (15,563 firms) available in the retail scanner and GS1 combined data. Table OA.25 columns (4)-(6) replicate Table 2 column (1), (3), and (4) by including all the firms (16,181 firms) available in the retail scanner and GS1 combined data. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table OA.26: The Exact Decomposition, Excluding Extreme Values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Ordinary Least Square, Decomposition						IV, Decomposition	
		$\tilde{\Delta}S_{cf}$		$\tilde{\Delta}S_{cf}$		$\tilde{\Delta}S^{R}_{cf}$		$\tilde{\Delta}S_{cf}$	
	$\tilde{\Delta}S_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$	$\tilde{\Delta}S^{R,M}_{cf}$	$\tilde{\Delta}S^{R,L}_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R,M}_{cf}$
$\tilde{\Delta}HP_c$	0.06**	0.05**	0.01						
	(0.03)	(0.02)	(0.01)						
$\tilde{\Delta}HP_{rf,07-09}$ (other)	0.56***	-0.14	0.70**	-0.09	0.74***	0.74***	-0.00	-0.04	0.61
	(0.20)	(0.12)	(0.26)	(0.18)	(0.26)	(0.26)	(0.00)	(0.14)	(0.40)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓						
Sector x County FE				✓	✓	✓	✓	✓	✓
First-stage F statistics								271.90	271.90
Hansen's J-stat p-value								0.15	0.81
R^2	0.21	0.23	0.29	0.44	0.42	0.42	0.34		
Observations	800673	800673	800673	800673	800673	800673	800673	399343	399343

Note. Table OA.26 replicates Table 4 by excluding extreme values. The extreme values are the observations that have higher than the 99th percentile of the indirect demand shock or lower than the 1st percentile of the indirect demand shock. These percentiles are calculated by weighting the observations with initial sales.

E.14 Accommodating Local Entry and Exit, Using a Conventional Growth Rate

Our main analyses use the Davis et al. (1996) growth rate, which helps to limit the influence of outliers. Another key advantage of using this growth rate is its ability to accommodate local firm entry. The conventional growth rate, $\tilde{\Delta}X \equiv \frac{X_{09}-X_{07}}{X_{07}}$ with variable X, uses the initial sales as a denominator and cannot integrate those firms that locally enter the market and have zero initial local sales. Although our baseline analyses abstract away from these locally entering and exiting firms, this section explicitly includes these firms; the sales growth is 2 with local market entry and -2 with local market exit. Moreover, as a robustness exercise, we also test whether the main results change with the conventional growth rate.

In accommodating local entry and exit of firms, we make two changes in our regression specification. First, we use 2007-2009 average sales for the regression weight. If we use 2007 initial sales as the weight as in our main analyses, it places 0 weight on those locally entering firms, effectively dropping these firms from the regression specification. Second, the initial log sales control at the county-firm level is undefined for locally entering firms with zero initial level of sales. We use the inverse hyperbolic sine transformation instead of the log transformation for the initial sales and control for it in the regression. Note that we cannot have firms that nationally enter the market because the construction of the indirect demand shock requires firms to sell their products initially.

Table OA.27 columns (1)-(4) presents the results when accommodating local entry and exit, and Table OA.27 columns (5)-(8) presents the results by using the conventional growth rates. Although accommodating local entry and exit of firms significantly increases the number of observations, the spillover effect and its decomposition are similar to what is reported in Tables 2 and 4. Using the conventional growth rates makes the spillover effect even more economically significant. Our results indicate that either accommodating local entry and exit or using a conventional growth rate does not alter the main results in the paper.

E.15 Alternative Measures of the Housing Price Growth

This section considers four other measures of demand changes. First, we consider the change in household net worth, which is precisely used in the seminal work of Mian and Sufi (2014) instead of using housing price changes. Second, we consider 2006-2009 housing price changes that utilize the whole period of housing market disruptions. Third, we define an indicator variable that

Table OA.27: Accommodating Local Entry and Exit, Using a Conventional Growth Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Accommodating Local Entry and Exit				Using Conventional Growth Rates			
	$\tilde{\Delta}\text{S}_{cf}$	$\tilde{\Delta}\text{S}^{\text{C}}_{cf}$	$\tilde{\Delta}\text{S}^{\text{R,M}}_{cf}$	$\tilde{\Delta}\text{S}^{\text{R,L}}_{cf}$	ΔS_{cf}	$\Delta\text{S}^{\text{C}}_{cf}$	$\Delta\text{S}^{\text{R,M}}_{cf}$	$\Delta\text{S}^{\text{R,L}}_{cf}$
$\tilde{\Delta}\text{HP}_{cf,07-09}$ (other)	0.38***	-0.04	0.43***	0.00				
	(0.14)	(0.08)	(0.16)	(0.00)				
$\Delta\text{HP}_{cf,07-09}$ (other)					0.60***	0.03	0.57***	0.00***
					(0.14)	(0.14)	(0.13)	(0.00)
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.41	0.44	0.41	0.38	0.02	0.19	0.01	0.02
Observations	1,319,601	1,319,601	1,319,601	1,319,601	840,681	840,681	840,681	840,681

Note. Table OA.27 columns (1)-(4) replicate Table 2 column (4) and Table 4 columns (4), (6), and (7), respectively, with an exception for accommodating local firm entry and exit. In accommodating local firm entry and exit, the regressions are weighted by county-firm-specific average sales across 2007 and 2009, and the local initial sales is not logged but inverse hyperbolic sine transformed. Table OA.27 columns (5)-(8) replicate Table 2 column (4) and Table 4 columns (4), (6), and (7), respectively, with the exception of using the conventional growth rates for both sales growth and housing price growth in the indirect demand shock. The conventional growth rate is defined as $\tilde{\Delta} X \equiv \frac{X_{09}-X_{07}}{X_{07}}$ for a variable X. * p < 0.10, ** p < 0.05, *** p < 0.01.

equals 1 when the housing price change is larger than the median value of housing price changes and 0 otherwise. Lastly, we use standardized housing price changes. The first two specifications confirm the spillover results by using alternative measures from previous literature, and the last two specifications help interpret the estimated coefficients. Other regression specifications are identical to those reported in Table 2.

Table OA.28 shows the spillover results using household net worth. The spillover effect is generally robust regardless of using different regression specifications. The relevant elasticity is still more prominent than the local elasticity. Note that the local elasticity estimate in column (1), 0.22, is comparable to that reported in Kaplan et al. (2020) with the Nielsen Retail Scanner data. Their estimates are 0.207 at the county level, 0.239 at the MSA level, and 0.341 at the CBSA level. Table OA.29 shows the results using 2006-2009 housing price changes, and again, the spillover results are generally robust to including 2006 in constructing housing price changes.

We also consider two alternative housing price changes that help interpret the coefficient. Instead of using a continuous measure, consider an indicator variable that equals 1 if the demand shock measure is greater than its median value and is 0 otherwise based on county-county-level

Table OA.28: Using the Change in Housing Net Worth

	$\tilde{\Delta}$ S_{cf}, 2007-2009								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ordinary Least Squares					IV Estimation Using			
						elasticity	sensitivity	lending	all
$\tilde{\Delta}NW_c$	0.22***	0.16***	0.16***						
	(0.02)	(0.02)	(0.02)						
$\tilde{\Delta}NW_{cf}$ (other)		0.55***		0.55***	0.66***	0.82***	1.12***	0.55**	0.57*
		(0.16)		(0.17)	(0.15)	(0.18)	(0.38)	(0.27)	(0.31)
County-Firm Controls		✓		✓	✓	✓	✓	✓	✓
County Controls	✓		✓						
Firm FE			✓						
Sector FE		✓		✓					
County FE				✓					
Sector x County FE					✓	✓	✓	✓	✓
First-stage F statistics						377.90	89.80	314.60	275.30
Hansen's J-stat p-value									0.19
R^2	0.02	0.21	0.62	0.24	0.39				
Observations	661,791	661,790	661,761	661,790	661,789	397,198	517,071	556,987	383,085

Note. All the regression specifications are the same as those in Table 2 except for the use of 2006-2009 household net worth change. * p < 0.10, ** p < 0.05, *** p < 0.01.

observations:

$$\tilde{\Delta}D_c = \begin{cases} 1, & \text{if } \tilde{\Delta}HP_c \geq \text{median}(\tilde{\Delta}HP_c) \\ 0, & \text{otherwise} \end{cases}$$

Given D_c, we construct the indirect demand shock by taking a weighted average across counties within each firm, which is denoted as D'$_c$, where the weight is the initial sales share. We rerun the main regression analysis (equation 3.1) by replacing the county housing price changes and the indirect demand shock with the dummy variables above:

$$\tilde{\Delta}S_{cf} = \beta_0 + \beta_1 D_{r,07-09} + \beta_2 D_{cf,07-09} \text{ (other)} + \boldsymbol{X'_{cf}\beta_3} + \varepsilon_{cf} \tag{E.3}$$

Table OA.30 presents the results. Column (1) shows that the indirect demand effect is approximately twice as larger than the direct effect, confirming the importance of the indirect effect. Column (2) considers an alternative direct demand change using an alternative median value. The baseline indicator variable, D_c, is defined with the median housing price at the county level. Alternatively, we define the median housing price based on the total number of observations at the county-firm level and measure the indicator variable ($\tilde{\Delta}D_c$). Again, the indirect effect is larger than

Table OA.29: Using the 2006-2009 Changes in Housing Prices

	$\tilde{\Delta}$ S_{cf}, 2007-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ordinary Least Squares				IV Estimation Using			
					elasticity	sensitivity	lending	all
$\tilde{\Delta}\text{HP}_c$	0.07***	0.07***						
	(0.02)	(0.02)						
$\tilde{\Delta}\text{HP}_{cf}$ (other)	0.28***		0.29***	0.33***	0.45***	0.49***	0.31*	0.34**
	(0.08)		(0.08)	(0.06)	(0.10)	(0.17)	(0.15)	(0.16)
County-Firm Controls	✓		✓	✓	✓	✓	✓	✓
County Controls		✓						
Firm FE		✓						
Sector FE	✓		✓					
County FE			✓					
Sector x County FE				✓	✓	✓	✓	✓
First-stage F statistics					522.10	266.80	554.10	319.00
Hansen's J-stat p-value								0.32
R^2	0.21	0.61	0.24	0.40				
Observations	750,769	836,280	750,769	744,165	446,869	584,954	655,617	416,953

Note. All the regression specifications are the same as those in Table 2 except for the use of 2006-2009 housing price growth. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the direct effect. Other results are generally robust to using these alternative measures of demand changes.

Lastly, Table OA.31 presents the results by using the standardized direct and indirect shocks, denoted by "$\tilde{\Delta}\text{HP}_c$, Std" and "$\tilde{\Delta}\text{HP}_{cf}$ (other), Std", respectively. Both shocks are standardized relative to their sample means and standard deviations. Therefore, the differences in the standard deviations of the direct and indirect shocks are normalized, allowing us to interpret the coefficients as the impact on firm sales of a one standard deviation change in the direct and indirect housing shocks, respectively. Column (1) shows that the indirect demand effect is larger than the direct effect, showing the prominence of the indirect demand shock. Other results are generally robust to this standardization.

E.16 Shift-share Robust Standard Error

This section considers a standard error robust to the shift-share structure in the main regression analyses. Our main analyses consider two-way clustered standard errors by state and sector, which

Table OA.30: Using Indicator Variables

	$\tilde{\Delta}$ S_{cf}, 2007-2009							
	Ordinary Least Squares				IV estimation using			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_c	0.013*							
	(0.006)							
D_c (other)	0.026***	0.027***	0.028***	0.034***	0.056***	0.087***	0.041**	0.045**
	(0.010)	(0.009)	(0.008)	(0.006)	(0.013)	(0.024)	(0.020)	(0.021)
D'$_c$		0.013						
		(0.008)						
County-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
County Controls								
Firm FE								
Sector FE	✓	✓	✓					
County FE			✓					
Sector x County FE				✓	✓	✓	✓	✓
First-stage F statistics					493.30	107.00	537.20	381.50
Hansen's J-stat p-value								0.18
R^2	0.20	0.20	0.24	0.39				
Observations	840,681	840,681	840,681	840,681	448,604	587,436	658,607	417,869

Note. All the regression specifications are the same as those in Table 2 except for the use of an indicator variable for the independent variables.

is probably the most standard specification. With the standard errors used in our analysis, we allow arbitrary correlation of errors across sectors within states and across states within sectors. However, a growing body of literature has recognized the importance of accounting for correlated errors in using an independent variable with the shift-share structure (see, e.g., Adao et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2022), among many others). Given that the indirect demand shock used in this paper has a shift-share structure, we also follow this literature to adjust for the correlation of errors arising from similar initial shares.

In particular, we follow Adao et al. (2019) in correcting for the correlated errors through the similar shares. Note that our regression specification does not directly map to the class of empirical models studied in this literature. For example, consider the seminal work of Autor et al. (2013). In this conventional setup, industry-level shifters ("China shocks") are converted into region-level (commuting zone) shocks with the initial region-industry employment share, and the final regression is performed at the region-level. Thus, the region-level residuals are converted back to the industry-level in constructing the shift-share robust standard error in the standard setup. However, our analysis converts county-level shifters (housing price changes) into county-firm-level

Table OA.31: Using the Standardized Independent Variables

	$\tilde{\Delta}$ S_{cf}, 2007-2009							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ordinary Least Squares				IV Estimation Using			
					elasticity	sensitivity	lending	all
$\tilde{\Delta}$HP$_c$, Std	0.008**	0.008**						
	(0.003)	(0.003)						
$\tilde{\Delta}$HP$_{cf}$ (other), Std	0.014***		0.014***	0.017***	0.025***	0.030***	0.017**	0.019**
	(0.005)		(0.005)	(0.004)	(0.006)	(0.010)	(0.008)	(0.009)
County-Firm Controls	✓		✓	✓	✓	✓	✓	✓
County 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	0.04	0.04	0.04	0.00
Observations	840681	840681	840681	840681	448604	587436	658607	417869

Note. All the regression specifications are the same as those in Table 2 except for the use of standardized independent variables. * p < 0.10, ** p < 0.05, *** p < 0.01.

shocks (indirect demand shocks) with the initial local firm sales share. The final regression is performed at the county-firm level. To apply the method developed in Adao et al. (2019), we convert county-firm-level residuals back to the county-level in constructing the shift-share robust standard errors.

Table OA.32 presents the main spillover result and its exact decomposition using the shift-share robust standard errors. We find that the magnitude of standard errors is similar to what is reported with the two-way clustered standard errors reported in Tables 2 and 4. In fact, the standard errors are smaller in studying the uniform product replacement channel, as shown in columns (3) and (4).

E.17 Heterogeneous Treatment Effect: Additional Results

This section revisits the results in Table 6 panel A columns (1)-(4) and panel B column (8). To make the table compact and coherent with other analyses reported in other columns, Table 6 suppresses the control variables included in the regression analyses and does not include alternative specifications for the interaction variable Z_{cf}. This section makes these presentations more explicit by showing the coefficients for control variables and considering alternative specifications. Table OA.33 presents the

Table OA.32: Alternative Standard Errors

	(1)	(2)	(3)	(4)	(5)
		$\tilde{\Delta}S_{cf}$		$\tilde{\Delta}S^{R}_{cf}$	
	$\tilde{\Delta}S_{cf}$	$\tilde{\Delta}S^{C}_{cf}$	$\tilde{\Delta}S^{R}_{cf}$	$\tilde{\Delta}S^{R,M}_{cf}$	$\tilde{\Delta}S^{R,L}_{cf}$
$\tilde{\Delta}HP_{cf}$ (other)	0.40**	-0.02	0.42***	0.42***	0.00
	(0.17)	(0.13)	(0.09)	(0.09)	(0.00)
County-Firm Controls	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓
R^2	0.39	0.43	0.41	0.41	0.22
Observations	840,681	840,681	840,681	840,681	840,681

Note. The regression specifications are the same as those in Table 2 column (4) except that we use the shift-share robust standard errors proposed by Adao et al. (2019). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

results, and many columns replicate what are in Table 6: Table OA.33 panel A column (4) replicates Table 6 panel A column (1), Table OA.33 panel A column (8) replicates Table 6 panel A column (2), Table OA.33 panel B column (4) replicates Table 6 panel A column (3), Table OA.33 panel B column (6) replicates Table 6 panel A column (4), and Table OA.33 panel B column (7) replicates Table 6 panel B column (8).

Table OA.33 panel A columns (1)-(4) consider the initial sales of products that are sold in multiple markets per firm f (S^{Organic}_{f}) as an interaction variable. Column (1) does not consider any initial sales-related controls. Column (2) adds sales decile fixed effect, column (3) adds the initial log sales interacted with the indirect demand shock, and column (4) adds both the sales decile fixed effect and log initial sales interacted with the indirect demand shock. All the results for the interaction effect are positive, showing that the indirect demand effect is stronger when firms initially generate larger sales from the products sold in multiple markets. Comparing firms that have similar sales makes the interaction effect even stronger. Panel A columns (5) and (6) consider the initial average number of counties per UPC ($\bar{N}^{\text{Counties}}_{u}$) as an interaction variable, and columns (7) and (8) additionally adjust for the number of counties per firm so that we can precisely capture the uniform product replacement channel. All the specifications generate the positive interaction coefficient, and the effect becomes strongest when we consider the most precise specification that captures the uniform product replacement channel in column (8).

Table OA.33 panel B columns (1)-(4) consider the initial sales of organic products per firm f (S^{Organic}_{f}) as an interaction variable. All the interaction coefficients are positive regardless of whether we include the initial log firm sales or the sales decile fixed effects. Panel B columns (5) and (6) consider a number of organic products. The interaction coefficient is positive but is not statistically significant, probably because a number of organic products do not precisely capture the firm-level quality. Panel B column (7) shows that the spillover effect is stronger when the distance to the local market is higher on average, but the effect disappears when we control for the initial firm sales, as shown in column (8).

Overall, Table OA.33 shows that the results reported in Table 6 are generally robust to using other specifications or excluding control variables.

Table OA.33: Heterogeneous Treatment Effect: With Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\tilde{\Delta}$ S_{cf}, 2007-2009							
	Panel A: Uniform Product Replacement							
Z_{cf} is	$\mathrm{S}_f^{\text{Multiple}}$				$\bar{\mathrm{N}}_u^{\text{Counties}}$		$\mathrm{N}_{u,f}^{\text{Counties}}$	
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x Z_{cf}	0.28***	0.54***	3.92***	3.46***	0.27***	0.22	0.95**	0.98**
	(0.05)	(0.09)	(1.15)	(1.00)	(0.09)	(0.13)	(0.45)	(0.43)
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other)	-4.37***				-1.21**			
	(0.80)				(0.51)			
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x S_f			-3.89***	-2.91***				
			(1.15)	(0.99)				
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x N_f^{UPC}						0.38		0.50*
						(0.30)		(0.27)
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.39	0.40	0.39	0.40	0.39	0.39	0.39	0.39
Sales Decile		✓	✓	✓				
# of UPCs Decile						✓	✓	✓
Observations	840,677	840,677	840,677	840,677	840,681	840,681	840,681	840,681
	Panel B: Product Value Downgrading							
Z_{cf} is	$\mathrm{S}_f^{\text{Organic}}$				$\mathrm{N}_f^{\text{Organic}}$		dist_{cf}	
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x Z_{cf}	0.94***	0.48*	0.99***	0.45**	1.69	1.00	0.22***	-0.09
	(0.31)	(0.29)	(0.32)	(0.20)	(1.37)	(1.08)	(0.08)	(0.06)
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other)	-9.77**				-0.02			
	(3.83)				(1.56)			
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x S_f		-0.19		2.20***				0.59***
		(0.19)		(0.75)				(0.10)
$\tilde{\Delta}\mathrm{HP}_{cf,07-09}$ (other) x N_f^{UPC}						3.41*		
						(1.69)		
Region-Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector x County FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.70	0.71	0.70	0.73	0.69	0.71	0.39	0.40
Sales Decile			✓	✓				
# of UPCs Decile						✓		
Observations	74,323	74,323	74,323	74,323	74,323	74,323	840,681	840,681

Note. The regression specification is the same as that in Table 2 Column (4) except that we include the exposure variable Z_{cf} and its interaction with the indirect demand shock $\tilde{\Delta}\mathrm{HP}_{07-09}$ (other) following Equation (4.2). $\mathrm{S}_f^{\text{Multiple}}$, $\mathrm{N}_{u,f}^{\text{Counties}}$, $\mathrm{S}_f^{\text{Organic}}$, and $\mathrm{N}_f^{\text{Organic}}$ are the same as what are used in Table 6. $\bar{\mathrm{N}}_u^{\text{Counties}}$ is the sales-weighted average of the initial number of counties per UPC: $\bar{\mathrm{N}}_u^{\text{Counties}} \equiv \sum_u w_{uf} \mathrm{N}_u^{\text{Counties}}$, where w_{uf} is sales share of UPC u out of total sales of firm f, and $\mathrm{N}_u^{\text{Counties}}$ is the initial number of counties per UPC u. $\mathrm{dist}_c f$ is the initial sales-weighted average of distance to the local market of interest across counties within all markets of firms. S_f denotes the initial log firm-level sales, and $\mathrm{N}_f^{\text{UPC}}$ is the initial log firm-level number of UPCs. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Theoretical Analyses

Motivated by the empirical evidence, we formalize the spillover mechanism by developing a multimarket model with endogenous product quality adjustments throughout Section F to Section H. For readability, Section F focuses on describing the key elements of the model and explaining its main implications. In Section G, we provide more technical details for interested readers, while Section H contains derivations and proofs of theoretical results.

We simplify and adjust the standard model environment in Melitz (2003) and Faber and Fally (2021) into a multimarket framework to match our empirical findings. The model further clarifies why firms that face negative shocks downgrade their product value uniformly across multiple markets, including the market where they do not face the shock and generate the spillover. In particular, it delivers an equation similar to the reduced-form regression equation (3.1), providing one way to micro-found the reduced-form analysis.

The baseline model in Section F.1 assumes that firms provide the same goods across multiple markets in 2007-2009, as shown in Tables 1 and OA.2, and shows how multimarket firms spill over the shocks by changing their product values. The extension in Section F.2 endogenizes the decision to provide the same goods across markets and highlights the tradeoff that firms face in changing their product values uniformly across markets. The counterfactual exercise in Section F.3 shows that the identified intrafirm spillover leads to a new interregional shock transmission of the shocks and mitigates the regional consumption inequality.

F.1 Baseline Model

Demand. Consider an economy with R markets indexed by $r \in \mathcal{R} \equiv \{1, 2, ..., R\}$. Each market is populated by a continuum of mass L_r of individuals, each of whom is endowed with total income y_r, which is the sum of the exogenous income I_r and the dividends from the production sector D_r. The dividends are assumed to be distributed proportionally to individuals' exogenous income.[19] 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. 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 the numeraire. The optimal consumption of CPG goods by an individual in market r, s_r, is the share of the individual's gross income, y_r. The CPG consumption

[19]Given the focus on the intrafirm spillover effects, we do not explicitly model housing prices but generate the heterogeneous demand changes with the heterogeneous change in household income.

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. The utility from CPG consumption is defined as:

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

where subscript f denotes a CPG firm, G_r is the set of firms selling in market r, q_{rf} is the quantity of the product bundle produced by firm f and consumed by individuals in market r, ζ_f refers to the perceived quality (or appeal, taste) of firm f's product bundle, and σ refers to the elasticity of substitution between the firms' product bundles.[20] We do not explicitly introduce multiple products within each firm, as we find that product variety changes within firms play a limited role in response to the indirect shocks (see Table 5 Columns (7)-(8)).

Following Faber and Fally (2021), we assume that the perceived quality ζ_f depends on an intrinsic quality (i.e., product attribute) choice by the firm:

$$\log \zeta_f \equiv \gamma \log \phi_f \tag{F.2}$$

where ϕ_f is firm f's intrinsic quality and γ is a multiplicative term. We interpret the change in the quality of a product bundle, ϕ_f, as product replacement within firms. Our empirical analyses of product values and organic shares suggest a change in product features that make it less desirable for consumers conditioning on output price, which is precisely linked to the definition of product quality in this model.[21]

This setup has two simplifying assumptions. First, firm f's choice of intrinsic product quality, ϕ_f, does not vary across markets. This assumption reflects the empirical findings in Tables 1 and OA.2, which show that firms generally provided the same products across multiple markets in 2007-2009.[22] Second, the household's taste for quality ζ_f does not vary across markets; the heterogeneous taste parameters across the market are not necessary for the spillover effects. Section

[20]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 Appendix H.2 for the proof.

[21]An organic identifier is often used as a measure of product quality. See, e.g., DeDad et al. (2021).

[22]Note that we make the baseline model simple by bringing in an extreme form of this empirical fact: We assume only one product quality in all markets in which firms operate. For the spillover effects, it is enough for firms to provide the same product in more than one market. It is straightforward to allow firms to choose the same product quality for a subset of their markets. See Appendix G.2.4.

F.2 relaxes these two assumptions by allowing (i) firms to choose a different quality of products across different markets and (ii) households to have different tastes in product quality depending on their consumption of outside goods and thus their incomes.

Each individual in market r solves for her optimal CPG consumption bundle by maximizing equation (F.1) subject to her budget constraint, $\int_{f\in G_r} p_{rf}q_{rf}df \leq s_r$, 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:

$$S_{rf} = (\zeta_f)^{\sigma-1}\left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} S_r \tag{F.3}$$

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

$$P_r \equiv \left[\int_{f\in G_r}(p_{rf})^{1-\sigma}(\zeta_f)^{\sigma-1}df\right]^{\frac{1}{1-\sigma}} \tag{F.4}$$

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 the empirical analyses consider sets of active firms in both pre- and post-shock periods, we abstract away from the firm's entry and exit decision and calibrate the model such that all firms enjoy a nonnegative profit in the equilibrium. In this way, the model directly maps the firms used in the empirical analyses.

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

$$mc(\phi_f; a_f) \equiv \frac{\phi_f^{\xi}}{a_f} \tag{F.5}$$

where the parameter ξ is the elasticity of the variable cost to the level of product quality. Note that Equation (F.5) assumes the standard constant marginal costs of quantity production. This assumption reflects our empirical finding that there is no intrafirm spillover effect through continuing products within domestic markets. Assuming increasing or decreasing marginal costs of quantity would generate the spillover effect through continuing products because firms would sell different quantities in the local market when the change in marginal costs is induced by shocks arising from their other markets.

The total fixed costs are given by $\tau(\phi_f) + \tau_0$, where $\tau(\phi_f)$ is the component of fixed costs that directly depends on quality. This component captures potential overhead costs such as design, marketing, real estate, or other contractual costs, which do not directly depend on the quantities being produced but affect product quality. Note that we are analyzing a relatively short period, 2007-2009, and any one-time costs that occur every two years are fixed cost in this setup. Assuming a simple log-linear parameterization leads to:

$$\tau(\phi_f) = b\beta\phi_f^{\frac{1}{\beta}} \tag{F.6}$$

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

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

$$\pi_f = \sum_{r \in k_f} \left(p_{rf} - mc(\phi_f; a_f)\right) q_{rf} L_r - \tau(\phi_f) - \tau_0 \tag{F.7}$$

subject to the market demand Equation (F.3). k_f is the set of markets in which firm f sells its products. We assume that each firm's markets are exogenous to each firm, reflecting our baseline empirical analyses that do not allow market entry and exit. This assumption is supported by previous studies, such as Bronnenberg et al. (2009, 2012), who document the historical persistence of firms' markets; it is especially true for the short period (2007-2009) we focus on. Consistent with this assumption, allowing market entry and exit makes negligible changes in the empirical spillover results, as shown in Appendix E.14.

Solving the firm's profit maximization problem and rearranging the terms, the optimal price (F.8), sales (F.9), and quality (F.10) are given by

$$p_{rf} = \mu \left(\frac{\phi_f^{\xi}}{a_f} \right) \tag{F.8}$$

$$S_{rf} = \phi_f^{(\sigma-1)(\gamma-\xi)} \left[\frac{a_f}{\mu} P_r \right]^{\sigma-1} S_r \tag{F.9}$$

$$\phi_f = \left[\left(\frac{(\gamma - \xi) a_f^{\sigma-1}}{\mu^\sigma b} \right) \sum_{r \in k_f} P_r^{\sigma-1} S_r \right]^{\frac{1}{1/\beta - (\sigma-1)(\gamma-\xi)}} \tag{F.10}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma-1}\right)$ indicates the price-cost markup, and the optimal price is a conventional markup over marginal cost.[23] Note that there are three important parametric restrictions necessary for optimality: $\sigma > 1$, $\gamma > \xi$, and $\beta(\sigma-1)(\gamma-\xi) < 1$. Appendices H.4, H.5 and H.6 show that these restrictions are required for the first-order and second-order conditions, and the equilibrium firm product quality ϕ_f, local sales S_{rf}, and profit π_f to increase monotonically with firm productivity a_f.[24] Our estimation of the structural parameters and the estimated values from previous studies are consistent with these restrictions, as shown in Appendix G.3.1.

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

The intrinsic product quality, in turn, depends on the primitive structural parameters and market characteristics. It is higher when households prefer high-quality products (high γ) but lower when the variable costs increase too much given a small increase in quality (high ξ) or when households do not easily switch their products (low σ or high μ). Firms that operate in larger markets (high

[23] The derivations for price and quality are reported in Appendix H.4, and the local firm's sales are derived by combining the local firm product demand (F.3), the definition of product quality (F.2), and the equilibrium firm local price (F.8).

[24] The economic intuition behind these parametric restrictions is as follows. If $\gamma < \xi$, firms choose the lowest product quality they can provide because the consumption gains from the high-quality goods (governed by γ) are less than the consumption loss from the associated increase in marginal costs and output price (governed by ξ). Assuming that product quality is nonnegative, the model generates a corner solution with the optimal product quality equaling zero, which does not reflect the heterogeneous product quality observed in the data. Furthermore, suppose that $\frac{1}{\beta} < (\sigma-1)(\gamma-\xi)$. Then firms increase product quality infinitely since the associated loss from the fixed costs (governed by β) is lower than the associated gains from the larger market share (governed by $(\sigma-1)(\gamma-\xi)$). The complementary product ($\sigma < 1$) is ruled out as in a canonical model with a CES demand system. This condition balances the marginal return and the marginal loss associated with an increase of product quality.

S_r) provide higher quality products because they have more revenues to recover high fixed costs in producing high-quality goods. For the same reason, more productive firms (high a_f) or firms that sell to markets with a high price index (high P_r) provide higher quality products because they set a relatively low price and have a larger market share as a result.

From Theory to Empirics. By replacing the firm quality in Equation (F.9) with the optimal quality in terms of local firm sales (H.14), taking the log difference of the combined equation, and rearranging terms, we obtain a structural equation that presents how a firm's local sales growth is affected by the firm's demand conditions in other markets:

$$\hat{S}_{rf} = \frac{\Upsilon}{1-\Upsilon w_{rf}} \sum_{r'\neq r} w_{r'f}\hat{S}_{r'f} + \frac{\sigma-1}{1-\Upsilon w_{rf}}\hat{a}_f + \frac{1}{1-\Upsilon w_{rf}}\hat{A}_r \tag{F.11}$$

where $\hat{x} \equiv \log(x'/x)$ is the growth rate of an arbitrary variable x, $\Upsilon \equiv \beta(\sigma-1)(\gamma-\xi)$, $w_{rf} \equiv \frac{S_{rf}}{\sum_{r'\in k_f} S_{r'f}}$ is the initial sales share, and $A_r \equiv (P_r)^{\sigma-1}S_r$ is the market-specific variable. Note that the structural equation (F.11) resembles the reduced-form equation (3.1): The dependent variable is identical across the two equations, and the indirect shock is measured by the weighted average of the demand change firms face in the other markets, where the weight is the initial sales share.[25] The demand change is measured with the local-firm sales growth in Equation (F.11) and with the regional house price growth in Equation (3.1). The term in front of the indirect shock, $\frac{\Upsilon}{1-\Upsilon w_{rf}}$, helps interpret the reduced-from indirect effect β_2 in terms of the deep structural parameters.

Equation (F.11) presents the interdependency of markets through the uniform product quality changes, which is closely linked to the empirical analyses. Consider firm f's sales growth in a particular market r, $\hat{S}_{rf}$. Holding everything else constant, suppose that the firm's sales growth in all other markets declines on average due to the negative shocks in these markets, such as a decrease in income (I_r) or the decline in housing price growth in 2007-2009. When firm sales growth in these markets decreases sufficiently, firms downgrade their product quality due to the scale effect: They lack sufficient revenue to recover the high fixed cost of producing high-quality products and downgrade their product quality. Because firms choose the same product quality across markets,

[25] Note that the initial weight is slightly different across two equations. It is straightforward to make the weights identical by rearranging Equation (F.11):

$$\hat{S}_{rf} = \Upsilon\left(\frac{1-w_{rf}}{1-\Upsilon w_{rf}}\right) \sum_{r'\neq r}\left(\frac{w_{r'f}}{1-w_{rf}}\right)\hat{S}_{r'f} + \frac{(\sigma-1)}{1-\Upsilon w_{rf}}\hat{a}_f + \frac{1}{1-\Upsilon w_{rf}}\hat{A}_r. \tag{F.12}$$

where $\left(\frac{w_{r'f}}{1-w_{rf}}\right)$ is the same as the leave-one-out weight in the indirect shock in Equation (2.5).

their product downgrading decision leads to a decline in product quality and sales in the local market and generates the spillover. This spillover effect through uniform product quality downgrading is consistent with the empirical results reported in Tables 2, 4, and 5.

The responsiveness of a firm's local sales to the firm's average sales growth in the other markets, $\frac{\Upsilon}{1-\Upsilon w_{rf}}$, consists of the inverse elasticity of the fixed cost (β), the elasticity of market share with respect to quality ($(\sigma-1)(\gamma-\xi)$), and initial sales share (ω_{rf}). From the cost side, if a firm can raise its product quality by paying small fixed costs (high β), it would raise quality and local sales more than its counterpart, conditional on the same firm's sales growth. From the demand side, if firms can acquire considerable market share by raising their product quality (high $(\sigma-1)(\gamma-\xi)$), firms that face overall sales growth would increase their quality and local sales more than their counterparts. As described in Equation (F.9), the effect of quality on market share depends on the substitutability of products (σ), individual preferences (γ), and the marginal cost of quality that passes through to the output price (ξ). However, if firms earn large revenues from the local market of interest (high w_{rf}), they would not be substantially affected by the economic conditions in other markets. Although the specific functional form is different, this prediction is consistent with the empirical results highlighted in Table 6, Panel B, columns (1) and (2). Appendix D.6 directly estimates the structural regression by using the house price change used in the reduced-form analyses as an IV. Appendix G.3.1 performs a similar analysis with the extended model presented in Section F.2.

The intuition described above, which explains the mechanism behind how the intrafirm spillover effect arises, can be formalized by the following propositions. Proposition OA.1 characterizes how firms respond to the demand changes arising from the shift in exogenous market income I_r.

Proposition OA.1. *Holding P_r and D_r fixed for all $r \in k_f$,*
$\frac{\partial \log \phi_f}{\partial \log I_r} > 0$, $\frac{\partial \log S_{rf}}{\partial \log I_r} > 0$, *and* $\frac{\partial \log S_{r'f}}{\partial \log I_r} = (\sigma-1)(\gamma-\xi)\frac{\partial \log \phi_f}{\partial \log I_r} > 0$ *for $r, r' \in k_f$ and $r \neq r'$.*

Proof. See Appendix H.8.1. □

That is, suppose that households living in region r confront an exogenous decrease in their income I_r. Holding the regional price index and dividend income fixed, firms that face this market decrease their local market r sales, product quality, and the other market r' sales through uniform quality downgrading across markets. The effect on the other market sales is the spillover effect, and it only works through the uniform product quality changes, formalizing the reduced-form empirical results. The effect of uniform product quality on local sales depends on $(\sigma-1)(\gamma-\xi)$, consistent with the local market sales expression in terms of product quality (F.9). The effect on local sales mirrors the direct demand effect identified in Table 2 columns (1) and (2), and the effect on product quality reflects the empirical results in Table 5 columns (1)-(6). As shown in Appendix H.8.1, the same results hold when P_r varies with I_r, as long as the variation is relatively small.

F.2 Extensions

The baseline model in Section F.1 highlights the importance of the uniform product quality changes—the uniform product replacement channel—in generating the spillover effect. This section further clarifies the mechanism by endogenizing firms' uniform product quality choices. To do so, we make three extensions. First, we allow households' tastes for product quality to vary across markets so that firms have an incentive to provide different product quality to different markets. Second, given that different product quality levels across markets require firms to produce different products and penetrate such products in each market, we allow costs associated with these activities. Lastly, we let firms choose between uniform product quality and market-specific product quality before deciding the optimal levels of price and quality. Here, firms face these two extreme choices for presentation purposes; Appendix G.2.4 generalizes it by allowing firms to choose an arbitrary number of markets in supplying the same quality products.

We allow the taste for product quality to vary across markets using the standard nonhomothetic demand system: The preference for product quality changes with the consumption of outside goods, which depends on household income. The following utility from CPG consumption and the associated product quality generalizes Equations (F.1) and (F.2):

$$U_r = \left[\int_{f \in G_r} (q_{rf} \zeta_{rf})^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}} \tag{F.13}$$

where $\log \zeta_{rf} \equiv \gamma_r \log \phi_{(r)f}$, $\gamma_r \equiv \gamma(z_r)$ with $\gamma' > 0$, and $\phi_{(r)f}$ can be either ϕ_f or ϕ_{rf}.[26] The only differences from the baseline model are that γ depends on market-specific outside goods consumption z_r and the intrinsic quality chosen by firms (ϕ) could vary across both firms and markets, depending on the strategy firms choose: Under uniform product quality, ϕ does not vary across markets ($\phi_{(r)f} = \phi_f$), whereas under market-specific product quality, ϕ varies across both firms and markets ($\phi_{(r)f} = \phi_{rf}$). In this framework, since individuals living in high-income regions purchase more outside goods, high-income markets prefer high-quality products.[27]

[26] Note that $\phi > 1$ is required for households perceived product quality to increase with product quality.

[27] Note that we only allow nonhomotheticity across quality (γ) but not across elasticity (σ) to make the model parsimonious. This specification is based on the previous analyses of the CPG industry that integrate both types of nonhomotheticity and find a dominant role of quality relative to the elasticity in explaining the heterogenous household consumption pattern. See, e.g., Faber and Fally (2021); Handbury (2021).

Given the demand conditions derived from the nonhomothetic demand system (G.24), firms choose between uniform product quality and market-specific product quality by comparing the profits generated from each choice. For uniform product quality, as in the baseline model, firms maximize profits (F.7) by optimally choosing a uniform quality ϕ_f and price p_{rf}. On the other hand, if firms wish to choose market-specific product quality, they maximize the following profit equation by choosing market-specific quality (ϕ_{rf}) and price (p_{rf}^m):

$$\pi_f^m = \sum_{r \in k_f} \left[\left(p_{rf}^m - mc(\phi_{rf}; a_f) \right) q_{rf}^m L_{rf} \right] - \sum_{r \in k_f} \left(\tau(\phi_{rf}) - \tau_r \right) - \tau_0 \tag{F.14}$$

where the superscript m denotes the market-specific case and is used to distinguish different variables from those in the uniform product quality case. Compared to the profit equation (F.7), firms choose different product quality levels across markets and thus have different optimal prices, quantities, and marginal costs. Depending on the level of product quality provided in each market, they pay different fixed costs ($\tau(\phi_{rf})$). These costs need to be paid separately for each market, reflecting the costs of installing multiple machines or factories that are necessary to produce multiple layers of product qualities provided to multiple markets. In addition, firms need to pay the market-specific fixed costs (τ_r). These costs are associated with the market penetration costs in selling different products in different markets, such as advertising and marketing costs.[28]

Solving for the optimal profit in the market-specific product quality case and comparing the optimal profits in two cases, firms choose uniform product quality if the following condition holds:

$$\sum_{r \in k_f} \tau_r > g \left(N_f, \text{Var}(\gamma_r), \ldots \right) \tag{F.15}$$

where g is the difference in optimal profit between the two choices excluding the market-specific penetration cost. Note that the g is a function of the number of markets per firm f (N_f), and the variance of the market taste for product quality (γ_r). The function g is decreasing in N_f with a sufficiently large N_f, and in a special case, g is larger with $\text{Var}(\gamma_r) > 0$ than that with $\text{Var}(\gamma_r) = 0$. See Appendix G.2.3 for details.

Equation (F.15) underscores two types of the market-specific fixed costs associated with market-specific product quality choice, which make firms choose uniform product quality as observed in

[28]See, e.g., Arkolakis (2010); Drozd and Nosal (2012); Afrouzi et al. (2021); Einav et al. (2021) for the importance of these market penetration margins. Moreover, in the data, firms may have already been producing a different quality of products before 2007 and reallocated the products across markets during the Great Recession. In this case, there is no cost of producing different product quality $\tau(\phi_{rf})$. However, firms still need to pay the market penetration costs, f_r.

Tables 1 and OA.2. First, the left-hand side of the equation presents the fixed costs invariant to the level of product quality, such as the market penetration costs. If these costs are high enough (large τ_r), firms avoid them by choosing uniform quality across markets. Second, choosing market-specific quality requires firms to pay separate fixed costs for the multiple levels of product quality offered in multiple markets ($\tau(\phi_{rf})$) instead of the single fixed cost associated with uniform product quality ($\tau(\phi_f)$). With a sufficiently large number of markets (large N_f), the market-specific fixed costs of quality accumulate and depress the optimal average market-specific product quality due to the scale effect.[29]

However, there is a revenue gain from optimally providing different quality products across heterogeneous markets. Given a heterogeneity in market income and corresponding taste differences for product quality ($Var(\gamma_r) > 0$), choosing market-specific product quality allows firms to offer higher product quality to high-income markets. As a result, firms enjoy larger revenues from their markets and have an incentive to choose market-specific product quality. Consistent with this idea, Table 6, Panel A, columns (7) and (8) show that the spillover effect is mitigated when firms face more heterogeneous households in terms of market income. Note that other forces influence this tradeoff, such as the revenue gains from providing higher product quality to larger markets.

For each of the two choices, the extended model confirms the spillover effect that works through the uniform product quality (replacement) channel: Intrafirm market interdependence exists with the uniform product quality choice but disappears when firms choose market-specific product quality. See Appendix G.2.2 for the proof. Moreover, the extended model features two separate reasons why firms change their product quality when they face regional demand changes: the scale effect, as discussed in the baseline model in Section F.1, and nonhomotheticity. Nonhomotheticity shows the idea that households suffering from lower income start to prefer lower quality products, which makes firms downgrade their product quality. The extended model predicts that the effect is stronger for a high-income market, consistent with the results in Table 6, Panel A, column (5), further confirming the uniform product replacement channel. See Appendix G.2 for further details.

[29]The following is another way to think of why firms choose lower average product quality when choosing market-specific product quality relative to the case of uniform product quality. If firms choose market-specific product quality, the quality choice problem is separable across markets: They must rely on the market-specific revenue to recover the high fixed costs of producing high market-specific quality goods. On the other hand, if firms choose uniform product quality, they can rely on the total firm-specific revenues generated from all of their markets, allowing firms to select higher product quality.

F.3 Regional Analyses

Does multimarket firms' uniform product replacement choice affect regional sales, prices, and consumption distribution? This section calibrates our model to provide a back-of-the-envelope calculation for this question.[30]

Based on the extended model with nonhomothetic preferences in Section F.2, we compare two economies to highlight the role of the spillover through multimarket firms: a benchmark economy where firms choose uniform product quality, and a counterfactual economy where firms choose market-specific product quality. In the former, firms spill over the regional shocks within their network through the uniform product quality choice, but there is no spillover in the latter with the market-specific quality choice. For both cases, we numerically solve for the equilibrium consumption across states and ask how the spillover shapes consumer welfare across states. Since Appendix E.3 shows that the spillover results are robust to using a state as the definition of a market, we define a market to be a state to reduce computational burden in matching the firm-level spatial network. Given the focus on the aggregate regional effect, we include both single-market firms and multimarket firms; note that the empirical results are robust to including single-market firms, as shown in Appendix E.12. The final sample yields 5,186 firms that sell in at most 49 states. See Appendix G.3.1 for the estimation and calibration of the parameters and the goodness of fit of the model.

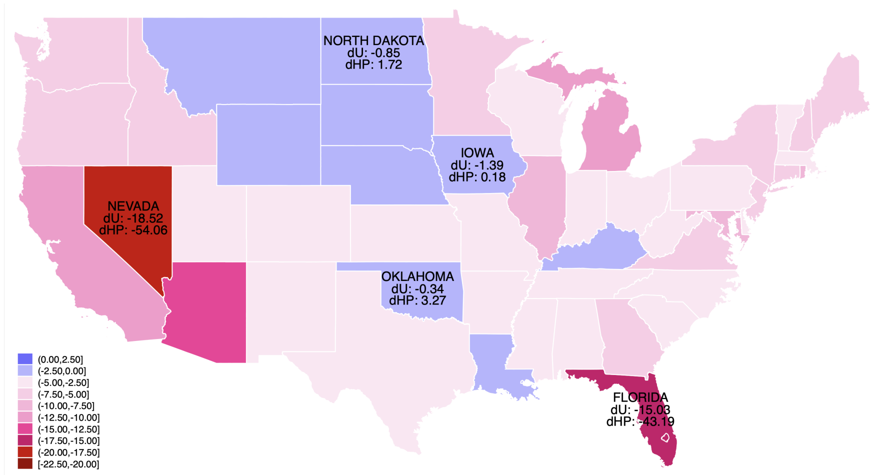
Figure OA.7 shows that the intrafirm spillover effect we identified in the data substantially reduced the real CPG consumption inequality across states. We plot both the baseline and counterfactual model-generated quality-adjusted CPG consumption per capita across states in Figures OA.7a and OA.7b, respectively; Figure OA.7a includes the intrafirm spillover effect, whereas Figure OA.7b shuts down this effect. Despite the same level of housing price changes across the two different economies, the counterfactual economy features a substantially larger variance of CPG consumption sales growth per capita across states than the baseline economy; see Table OA.38 for a full description of the utility and housing price growth across states. In the counterfactual economy, the standard deviation of the CPG consumption growth per capita is 5.28, which is approximately 28% larger than the standard deviation of 4.13 in the benchmark economy. The same qualitative results are obtained when using the total consumption of households instead of CPG consumption.

The underlying mechanism behind the consumption redistribution is the intrafirm uniform product quality decision across markets. Firms supply the same product quality to both negatively

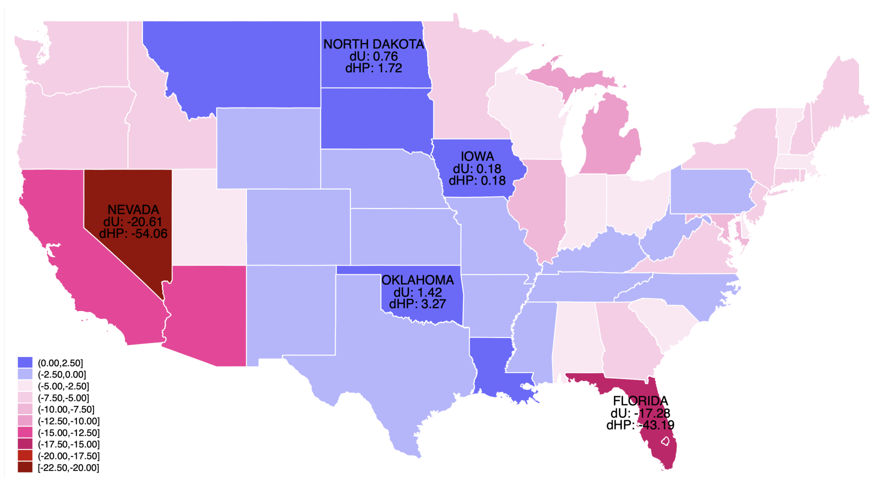
[30] An alternative way to proceed is to aggregate the indirect shock at the region level and estimate the spillover at the region level. In unpublished work, we find that the empirical results are consistent with the theoretical predictions.

Figure OA.7: Regional Redistribution across US States

(a) Benchmark Economy



(b) Counterfactual Economy



Note. dU is the state-level CPG consumption growth, mapped with different colors across states, and dHP is the state-level housing price growth. The benchmark economy in Figure OA.7a 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 OA.7a plots CPG utility growth by assuming market-specific quality choices by firms, as in Appendix G.2.2. Table OA.38 reports a full description of the utility and housing price growth.

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, Iowa experienced a modest increase in housing prices in this period (dHP=0.18). Nevertheless, with the intrafirm spillover effect, the state's real consumption growth is negative (dU=-1.39) because it is offered lower-quality products. If firms had supplied market-specific product quality, Iowa would have experienced positive CPG consumption growth (dU=0.18). On the other hand, Florida experienced a large decrease in housing price growth (dHP=-43.19), resulting in a decrease in real consumption by 15.03 percent. If firms had provided market-specific product quality in Florida, their real consumption would have fallen by 17.28 percent.[31]

A simple calculation reveals that the intrafirm spillover effects correspond to a one-time $400 per-household tax on below-average shocked states (i.e., states that experienced less severe housing market shocks) and transferring it to above-average shocked states (i.e., states that experienced more severe housing market shocks), an amount comparable to that of transfer policies implemented during the Great Recession. In the counterfactual economy, we reduce the dispersion of regional shocks to the extent that the standard deviation of the quality-adjusted consumption growth across states equals that of the benchmark. On average, this reduction requires a 0.56 percentage point change in income growth in the corresponding states. Since the initial cross-state average of the median household income was approximately $70,000, the dollar transfer would be $\$400 \approx \$70,000 \times 0.0056$. 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.

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

G Detailed Descriptions of the Models

This section provides the full descriptions of the models presented in Section F.

G.1 Baseline Model

Demand. Consider an economy with R markets indexed by $r \in \mathcal{R} \equiv \{1, 2, ..., R\}$. Each market is populated by a continuum of mass L_r of individuals, each of whom is endowed with total income y_r, which is the sum of the exogenous income I_r and the dividends from the production sector D_r. The dividends are assumed to be distributed proportionally to individuals' exogenous income. Given the focus on intrafirm spillover effects, we do not explicitly model housing price but generate the heterogeneous demand changes with the heterogeneous change in household income.

The economy consists of two broad sectors: the consumer packaged good (CPG) sector, which is the focus of this paper, and the outside goods sector. 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 the numeraire:

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

where $\eta \geq 1$.

The optimal total CPG expenditure by an individual in market r, s_r, is a function of total household income y_r and the CPG consumption bundle price index:

$$s_r = \Theta_r y_r \tag{G.2}$$

and

$$\Theta_r \equiv \frac{\alpha^\eta}{\alpha^\eta + (1-\alpha)^\eta (P_r)^{\eta-1}} \tag{G.3}$$

where Θ_r is the share of total income y_r allocated to CPG expenditures, and P_r is the CPG consumption bundle price index. See Appendix H.1 for the derivation. The CPG consumption 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.

Within the CPG sector, Each individual enjoys utility from both the quantity and quality of CPG product bundles produced by a continuum of firms. The utility from CPG consumption is defined as:

$$U_r = \left[\int_{f \in G_r} (q_{rf}\zeta_f)^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}} \tag{G.4}$$

where the subscript f denotes a CPG firm, G_r is the set of firms selling in market r, q_{rf} is the quantity of the product bundle produced by firm f and consumed by individuals in market r, ζ_f refers to the perceived quality (or appeal, taste) of firm f's product bundle, and σ refers to the elasticity of substitution between the firms' product bundles. Following Faber and Fally (2021), we assume that the perceived quality depends on an intrinsic quality (i.e., product attribute) choice $\log \phi_f$ by firm f and a multiplicative term γ:

$$\log \zeta_f \equiv \gamma \log \phi_f \tag{G.5}$$

Each Individual solves for her optimal CPG consumption bundle by maximizing (G.4) subject to 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. By defining individual expenditures on firm f's product bundle in market r as $s_{rf} \equiv p_{rf} q_{rf}$, optimality implies

$$s_{rf} = \frac{\left(\frac{\zeta_f}{p_{rf}}\right)^{\sigma-1}}{\int_{f \in G_r} \left(\frac{\zeta_f}{p_{rf}}\right)^{\sigma-1} df} s_r = (\zeta_f)^{\sigma-1} \left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} s_r \tag{G.6}$$

where the quality-adjusted CPG price index is given by

$$P_r \equiv \left[\int_{f \in G_r} (p_{rf})^{1-\sigma} (\zeta_f)^{\sigma-1} df \right]^{\frac{1}{1-\sigma}} \tag{G.7}$$

with $s_r = P_r U_r$. Note that by multiplying L_r on both sides of Equation (G.6), we recover the total expenditure of market r on firm f's product bundles $S_{rf} \equiv s_{rf} L_r$ shown in Equation (F.3). Combining (G.5) and (G.6) leads to firm f's sales and quantity sold in market r:

$$S_{rf} = \phi_f^{(\sigma-1)\gamma} \left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} S_r \tag{G.8}$$

and

$$Q_{rf} = \phi_f^{(\sigma-1)\gamma} p_{rf}^{-\sigma} P_r^{\sigma-1} S_r \tag{G.9}$$

where $Q_{rf} \equiv q_{rf} L_r$ denotes the total quantity firm f sells in market r, and $S_r \equiv s_r L_r$ denotes the total CPG expenditures in market r.

Outside Good Production and the Labor Market. Given the focus on the CPG sector, we make the simplest assumptions on the outside good and the labor market. A unit of the outside good is produced with a unit of labor input. The labor market is perfectly competitive and is not separated between CPG production and outside good production, implying that the cost of labor (wage) equals unity.

CPG Production. There is a continuum measure of N firms that produce differentiated CPG bundles. Each firm simultaneously chooses the optimal quality and prices subject to monopolistic competition.

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

$$mc(\phi_f; a_f) \equiv \frac{\phi_f^{\xi}}{a_f} \tag{G.10}$$

where the parameter ξ is the elasticity of the variable cost to the level of quality.

The total fixed costs are given by $\tau(\phi_f) + \tau_0$, where $\tau(\phi_f)$ is the part of fixed costs that directly depends on quality. These are the costs that do not directly depend on quantities, such as design, marketing, land size, or other contractual costs. Assuming a simple log-linear parameterization leads to:

$$\tau(\phi_f) = b\beta\phi_f^{\frac{1}{\beta}} \tag{G.11}$$

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

Firm f optimally chooses the intrinsic quality of the product (product attribute) ϕ_f, which applies uniformly across its markets, and market-specific price p_{rf} by maximizing its profit. The quality and price-setting problem for a firm f can be formally written as follows:

$$\max_{\phi_f, \{p_{rf}\}_{r \in k_f}} \pi_f = \sum_{r \in k_f} \left(p_{rf} - mc(\phi_f; a_f)\right) Q_{rf} - \tau(\phi_f) - \tau_0 \tag{G.12}$$

subject to the demand condition in (G.9). Note that the set of markets for each firm k_f is exogenously given for each firm in this model. $\mathcal{M}^r \equiv \{k \in 2^{\mathcal{R}} : r \in k\}$ denotes the collection of market networks that contain market r.

As shown in Appendix H.4, the optimal price (G.13) and quality (G.14) are given by

$$p_{rf} = \mu \left(\frac{\phi_f^{\xi}}{a_f} \right) \tag{G.13}$$

and

$$\phi_f = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma - \xi}{\mu} \right) \right]^{\beta} \tag{G.14}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma-1}\right)$ indicates the price-cost markup. Note that $\sigma > 1$, $\gamma > \xi$, and $\beta(\sigma-1)(\gamma-\xi) < 1$ are necessary for these optimal solutions.

Combining (G.12), (G.11), and (G.14), the optimal profit condition is:

$$\pi_f = \sum_{r \in k_f} \frac{1}{\sigma} \left[1 - \beta(\sigma - 1)(\gamma - \xi) \right] S_{rf} - \tau_0 \tag{G.15}$$

The equilibrium local sales of firm f is derived by combining (G.8), (G.13) and (G.14):

$$S_{rf} = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma - \xi}{\mu} \right) \right]^{\beta(\sigma-1)(\gamma-\xi)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} P_r^{\sigma-1} S_r \tag{G.16}$$

and the equilibrium local price of a firm f in terms of local firms sales is

$$p_{rf} = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma - \xi}{\mu} \right) \right]^{\beta\xi} \left[\frac{\mu}{a_f} \right] \tag{G.17}$$

The equilibrium CPG price in market r is expressed as

$$P_r = \left[\int_{f \in G_r} \left[\phi_f^{-(\gamma-\xi)} \left(\frac{\mu}{a_f} \right) \right]^{1-\sigma} df \right]^{\frac{1}{1-\sigma}} \tag{G.18}$$

The aggregate profits in the economy are givne by:

$$\overline{\Pi} \equiv \int_f \pi_f df \tag{G.19}$$

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

$$D_r \equiv \frac{I_r}{\sum_{r\in\mathcal{R}} I_r L_r} \overline{\Pi} \tag{G.20}$$

which implies

$$y_r = I_r + D_r = I_r \left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right) \tag{G.21}$$

G.2 Extensions

This section presents a more detailed description of the extended model presented in Section F.2. First, given the demand condition, firms in the CPG sector choose between uniform product quality and market-specific product quality. After this choice, firms choose price and quality to maximize their profit. In presenting this model, we first show the household problem with nonhomothetic preferences. Then we separately present the optimality conditions for the uniform product quality choice and the market-specific quality choice. Lastly, we compare the optimal profit between the two choices to highlight the economic intuitions relevant to choosing uniform product quality across markets. All other structures of the model, such as the upper-tier utility across CPG goods and an outside good, outside good production, and labor market, are identical to those presented in Appendix G.1.

Demand. Each individual enjoys utility from both the quantity and quality of CPG product bundles produced by a continuum of firms. Individuals value product quality differently depending on their consumption of outside goods, which depends on their income. The utility from the CPG consumption is defined as:

$$U_r = \left[\int_{f \in G_r} (q_{rf} \zeta_{rf})^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}} \tag{G.22}$$

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

The perceived quality (ζ_{rf}) is determined by the following equation:

$$\log \zeta_{rf} \equiv \gamma_r \log \phi_{(r)f} \tag{G.23}$$

where $\gamma_r \equiv \gamma(z_r)$ with $\gamma' > 0$, and $\phi_{(r)f}$ can be either ϕ_f or ϕ_{rf}. The only differences from the baseline model is that the γ depends on market-specific outside goods consumption z_r, and the intrinsic quality chosen by firms (ϕ) could vary across both firms and markets, depending on the strategy firms choose: Under the uniform product quality, ϕ does not vary across markets ($\phi_{(r)f} = \phi_f$), whereas under the market-specific product quality, ϕ varies across both firms and markets ($\phi_{(r)f} = \phi_{rf}$). In this framework, since individuals living in high-income regions purchase more outside goods, high-income markets prefer high-quality products.[32]

Each individual in market r solves for her optimal CPG consumption bundle by maximizing equation (G.22) subject to her budget constraint, $\int_{f \in G_r} p_{rf} q_{rf} df \leq s_r$, 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:

$$S_{rf} = (\zeta_{rf})^{\sigma-1} \left(\frac{p_{rf}}{P_r} \right)^{1-\sigma} S_r \tag{G.24}$$

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

$$P_r \equiv \left[\int_{f \in G_r} (p_{rf})^{1-\sigma} (\zeta_{rf})^{\sigma-1} df \right]^{\frac{1}{1-\sigma}} \tag{G.25}$$

Timing of Events. First, each firm decides whether to choose a uniform quality that applies to all its markets or market-specific quality. Then, each firm simultaneously chooses the optimal quality and prices. Finally, production occurs, and markets clear subject to monopolistic competition.

G.2.1 Uniform Product Quality Choice

If firms choose uniform product quality, their problem becomes identical to that presented in G.1 except that households' taste for product quality varies across markets for the CPG products.

CPG Production. CPG production is identical to that in Appendix G.1 except that now firms maximize their profit (F.7) subject to the demand condition with nonhomotheticity (G.24). The resulting optimal price (G.26), local sales (G.27), and quality (G.28) are identical to those in the main body of the paper except that γ varies across markets:

$$p_{rf} = \mu \left(\frac{\phi_f^{\xi}}{a_f} \right) \tag{G.26}$$

[32]Note that we only allow nonhomotheticity across quality (γ) but not across elasticity (σ) to make the model parsimonious. This specification is based on the previous analyses of the consumer packaged goods industry that integrate both types of nonhomotheticity and find the dominant role of quality relative to the elasticity in explaining the heterogenous household consumption pattern. See, e.g., Faber and Fally (2021); Handbury (2021).

$$S_{rf} = \phi_f^{(\sigma-1)(\gamma_r-\xi)} \left[\frac{a_f}{\mu} P_r\right]^{\sigma-1} S_r \tag{G.27}$$

$$\phi_f = \left[\sum_{r\in k_f} S_{rf} \left(\frac{1}{b}\frac{\gamma_r - \xi}{\mu}\right)\right]^{\beta} \tag{G.28}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma-1}\right)$ indicates the price-cost markup, and the optimal price is a conventional markup over marginal cost. Note that we still need three important parametric restrictions for the optimality: $\sigma > 1$, $\gamma_r > \xi\ \forall r$, and $\beta(\sigma-1)(\gamma_r - \xi) < 1\ \forall r$.

Within-Firm Market Interdependence. By replacing the equilibrium firm quality in Equation (G.27) with the optimal quality (G.28) and taking the log difference of the combined equation, we derive the expression for the local firm's sales growth that depends on total firm sales growth and the change in market taste for product quality, along with other terms:

$$\hat{S}_{rf} = \Upsilon_r \sum_{r\in k_f} w_{rf} \left[\hat{S}_{rf} + \hat{\psi}_r\right] + (\sigma-1)\hat{a}_f + (\log X_f)\Upsilon_r\hat{\psi}_r + \hat{A}_r \tag{G.29}$$

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

Equation (G.29) extends the within-firm market-interdependency through uniform product quality downgrading highlighted in Equation (F.11) with nonhomotheticity.[33] When firms face a negative demand shock in other markets, they have an incentive to lower their product quality for two separate reasons: the scale effect and nonhomotheticity. The scale effect is captured by the overall firm-specific sales growth ($\sum_{r\in k_f} w_{rf}\hat{S}_{rf}$), and the nonhomothetic preference is captured by the overall household preference on product quality ($\sum_{r\in k_f} w_{rf}\hat{\psi}_r$); both of them decline due to indirect demand shocks. Once firms downgrade their product quality, local firm sales decrease, generating spillover across markets within firms. The strength of the spillover is governed by Υ_r, the responsiveness of a firm's local sales with respect to the indirect demand shock. Note that Υ_r is higher with market income with nonhomotheticity, which is consistent with the empirical evidence documented in Table 6.

[33]Note that, for simplicity, Equation (G.29) expresses the market-interdependency with the overall changes in market conditions firms face. It is straightforward to rearrange the terms to obtain the leave-one-out specification as in Equation (G.29).

Note that Proposition OA.1 holds with nonhomothetic preferences, and we formalize it in Proposition OA.2:

Proposition OA.2. *Holding P_r and D_r fixed for all $r \in k_f$,*
$\frac{\partial \log \phi_f}{\partial \log I_r} > 0$, $\frac{\partial \log S_{rf}}{\partial \log I_r} > 0$, *and* $\frac{\partial \log S_{r'f}}{\partial \log I_r} = (\sigma - 1)(\gamma_r - \xi)\frac{\partial \log \phi_f}{\partial \log I_r} > 0$ *for* $r, r' \in k_f$ *and* $r \neq r'$.

Proof. See Appendix H.8.1.

□

G.2.2 Market-Specific Quality Choice

CPG Production. Denote the market-specific choice of quality by ϕ_{rf}. To distinguish optimal prices under market-specific quality from those under uniform quality, denote the optimal price under market-specific quality by p^m_{rf}. The corresponding quantity, sales, and profit are Q^m_{rf}, S^m_{rf}, and π^m_f, respectively. Whenever the variables and parameters are not clearly different from those in the uniform product quality choice, we explicitly denote them with the superscript m.

If a firm chooses market-specific quality, it incurs two different types of market-specific fixed costs. First, firms need to pay for the fixed costs separately for different qualities of products they want to provide, such as the one-time cost of land and machines associated with different layers of product quality. Second, firms need to pay the quality-invariant market-specific fixed costs to penetrate the products separately for each product in each market, such as marketing and advertising expenses.

With the new fixed costs, the profit maximization problem under the market-specific quality choice is:

$$\max_{\{\phi_{rf}, p^m_{rf}\}_{r \in k_f}} \pi^m_f = \sum_{r \in k_f} \left[\left(p^m_{rf} - mc(\phi_{rf}; a_f) \right) q^m_{rf} L_{rf} \right] - \sum_{r \in k_f} \left(\tau^m(\phi_{rf}) + \tau^m_r \right) - \tau_0 \tag{G.30}$$

subject to the demand conditions with nonhomotheticity (G.24), the functions of the marginal cost (F.5) and fixed cost (F.6). Note that in addition to the economy-wide fixed costs, there are two additional market-specific fixed costs in the profit equation, one that varies with product quality ($\tau^m(\phi_{rf})$) and another invariant to the level of product quality (τ^m_r). We allow the constant parameter "b" in $\tau^m(\phi_{rf})$ to be different from the uniform quality choice and denote it by b^m: $\tau^m(\phi_{rf}) \equiv b^m \beta (\phi_{rf})^{\frac{1}{\beta}}$.

Solving the profit maximization problem and rearranging the equations, the optimal market-specific price (G.31), local sales (G.32), and quality (G.33) are:

$$p_{rf}^m = \frac{\phi_{rf}^{\xi}}{a_f}\mu \tag{G.31}$$

$$S_{rf}^m = (\phi_{rf})^{(\sigma-1)\gamma_r}\left(\frac{p_{rf}^m}{P_r}\right)^{1-\sigma} S_r \tag{G.32}$$

$$\phi_{rf} = \left[S_{rf}^m\left(\frac{1}{b^m}\frac{\gamma_r-\xi}{\mu}\right)\right]^{\beta} \tag{G.33}$$

where $\mu \equiv \left(\frac{\sigma}{\sigma-1}\right)$ indicates the price-cost markup, and the optimal price is a conventional markup over the marginal cost. Again, we still need three important parametric restrictions for the optimality: $\sigma > 1$, $\gamma_r > \xi\ \forall r$, and $\beta(\sigma-1)(\gamma_r-\xi) < 1\ \forall r$. The optimal profit under market-specific quality is the following:

$$\pi_f^m = \sum_{r\in k_f}\left[\frac{1}{\sigma}\left[1-\beta(\sigma-1)(\gamma_r-\xi)\right]S_{rf}^m - \tau_r^m\right] - \tau_0 \tag{G.34}$$

Under the market-specific quality choice, we can derive the closed-form solution for the optimal price, local firm sales, and product quality. Combining (G.31), (G.32), and (G.33), we obtain:

$$S_{rf}^m = \left(\frac{1}{b^m}\frac{\gamma_r-\xi}{\mu}\right)^{\frac{\beta(\sigma-1)(\gamma_r-\xi)}{1-\beta(\sigma-1)(\gamma_r-\xi)}}\left[\frac{\mu}{a_f}\right]^{\frac{1-\sigma}{1-\beta(\sigma-1)(\gamma_r-\xi)}}\left[(P_r)^{\sigma-1}S_r\right]^{\frac{1}{1-\beta(\sigma-1)(\gamma_r-\xi)}} \tag{G.35}$$

and the optimal price of a firm with a^k in market r as a function of local sales is:

$$p_{rf}^m = \left[S_{rf}^m\left(\frac{1}{b^m}\frac{\gamma_r-\xi}{\mu}\right)\right]^{\beta\xi}\left[\frac{\mu}{a_f}\right] \tag{G.36}$$

and the optimal quality equation is already in terms of local firm sales. Substituting local firm sales (G.35) in the price (G.36) and quality (G.33) expressions, we express all three variables in terms of parameters and regional variables.

Within-Firm Market Independence. Under the market-specific quality choice, firms make their decision entirely based on market conditions. We formalize the no spillover results in Proposition OA.3:

Proposition OA.3. *Holding P_r^m and D_r^m fixed for all $r \in k_f$,* $\frac{\partial \log \phi_{r'f}}{\partial \log I_r} = \frac{\partial \log S_{r'f}^m}{\partial \log I_r} = \frac{\partial \log p_{r'f}^m}{\partial \log I_r} = 0$

for $r, r' \in k_f$ and $r \neq r'$.

Proof. Since D^m_r is fixed, $\frac{\partial \log y_r}{\partial \log I_r} = \frac{I_r}{I_r + D^m_r} > 0$ holds and differentiation of a variable with respect to $\log y_r$ yields the same sign as the differentiation with respect to $\log I_r$. Given this condition, it is enough to show that $\frac{\partial \log \phi_{r'f}}{\partial \log y_r} = \frac{\partial \log S^m_{r'f}}{\partial \log y_r} = \frac{\partial \log p^m_{r'f}}{\partial \log y_r} = 0$ for $r, r' \in k_f$. $\frac{\partial \log S^m_{r'f}}{\partial \log y_r} = 0$ is immediate from (G.35) and the fact that $\frac{\partial \log P^m_{r'}}{\partial \log y_r} = \frac{\partial \log S^m_{r'}}{\partial \log y_r} = 0$ holding $P^m_{r'}$ fixed. Given $\frac{\partial \log S^m_{r'f}}{\partial \log y_r} = 0$, $\frac{\partial \log p^m_{r'f}}{\partial \log y_r} = \frac{\partial \log \phi_{r'f}}{\partial \log y_r} = 0$ follows immediately from (G.31) and (G.33).

□

G.2.3 Uniform vs. Market-specific Quality Choice

Firms choose uniform quality across markets if and only if their profits under this choice exceed those under market-specific quality, $\pi_f > \pi^m_f$. Comparing the optimal profit in terms of optimal sales under the uniform quality choice (G.15) and the market-specific quality choice (G.34), firms choose uniform product quality if the following condition holds:

$$\sum_{r \in k_f} \frac{1}{\sigma} \left[1 - \beta(\sigma - 1)(\gamma_r - \xi)\right] S_{rf} - \tau_0 > \sum_{r \in k_f} \frac{1}{\sigma} \left[1 - \beta(\sigma - 1)(\gamma_r - \xi)\right] S^m_{rf} - \sum_{r \in k_f} \tau^m_r - \tau_0 \tag{G.37}$$

Substituting the optimal local sales in terms of product quality in each case, (G.27) and (G.32), into Equation G.37 and rearranging the equation, we can recover the inequality Equation (F.15) presented in the main body of the paper:

$$\sum_{r \in k_f} \tau_r > g\left(N_f, \text{Var}(\gamma_r), ...\right) = a_f \sum_{r \in k_f} M_r \left(\phi^{\Gamma_r}_{rf} - \phi^{\Gamma_r}_f\right) \tag{G.38}$$

where $M_r \equiv \left[\frac{P_r}{\mu}\right]^{\sigma-1} S_r \left[\frac{1-\beta(\gamma_r - \xi)(\sigma-1)}{\sigma}\right]$ and $\Gamma_r \equiv (\sigma - 1)(\gamma_r - \xi)$. Note that both M_r and Γ_r are positive with the parametric restrictions in this model, and $\phi^{\Gamma_r}_{rf} - \phi^{\Gamma_r}_f$ increases with ϕ_{rf} but decreases with ϕ_f.

There are two claims we made in the paper: (i) The function g decreases in N_f with a sufficiently large N_f, and in a special case, g is larger with Var(γ_r) > 0 than that with Var(γ_r) = 0.

(i) Holding everything else constant, g decreases in N_f with sufficiently large N_f.

For a given firm, consider adding one additional market with the average market characteristics. Adding one more market increases g by $a_f \bar{M}_r \left(\bar{\phi}^{\bar{\Gamma}_r}_{rf} - \phi^{\bar{\Gamma}_r}_f\right)$, where $\bar{x}_r$ denotes the average value across market r. Since $a_f \bar{M}_r > 0$, the change in g depends on the optimal quality choice in each case.

If firms choose to provide different qualities of products across markets, the optimal level of product quality does not depend on the number of markets. The problem is separable across markets, and firms choose quality based on market demand conditions and their technology, as shown in the optimal quality expression (G.33) with the optimal market share expression (G.35).

On the other hand, if firms provide uniform quality across markets, the optimal product quality increases with the number of markets (N_f). As firms generate more revenues from the larger markets they face, they have more incentive to raise their product quality. As shown in the optimal quality expression (G.28) and the optimal market share expression (G.27), both quality and market share increase with the number of markets.[34] Thus, with sufficiently large N_f, $\phi_f > \phi_{rf}$ and $\phi_{rf}^{\Gamma_r} - \phi_f^{\Gamma_r} < 0$. Therefore, with sufficiently large N_f, g decreases in N_f.

(ii) In a special case, g is larger with Var(γ_r) > 0 than that with Var(γ_r) = 0.

Using the property of covariance, we can exactly decompose the function g into the two parts:

$$g(N_f, Var(\gamma_r), ...) = a_f \bar{M}_r \sum_{r \in k_f} \left(\phi_{rf}^{\Gamma_r} - \phi_f^{\Gamma_r}\right) + a_f N_f Cov\left(M_r, \left(\phi_{rf}^{\Gamma_r} - \phi_f^{\Gamma_r}\right)\right) \qquad \text{(G.39)}$$

where $\bar{M}_r \equiv \frac{1}{N_f}\sum_{r \in k_f} M_r$. The first term shows an increase in the difference in revenues when the difference in product quality increases. The second covariance term is larger when firms can provide high market-specific product quality goods to larger markets (corr(ϕ_{rf}, S_r)>0) or markets where the price is high (corr(ϕ_{rf}, P_r)>0); firms internalize these market characteristics in choosing market-specific product quality, as shown in (G.33) and (G.35). Fixing the revenue from these markets, gains from the increase in product quality are partially mitigated by the higher fixed costs that are required to offer high product quality (corr(ϕ_{rf}, γ_r)>0).

Consider a special case when the optimal uniform quality ϕ_f equals the lowest optimal market-specific quality ϕ_{lf} across all markets ($\phi_f = \phi_{lf} \leq \phi_{rf}$ for all $r \in k_f$).[35] Moreover, assume

[34] Note that both quality and market share depend on each other in these two expressions. There is a fixed point in the system of equations because both quality and market share increase with the number of markets at decreasing rates.

[35] This simplification makes firms generate a larger revenue from all of their markets by choosing market-specific product quality. One way to generate this case is to allow a larger fixed cost parameter b in the uniform product quality choice than that in the market-specific product quality choice.

that γ_r is the only source of market heterogeneity by assuming Var(S_r) = 0 and Var(P_r) = 0. Lastly, assume that the increase in fixed costs associated with the increase in product quality is small such that the second covariance term in expression G.39 does not change substantially with the variance of γ_r. Note that we already assumed that $\phi_{rf} > 1$ for all r and $\phi_f > 1$ to make γ and ϕ complements.[36]

In this case, Equation (G.39) is larger with a positive variance of γ_r. To show this part explicitly, note that we can rewrite the difference in quality as follows:

$$\left(\phi_{rf}^{\Gamma_r} - \phi_f^{\Gamma_r}\right) = \phi_f^{\Gamma_r}\left(\left(\frac{\phi_{rf}}{\phi_f}\right)^{\Gamma_r} - 1\right) \tag{G.40}$$

It suffices to show that this expression is larger with positive variance of γ_r. Compare an arbitrary region $r \in k_f$ with the baseline, lowest-quality region l. Suppose that Var$(\gamma_r) > 0$. Then we know that for some r, $\gamma_r \neq \gamma_l$ holds. Since the optimal market-specific product quality is always increasing in γ_r, as shown in (G.33) and (G.35), $\gamma_r > \gamma_l$ holds fixing P_r and S_r across r and l. In this setup, because $\left(\frac{\phi_{rf}}{\phi_f}\right) > 1$, $\phi_f > 1$, and $\Gamma_r > 0$ for all r, we have:

$$\phi_f^{\Gamma_r}\left(\left(\frac{\phi_{rf}}{\phi_f}\right)^{\Gamma_r} - 1\right) > \phi_f^{\Gamma_l}\left(\left(\frac{\phi_{lf}}{\phi_f}\right)^{\Gamma_l} - 1\right) = 0 \tag{G.41}$$

On the other hand, suppose that Var$(\gamma_r) = 0$. Then $\gamma_r = \gamma_l$ and for any $r \in k_f$. Holding P_r and S_r fixed across r and l, $\phi_{lf} = \phi_{rf}$. Based on the inequality above, it is clear that the first term in Equation (G.40) is larger when Var$(\gamma_r) > 0$.

Note that we assumed away the second covariance term, which is smaller with a positive variance of ϕ_{rf}. One can see that M_r is smaller, but the difference in quality is higher with higher γ_r. Holding the optimal market revenue fixed, higher customer taste for product quality (higher γ_r) leads to higher product quality being offered by firms, which requires them to pay higher associated fixed costs of product quality. Thus, if the fixed cost of quality is too elastic with respect to quality, the increase in the variance of γ_r may not lead firms to target product quality market by market (because it decreases the second covariance term and thus the function g).

[36]Otherwise, $\xi = \phi^\gamma$ does not increase in γ, implying that households with a higher taste for quality experience a decrease in their utility when they are offered high intrinsic quality.

G.2.4 Partially Uniform Product Quality Choice

Although we compared two extreme cases—uniform vs. market-specific quality—the spillover through the uniform quality channel extends to more general circumstances under which firms partially synchronize their product replacement decisions. This section extends the model to allow firms to choose partially uniform product quality and shows that the intrafirm spillover effect arises as long as firms provide uniform product quality across more than one market.

Consider an arbitrary partition of a firm f's market network k_f, denoted by $\mathcal{K} \equiv \cup_j k_{jf}$. Assume that at least one subset in the partition contains more than one market. In this environment, suppose that firms uniformly choose product quality across markets *within each subset* in the partition but can choose different product quality *across subsets*. For example, if the market network involves three markets ($k_f = \{a, b, c\}$) and the partition is given by $k_{1f} = \{a, b\}$ and $k_{2f} = \{c\}$, firm f chooses uniform product quality ϕ_{1f} supplied to market a and b (in k_{1f}) and separately chooses (potentially different) quality ϕ_{2f} supplied to market c (in k_{2f}).

Then the firm's problem becomes

$$\max_{\{\phi_{jf}\}_j, \{p_{rf}\}_{r\in k_f}} \pi_f^{\mathcal{K}} = \sum_j \left[\sum_{r\in k_{jf}} \left(p_{rf} - mc(\phi_{jf}; a_f)\right) Q_{rf} - \tau(\phi_{jf}) - \tau_{j0} \right] \tag{G.42}$$

subject to the demand condition $Q_{rf} = \phi_{jf}^{(\sigma-1)\gamma_r} (p_{rf})^{-\sigma} P_r^{\sigma-1} S_r$, where ϕ_{jf} is the uniform quality supplied to markets in k_{jf} and $f(\phi_{jf}) \equiv b\beta\phi_{jf}^{\frac{1}{\beta}}$. We use superscript $\mathcal{K}$ to distinguish variables under the partial uniform quality choice.

Since this problem is separable across subsets in the partition, we only need to solve

$$\max_{\phi_{jf}, \{p_{rf}\}_{r\in k_{jf}}} \pi_{jf} = \sum_{r\in k_{jf}} \left(p_{rf} - mc(\phi_{jf}; a_f)\right) Q_{rf} - \tau(\phi_{jf}) - \tau_{j0} \tag{G.43}$$

By comparing (G.43) with (F.7), it is straightforward to see that the structure of the model with partial uniform quality is isomorphic to the model with uniform quality once we focus on a specific subset k_{jf} in the partition. Applying the same logic as in Appendix G.2.1, the within-firm market interdependence that arises under this setup is:

$$\hat{S}_{rf} = \Upsilon_r \sum_{r\in k_{jf}} \omega_{rf} \left[\hat{S}_{rf} + \hat{\psi}_r\right] + (\sigma - 1)\hat{a}_f + (\log X_{jf})\Upsilon_r \hat{\psi}_r + \hat{A}_r \tag{G.44}$$

where $\omega_{rjf} \equiv \frac{S_{rf}\psi_r}{\sum_{r'\in k_{jf}} S_{r'f}\psi_r}$, $X_{jf} \equiv \sum_{r\in k_{jf}} S_{rf}\left(\frac{1}{b}\frac{\psi_r}{\mu}\right)$, and $A_r \equiv (P_r)^{\sigma-1}S_r$. The intrafirm spillover effect arises as long as firms choose to provide uniform product quality across more than one market.

Finally, the profit can be expressed as

$$\pi_f^{\mathcal{K}} = \sum_j \left[\sum_{r\in k_{jf}} \frac{1}{\sigma}\left[1-\beta(\sigma-1)(\gamma_r-\xi)\right] S_{rf} - \tau_j\right] - \tau_0$$

The key tradeoff between the benefit of providing uniform product quality across multiple markets and the associated cost still exists in this setup, similar to what is presented in Appendix G.2.3. By providing uniform product quality across multiple markets, firms reduce the market-specific fixed costs associated with producing and penetrating different qualities of products to different markets. On the other hand, firms cannot tailor their product quality to each market and must forgo larger sales generated from each market with nonhomothetic preferences. In this general setup, firms choose partition of k_f (among all possible partition) that generates the largest profit.[37]

[37]Formally, by defining the collection of all possible partition of k_f as Part(k_f), firm f will eventually choose partition $\mathcal{K} \in$ Part(k_f)—i.e., will choose the partial uniform product quality strategy according to the partition $\mathcal{K}$—if $\mathcal{K} = \arg\max_{\mathcal{K}'\in \text{Part}(k_f)} \pi_f^{\mathcal{K}'}$. Although this is a theoretically simple statement, from a computational perspective, it is more complicated as it suffers from the "curse of dimensionality". The total number of partitions, the so-called Bell numbers, grows exponentially with the number of markets in k_f.

G.3 Regional Analyses

Does multimarket firms' uniform product replacement channel affect regional sales, prices, and welfare distribution? This section calibrates our model to provide a back-of-the-envelope calculation for this question.[38]

Based on the extended model with nonhomothetic preferences in Section F.2, we compare two economies to highlight the role of the spillover through multimarket firms: a benchmark economy where firms choose uniform product quality, and a counterfactual economy where firms choose market-specific product quality. In the former, firms spill over the regional shocks within their network through the uniform product quality choice, but there is no spillover in the latter with the market-specific quality choice. For both cases, we numerically solve for the consumption redistribution across states and ask how the spillover reshapes consumer welfare across states. Since Appendix E.3 shows that the spillover results are robust to using a state as the definition of a market, we define a market to be a state to reduce computational burden in matching the firm-level spatial network. Given the focus on the aggregate regional effect, we include both single-market firms and multimarket firms; note that the empirical results are robust to including single-market firms, as shown in Appendix E.12. The final sample yields 5,186 firms that sell in at most 49 states.

G.3.1 Parameter Calibration and Estimation

Calibration. Both the benchmark economy with uniform product quality and the counterfactual economy with market-specific quality are calibrated to match the same moments except for the fixed cost parameter. We allow the normalization parameter under the counterfactual, b^m, to be different from b under the benchmark. We match b_m such that average product quality is the same across both economies.

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 mapped 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). 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

[38] An alternative way to proceed is to aggregate the indirect demand shock at the region level and estimate the spillover at the region level. Empirical analyses that aggregate the data at the region-level estimate an unstable spillover effect with the control variables, likely because of the confounding market characteristics that cannot be absorbed by the fixed effects in this analysis. These results highlight the importance of using micro-level data in empirically identifying the spillover effect within multimarket firms.

implications of the model. We abstract away from productivity heterogeneity (i.e., $a_f = \bar{a}$) since it plays a minor role for the set of balanced firms we consider. Nevertheless, for each firm, we match the sales distribution across states by using the sales per firm in each state.[39]

We set the CPG expenditure share parameter α to 0.20, which is close to the United States counterpart. This number is calculated based on a BLS report—*Consumer Expenditures in 2007*. We categorize the following major categories as CPG expenditures: Food, Alcoholic beverages, Apparel and services, Personal care products and services, and Tobacco products and smoking supplies. For the elasticity of substitution parameter η in the upper-tier utility, we impose the limiting case $\eta \to 1$, implying the Cobb-Douglas upper-tier utility function. Using a larger η only strengthens the implication that we find (i.e., it generates stronger mitigation of regional consumption and welfare inequality). We bring in the elasticity of substitution σ from Faber and Fally (2021), which is $\sigma = 2.2$. Since the estimate is based on the pooled estimation of the within-module cross-firm elasticity of substitution, σ is interpreted as a proxy measure for the average within-module elasticity of substitution across firms. As discussed in Appendix D.5, the product module is a granular categorization of each barcode (product) in the data.

Estimation. The parameters we need to recover are β, ξ, and $\gamma_{rt} = \gamma(z(y_{rt}); \delta_1, \delta_2)$.

(1) $\gamma_{rt} = \gamma(z(y_{rt}); \delta_1, \delta_2)$

Replacing the definition of product quality (G.23) in state-firm-level sales (G.24) and taking the log of the combined equation, we have

$$\log S_{rft} = (1-\sigma)\log p_{rft} + (\sigma - 1)\gamma_{rt}\log \phi_{ft} + (1-\sigma)\log P_{rt} + \log S_{rt} \tag{G.45}$$

where subscript t denotes year. We filter out state-time-specific components ($(1-\sigma)\log P_{rt} + \log S_{rt}$) 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

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

Table OA.34: Parameter Values

Parameter	Value	Description	Source
σ	2.20	EoS across firm's product bundle	Faber and Fally (2021)
ξ	0.39	Elasticity of marginal cost to quality	Own estimation
β	0.81	Elasticity of fixed cost to quality	Own estimation
δ_2	0.17	Elasticity of perceived quality to income	Own estimation
b	1	Fixed cost parameter	Normalize
b^m	0.04	Fixed cost parameter	Match average quality in benchmark
η	1	EoS across CPG and outside goods	Cobb-Douglas
α	0.20	CPG share parameter	Match CPG share = 0.20
$\bar{\gamma}$	1.04	Avg. perceived quality	Own estimation
$\bar{\Upsilon}$	0.62	Avg. elasticity of local sales to ($\sum_{r\in k_f} w_{rf}\left[\hat{S}_{rf}+\hat{\psi}_r\right]$)	Own estimation
$\beta\times\xi$	0.32	Elasticity of local price to ($\sum_{r\in k_f} w_{rf}\left[\hat{S}_{rf}+\hat{\psi}_r\right]$)	Own estimation

Note. $\sum_{r\in k_f} w_{rf}\left[\hat{S}_{rf}+\hat{\psi}_r\right]$ is defined in Equation (G.29). b is the benchmark fixed cost parameter, and b^m is the counterfactual fixed cost parameter. EoS stands for the elasticity of substitution, and Avg. stands for the average.

$\Delta' x_{rft} \equiv x_{rFt} - x_{rft}$. By rearranging terms, we have

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

where $\Xi_{rft} \equiv \frac{1}{(\sigma-1)}\left[\Delta' \log S_{rft} - (1-\sigma)\Delta' \log p_{rft}\right]$, which can be measured in the data with the calibration of $\sigma = 2.2$. Taking the log of the expression leads to:

$$\log \Xi_{rft} = \log \gamma_{rt} + \log\left(\Delta' \log \phi_{ft}\right) \tag{G.46}$$

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

Having the measure of perceived product quality by state and time ($\gamma_{rt} = \gamma(z_{rt})$), we measure its dependence on the household income. First, impose a simple log-linear functional form with respect to the outside good z_{rt}:

$$\log \gamma_{rt} \equiv d_1 + d_2 \log z_{rt}$$

Given the calibration of $\eta = 1$, the outside good is proportional to household income: $z_{rt} = (1-\alpha)y_{rt}$ (Appendix H.3). Defining δ_1 and δ_2 such that $d_1 = \delta_1 - \delta_2 \log(1-\alpha)$ and $d_2 = \delta_2$ leads to the following equation that links perceived product quality γ_{rt} with household income y_{rt}:

$$\log \gamma_{rt} \equiv \delta_1 + \delta_2 \log y_{rt} \tag{G.47}$$

where δ_2 governs the strength of the nonhomotheticity. It measures the responsiveness of the perceived product quality demanded to a change in individuals' income in the market r.

Table OA.35 column (1) estimates Equation (G.47). Consistent with the presence of nonhomotheticity, an increase in household income leads to a higher taste for product quality with $\delta_2 \approx 0.17$. The positive estimate of δ_2 ensures that the estimated γ_{rf} does not purely arise from measurement errors. Columns (2) and (3) add the year (2009) fixed effect and Census Division fixed effect, respectively. Adding the year fixed effect does not change the estimation of δ_2, and including the Census Division fixed effect in addition only makes δ_2 larger. Given the use of housing prices in the main body of the paper, columns (4)-(6) test the nonhomotheticity associated with the house price. The qualitative results are similar to those using market income, indicating that a higher housing price leads to a higher taste for product quality, probably because of the wealth effect. We rely on this relationship in using housing prices as an instrumental variable to estimate Equation (G.29).

In obtaining γ_{rt} for the quantitative analyses, we use the predicted value of γ_{rt} based on the estimation results reported in Table OA.35 column (1). Using the predicted value of γ_{rt} filters out measurement errors and ensures the model-predicted monotonic relationship between total household income ($\log I_r$) and perceived product quality ($\log \gamma_r$). The average value of γ_{rt} in 2007, $\bar{\gamma}$, is 1.04, as reported in Table OA.34. Since Equation (G.29) requires $\hat{\gamma}_r$, we take the first difference of γ_{rt} over time to recover $\hat{\gamma}_r$.

(2) β and ξ

With the measure of γ_{rt}, β and ξ are obtained in the following way. We first conjecture the initial value of ξ. Given ξ, the model allows us to estimate the average Υ_r ($\bar{\Upsilon}$) and $\beta \times \xi$, which in turn provide a new value for ξ. We iterate this process until the initial value is the same as the final value of ξ. Given the coherent measures of ξ and $\beta \times \xi$, $\beta = \frac{\beta\xi}{\xi}$ can be recovered. We illustrate this calibration process below and report the final results when the initial and final values of ξ are the same.

Given the value of ξ, the average Υ_r, $\bar{\Upsilon}$, can be estimated from the structural equation (G.29), which is the extended model counterpart of the reduced-form regression equation (3.1). Since ξ appears multiple times in Equation (H.22) and complicates the calibration process, we rewrite this

Table OA.35: Perceived Product Quality, Household Income, and Housing Price

	(1)	(2)	(3)	(4)	(5)	(6)
	ln γ_{rt}					
Income$_{rt}$	0.166***	0.166***	0.202***			
	(0.033)	(0.033)	(0.045)			
HP$_{rt}$				0.032**	0.033**	0.089***
				(0.013)	(0.013)	(0.022)
D_{2009}		0.002	0.002		0.007	0.016
		(0.012)	(0.011)		(0.013)	(0.011)
Constant	-1.823***	-1.825***	-2.222***	-0.356**	-0.381**	-1.067***
	(0.372)	(0.373)	(0.500)	(0.152)	(0.159)	(0.269)
Census Division FE			✓			✓
R^2	0.153	0.153	0.561	0.050	0.053	0.540
Observations	98	98	98	98	98	98

Note. The sample covers both 2007 and 2009. Income$_{rt}$ is the log of state-level average income in year t, HP$_{rt}$ is the log of the state-level house price in year t, and D_{2009} equals 1 if the year = 2009 and 0 otherwise. 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.

equation for the estimation:

$$\hat{S}_{rf} = \Upsilon_r \sum_{r' \in k_f} \left[\omega_{r'f} \hat{S}_{r'f} + \theta_{r'f} \hat{\gamma}_{r'} \right] + (\log X_f) \Upsilon_r \hat{\Upsilon}_r + \hat{A}_r + (\sigma - 1)\hat{a}_f \tag{G.48}$$

where $\theta_{rf} \equiv \frac{S_{rf}\gamma_r}{\sum_{r' \in k_f} S_{r'f}(\gamma_{r'} - \xi)}$.

Table OA.36 columns (1) and (2) report the estimation results with control variables. Column (1) estimates OLS, which yields a coefficient mechanically equal to 1 (Angrist 2014). Column (2) utilizes the indirect demand shock used in our reduced-form analyses as an instrumental variable to avoid the mechanical correlation problem. The estimation result suggests that $\bar{\Upsilon} = 0.618$, as reported in Table OA.34.

Having obtained $\bar{\Upsilon}$, we estimate $\beta \times \xi$. Combining the equilibrium local price (G.26) and

Table OA.36: Estimation of $\bar{\Upsilon}$ and $\beta\xi$

	$\tilde{\Delta}$Sale		$\tilde{\Delta}$Price	
	(1)	(2)	(3)	(4)
$\sum_{r\in k_f}\left[\omega_{r'f}\hat{S}_{r'f}+\theta_{r'f}\hat{\gamma}_{r'}\right]$	0.996***	0.618***	0.144***	0.317**
	(0.007)	(0.096)	(0.020)	(0.152)
IV		✓		✓
First-stage F stat		22.1		22.1
State-Firm Controls	✓	✓	✓	✓
State FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
R^2	0.707		0.327	
Observations	83550	83550	83550	83550

Note. The regression specification is the same as that in Table 2 column (3) except that we use $\sum_{r\in k_f}\left[\omega_{r'f}\hat{S}_{r'f}+\theta_{r'f}\hat{\gamma}_{r'}\right]$ as a regressor and the market is defined as a state. $\tilde{\Delta}$S is the state-firm-specific sales growth between 2007 and 2009, and $\tilde{\Delta}$Price is the state-firm-specific price growth between 2007 and 2009. Columns (2) and (4) use the indirect demand shock, $\tilde{\Delta}\text{HP}_{(07-09)}$ (other), as an instrumental variable. * p < 0.10, ** p < 0.05, *** p < 0.01.

quality (G.28) leads to:

$$p_{rf} = \left[\sum_{r\in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r-\xi}{\mu}\right)\right]^{\beta\xi}\left[\frac{\mu}{a_f}\right] \tag{G.49}$$

Taking the log difference, we obtain

$$\hat{p}_{rf} = \beta\xi\sum_{r\in k_f}\left[\omega_{rf}\hat{S}_{rf}+\theta_{rf}\hat{\gamma}_r\right]-\hat{a}_f \tag{G.50}$$

where Equation (G.50) has the same regressor $\left[\omega_{rf}\hat{S}_{rf}+\theta_{rf}\hat{\gamma}_r\right]$ but a different dependent variable, $\hat{p}_{rf}$, the local firm price index. $\hat{p}_{rf}$ is measured by taking a first difference of a simple average of price across all products within state, firm, and time, similar to that used in Table 5, column (2).

Table OA.36 columns (3) and (4) report the estimation results. Regardless of using OLS or IV, the coefficient is positive, suggesting that the increase in overall sales and households' taste for product quality leads to the increase in local prices. Within the structure of the extended model, this increase is governed by the responsiveness of fixed costs with respect to the supply of high product quality (β) multiplied by the elasticity of variable cost to the level of product quality (ξ). Identical to the calibration of $\bar{v}$, we use IV estimation of $\beta\xi = 0.317$ as a baseline measure.

With the measures of $\bar{\Upsilon} \equiv \beta(\sigma - 1)(\bar{\gamma} - \xi)$ and $\beta\xi$, it is straightforward to recover ξ and β. Defining $\kappa \equiv \frac{\bar{\Upsilon}}{\beta\xi} = \frac{\beta(\sigma-1)(\bar{\gamma}-\xi)}{\beta\xi}$ and rearranging this expression leads to:

$$\xi = \frac{\sigma - 1}{\kappa + \sigma - 1}\bar{\gamma} \tag{G.51}$$

Given κ, σ and $\bar{\gamma}$, Equation (G.51) recovers ξ. Additionally, β is recovered using $\beta = \frac{\beta\xi}{\xi}$.

Goodness of Fit. With the calibrated parameters, Table OA.37 tests the goodness of fit by revisiting the reduced-form analyses with model-simulated data. Columns (1) and (2) allow for local housing price growth, and columns (3) and (4) absorb all the local variation by using the state fixed effect. Both direct and indirect effects estimated from the model-simulated data are comparable to those estimated with the actual data.

Table OA.37: Goodness of Fit: Data vs. Model (Firm-State Level)

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}$Sale			
$\tilde{\Delta}$HP	0.159***	0.144***		
	(0.051)	(0.003)		
$\tilde{\Delta}$HP (other)	0.203*	0.186***	0.238***	0.233***
	(0.104)	(0.016)	(0.085)	(0.018)
State-Firm Controls	✓	✓	✓	✓
State FE	-	-	✓	✓
Source	Data	Model	Data	Model
Observations	83610	83610	83610	83610

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

G.3.2 Additional Results

Section F.3 compares two different economies with the calibrated parameters: a benchmark economy with uniform product replacement and a counterfactual economy with market-specific product quality choice. Table OA.38 provides a full description of the utility and housing price growth across states.

Table OA.38: Regional Redistribution across States

State	$\hat{HP}_r(\%)$	$\hat{I}_r(\%)$	$\hat{U}_r(\%)$ Benchmark	$\hat{U}_r(\%)$ Counterfactual	$\hat{U}_r(\%)$ Abs. Diff.	$\hat{V}_r(\%)$ Benchmark	$\hat{V}_r(\%)$ Counterfactual	$\hat{V}_r(\%)$ Abs. Diff.	Pop. Weight (%)
AL	-7.88	-1.81	-3.94	-3.01	0.92	-2.18	-2.00	0.19	1.54
AZ	-38.13	-8.77	-13.50	-14.91	1.41	-9.69	-9.98	0.30	2.12
AR	-4.68	-1.08	-2.85	-1.70	1.15	-1.38	-1.14	0.23	0.95
CA	-33.11	-7.61	-12.17	-13.83	1.66	-8.49	-8.84	0.35	12.20
CO	-5.53	-1.27	-3.34	-2.15	1.19	-1.63	-1.39	0.24	1.62
CT	-13.04	-3.00	-5.89	-5.27	0.62	-3.53	-3.40	0.13	1.17
DE	-8.14	-1.87	-4.14	-3.04	1.09	-2.27	-2.05	0.22	0.29
DC	-11.91	-2.74	-5.51	-4.63	0.88	-3.24	-3.06	0.18	0.20
FL	-43.19	-9.93	-15.03	-17.28	2.25	-10.93	-11.41	0.48	6.09
GA	-17.11	-3.93	-6.92	-6.84	0.08	-4.48	-4.47	0.02	3.19
ID	-14.74	-3.39	-6.16	-5.54	0.62	-3.90	-3.77	0.13	0.50
IL	-20.33	-4.68	-7.98	-8.25	0.27	-5.29	-5.35	0.05	4.29
IN	-8.76	-2.02	-4.24	-3.41	0.83	-2.41	-2.24	0.17	2.12
IA	0.18	0.04	-1.39	0.18	1.57	-0.19	0.13	0.32	1.00
KS	-3.59	-0.83	-2.60	-1.31	1.29	-1.13	-0.86	0.26	0.93
KY	-2.36	-0.54	-2.16	-0.82	1.33	-0.81	-0.54	0.27	1.42
LA	1.28	0.30	-1.02	0.62	1.65	0.09	0.42	0.33	1.43
ME	-14.07	-3.24	-5.94	-5.28	0.66	-3.73	-3.59	0.14	0.44
MD	-22.93	-5.27	-8.98	-9.31	0.32	-5.97	-6.04	0.07	1.87
MA	-10.19	-2.34	-4.90	-4.12	0.78	-2.80	-2.64	0.16	2.15
MI	-29.68	-6.83	-10.85	-11.80	0.95	-7.59	-7.79	0.20	3.36
MN	-16.95	-3.90	-6.94	-6.73	0.21	-4.46	-4.42	0.04	1.73
MS	-4.51	-1.04	-2.81	-1.64	1.17	-1.34	-1.10	0.24	0.97
MO	-6.47	-1.49	-3.50	-2.48	1.02	-1.84	-1.63	0.21	1.96
MT	0.06	0.01	-1.43	0.13	1.56	-0.22	0.10	0.32	0.32
NE	-1.67	-0.38	-1.98	-0.54	1.45	-0.65	-0.36	0.29	0.59
NV	-54.06	-12.43	-18.52	-20.61	2.09	-13.64	-14.09	0.45	0.86
NH	-13.11	-3.02	-5.80	-5.07	0.73	-3.52	-3.37	0.15	0.44
NJ	-17.26	-3.97	-7.20	-7.10	0.10	-4.57	-4.55	0.02	2.90
NM	-5.18	-1.19	-3.09	-1.90	1.19	-1.52	-1.27	0.24	0.66
NY	-15.23	-3.50	-6.43	-6.30	0.13	-4.04	-4.01	0.03	6.44
NC	-6.23	-1.43	-3.44	-2.42	1.02	-1.78	-1.57	0.21	3.02
ND	1.72	0.39	-0.85	0.76	1.61	0.20	0.53	0.32	0.21
OH	-9.11	-2.10	-4.34	-3.60	0.74	-2.49	-2.34	0.15	3.83
OK	3.27	0.75	-0.34	1.42	1.76	0.59	0.95	0.36	1.21
OR	-15.86	-3.65	-6.57	-6.16	0.41	-4.18	-4.10	0.09	1.25
PA	-4.56	-1.05	-2.93	-1.77	1.16	-1.37	-1.14	0.24	4.15
RI	-18.61	-4.28	-7.50	-7.12	0.39	-4.88	-4.80	0.08	0.35
SC	-8.37	-1.92	-4.10	-3.20	0.90	-2.31	-2.12	0.18	1.47
SD	0.72	0.16	-1.18	0.38	1.56	-0.05	0.27	0.31	0.27
TN	-5.76	-1.33	-3.25	-2.19	1.06	-1.66	-1.44	0.22	2.05
TX	-5.93	-1.36	-3.38	-2.38	1.00	-1.71	-1.51	0.20	7.98
UT	-10.82	-2.49	-4.99	-4.20	0.79	-2.94	-2.78	0.16	0.88
VT	-7.40	-1.70	-3.85	-2.71	1.15	-2.08	-1.84	0.23	0.21
VA	-15.83	-3.64	-6.62	-6.40	0.23	-4.19	-4.14	0.05	2.57
WA	-17.97	-4.13	-7.34	-7.19	0.14	-4.73	-4.70	0.03	2.16
WV	-4.02	-0.92	-2.63	-1.42	1.21	-1.21	-0.96	0.25	0.60
WI	-7.07	-1.63	-3.74	-2.74	0.99	-2.00	-1.79	0.20	1.87
WY	-1.32	-0.30	-1.93	-0.39	1.54	-0.57	-0.26	0.31	0.17
Mean	-16.60	-3.82	-6.79	-6.68	0.98	-4.37	-4.35	0.20	Sum: 100
Std	12.97	2.98	4.13	5.28		3.22	3.46		

Note. $\hat{HP}_r(\%)$ is the state-level house price growth. $\hat{I}_r(\%)$ is the exogenous regional income growth which is calculated as $\hat{HP}_r(\%) \times 0.23$. Benchmark indicates the model with uniform quality choice in Section F.2, and counterfactual indicates the model with market-specific quality choice in Appendix G.2.2. $\hat{U}_r(\%)$ 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.

H Derivations and Proofs

For all the proofs in this section, we prove under the general setup that allows both the scale effect and nonhomothetic preferences presented in F.2. The baseline model is a special case of the extended model, which is obtained by assuming a constant γ.

H.1 Upper-Tier Optimality

The upper-tier problem is given as follows:

$$\max_{z_r, U_r} V_r = \left[(1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} + \alpha(U_r)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \quad s.t. \quad z_r + P_r U_r \leq y_r$$

where P_r is the CPG consumption bundle price index that each individual takes as given, U_r is utility from CPG consumption, and z_r is outside expenditure used as the numeraire.

The Lagrangian is

$$\mathcal{L}_r = \left[(1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} + \alpha(U_r)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} + \Lambda_r\left[y_r - z_r - P_r U_r\right]$$

The first-order conditions are given by

$$\partial U_r \ : \ (V_r)^{\frac{1}{\eta}}(\alpha)(U_r)^{-\frac{1}{\eta}} = \Lambda_r P_r \tag{H.1}$$

$$\partial z_r \ : \ (V_r)^{\frac{1}{\eta}}(1-\alpha)(z_r)^{-\frac{1}{\eta}} = \Lambda_r \tag{H.2}$$

which implies

$$\alpha(U_r)^{\frac{\eta-1}{\eta}} = (\Lambda_r)^{1-\eta}(P_r)^{1-\eta}[V_r]^{\frac{\eta-1}{\eta}}\alpha^\eta$$

$$(1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} = (\Lambda_r)^{1-\eta}[V_r]^{\frac{\eta-1}{\eta}}(1-\alpha)^\eta$$

Thus,

$$\begin{aligned}(V_r)^{\frac{\eta-1}{\eta}} &= (1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} + \alpha(U_r)^{\frac{\eta-1}{\eta}} \\ &= (\Lambda_r)^{1-\eta}(V_r)^{\frac{\eta-1}{\eta}}\left[(1-\alpha)^\eta + (P_r)^{1-\eta}\alpha^\eta\right]\end{aligned}$$

which yields the upper-tier price index $\mathcal{P}_r^V$ defined by

$$\mathcal{P}_r^V \equiv (\Lambda_r)^{-1} \equiv \left[(1-\alpha)^\eta + (P_r)^{1-\eta}\alpha^\eta\right]^{\frac{1}{1-\eta}} \tag{H.3}$$

which also satisfies

$$\begin{aligned} y_r &= z_r + P_r U_r \\ &= \mathcal{P}_r^V V_r \end{aligned}$$

By combining (H.1) and (H.2), we have

$$P_r = \frac{\alpha (U_r)^{-\frac{1}{\eta}}}{(1-\alpha)(z_r)^{-\frac{1}{\eta}}}$$

or

$$P_r U_r = \left(\frac{\alpha}{1-\alpha}\right)(z_r)^{\frac{1}{\eta}}(U_r)^{1-\frac{1}{\eta}}$$

Since $z_r = y_r - P_r U_r$,

$$P_r U_r = \left(\frac{\alpha}{1-\alpha}\right)(y_r - P_r U_r)^{\frac{1}{\eta}}(U_r)^{1-\frac{1}{\eta}}$$

Thus, we have

$$\frac{P_r U_r}{y_r} = \left(\frac{\alpha}{1-\alpha}\right)(\frac{y_r - P_r U_r}{y_r})^{\frac{1}{\eta}}(\frac{U_r}{y_r})^{1-\frac{1}{\eta}}$$

which implies

$$1 = \left(\frac{\alpha}{1-\alpha}\right)(\frac{y_r}{P_r U_r} - 1)^{\frac{1}{\eta}}(\frac{1}{P_r})^{1-\frac{1}{\eta}}$$

By defining CPG expenditure as $s_r \equiv P_r U_r$, the CPG expenditure share as $\Theta_r \equiv \frac{s_r}{y_r}$ and rearranging terms, we obtain

$$\Theta_r = \frac{\alpha^\eta}{\alpha^\eta + (1-\alpha)^\eta (P_r)^{\eta-1}} \equiv \Theta(P_r) \tag{H.4}$$

This implies that for a given level of y_r, Θ_r is decreasing with P_r. Thus, if negative demand shocks in other markets induce an increase in P_r (while market r income remains fixed at y_r), then both the CPG expenditure level and its share decrease in market r.

H.2 Equivalent Discrete-Choice Model

This section shows how the discretized version of the utility function (G.22) given by

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

can be derived as the aggregation of heterogeneous consumers buying only one product bundle (corresponding to one firm). Without loss of generality, we consider market r, where for notational simplicity, we omit the market subscript r.

Suppose that consumer h with total income y has utility given by

$$U_{y,h} = \max_{f \in G, q_{f,y,h}} \left[\log q_{f,y,h} + \log \zeta_{f,y} + \mu_y \epsilon_{f,y,h}\right] \tag{H.5}$$

subject to the budget constraint

$$p_f q_{f,y,h} \leq s_y$$

where s_y refers to total income allocated to CPG expenditure, $\log \zeta_{f,y}$ is a quality shifter associated with y and firm f, and $\mu_y \epsilon_{f,y,h}$ is a specific taste shock for each consumer h with y associated with firm f.

With these preferences, each consumer h consumes a unique product bundle produced by firm f^* determined by

$$f^* = \arg\max_{f \in G} \left[\log s_y - \log p_f + \log \zeta_{f,y} + \mu_y \epsilon_{f,y,h}\right]$$

implying that the choice of firm f by individual h does not depend on s_y. Thus, the problem can be expressed as

$$f^* = \arg\max_{f \in G} \left[-\log p_f + \log \zeta_{f,y} + \mu_y \epsilon_{f,y,h}\right] \tag{H.6}$$

Suppose that we have a large number of consumers and that $\epsilon_{f,y,h}$ is i.i.d. and drawn from a Gumbel distribution (type-II extreme value distribution) as in Anderson et al. (1987). This implies that a share

$$s_{f,y} = \frac{\left(\frac{\zeta_{f,y}}{p_f}\right)^{\frac{1}{\mu_y}}}{\sum_{f' \in G} \left(\frac{\zeta_{f',y}}{p_{f'}}\right)^{\frac{1}{\mu_y}}}$$

of consumers will choose the product bundle produced by firm $f \in G$. As a consumer with y choosing firm f has expenditure on that firm's product bundle given by s_y, we obtain the following aggregate expenditures for firm f's product bundle associated with y:

$$s_{f,y} = \frac{\left(\frac{\zeta_{f,y}}{p_f}\right)^{\sigma_y - 1}}{\sum_{f' \in G} \left(\frac{\zeta_{f',y}}{p_{f'}}\right)^{\sigma_y - 1}} s_y \tag{H.7}$$

where $\sigma_y \equiv 1 + \frac{1}{\mu_y}$ denotes the elasticity of substitution between firms f on aggregate for consumers with y. Note that (H.7) is exactly the discretized version of (G.24). This shows that the utility described in (H.5) is equivalent to the consumption patterns obtained with the preferences described in (G.22) (except for the discrete vs. continuum measure of firms).

H.3 Relationship between the Outside Good and Income

By combining $y_r = z_r + P_r U_r$, (G.21) and (H.4), we have

$$\begin{aligned} z_r &= (1 - \Theta_r)\, y_r = (1 - \Theta_r)(I_r + D_r) \\ &= (1 - \Theta_r) \left(1 + \frac{\overline{\Pi}}{\sum_{r \in \mathcal{R}} I_r L_r} \right) I_r \end{aligned} \tag{H.8}$$

From (H.4), $\Theta_r = \alpha$ if $\eta \to 1$ (i.e., Cobb-Douglas upper-tier utility). This implies

$$\begin{aligned} z_r &= (1 - \alpha)\, y_r = (1 - \alpha)(I_r + D_r) \\ &= (1 - \alpha) \left(1 + \frac{\overline{\Pi}}{\sum_{r \in \mathcal{R}} I_r L_r} \right) I_r \end{aligned} \tag{H.9}$$

Therefore, under the Cobb-Douglas upper-tier utility, the outside consumption z_r is exactly proportional to both the total income y_r and its exogenous component I_r.

H.4 Derivation of Optimal Prices and Quality

From the profit function (F.7), we have

$$\pi_f = \sum_{r \in k_f} \left(S_{rf} - \frac{c(\phi_f)}{a_f} Q_{rf} \right) - \tau(\phi_f) - \tau_0$$

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

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

$\frac{\partial S_{rf}}{\partial \phi_f}$, $\frac{\partial Q_{rf}}{\partial \phi_f}$, $\frac{\partial c(\phi_f)}{\partial \phi_f}$, and $\frac{\partial f(\phi_f)}{\partial \phi_f}$:

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

We derive the first-order conditions for prices and quality below.

H.4.1 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

$$\begin{aligned} 0 = \frac{\partial \pi_f}{\partial p_{rf}} =& (1-\sigma){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r + \frac{c(\phi_f)}{a_f}\sigma {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma-1} A_r \\ =& \left[(1-\sigma) + \frac{c(\phi_f)}{a_f}\frac{\sigma}{p_{rf}}\right] {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r \end{aligned} \tag{H.10}$$

This implies an optimal price

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

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

H.4.2 First-Order Condition in Quality

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

$$
\begin{aligned}
0 = \frac{\partial \pi_f}{\partial \phi_f} &= \sum_{r \in k_f} \frac{\partial S_{rf}}{\partial \phi_f} - \frac{1}{a_f}\frac{\partial c(\phi_f)}{\partial \phi_f}\sum_{r \in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r \in k_f}\frac{\partial Q_{rf}}{\partial \phi_f} - \frac{\partial f(\phi_f)}{\partial \phi_f} \\
&= \sum_{r \in k_f} (\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r - 1} p_{rf}^{1-\sigma} A_r - \frac{1}{a_f}\xi(\phi_f)^{\xi-1}\sum_{r \in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r \in k_f}(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&= \sum_{r \in k_f}\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{1-\sigma} A_r - \sum_{r \in k_f}\xi\left(\frac{\phi_f^{\xi-1}}{a_f}\frac{1}{p_{rf}}\right){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&= (\phi_f)^{-1}\left[\sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\xi\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \\
&= (\phi_f)^{-1}\left[\sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)(\gamma_r - \xi)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \quad \text{(H.11)}
\end{aligned}
$$

where in the last equality we used the relationship $\frac{\sigma-1}{\sigma} = \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}$ ($\Leftrightarrow \left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right) = \left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma - 1)$) from the first-order condition w.r.t. price. Note that if either $\sigma < 1$ or $\gamma_r < \xi$, $\frac{\partial \pi_f}{\partial \phi_f} < 0$ for any positive ϕ_f. Therefore, in this case, the corner solution arises and firms will choose the lowest possible ϕ_f.

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

$$
\begin{aligned}
0 &= \sum_{r \in k_f}\left[\left(1 - \frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \xi\left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}} \\
&= \sum_{r \in k_f}\left(\frac{\sigma-1}{\sigma}\right)(\gamma_r - \xi) S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \\
&= \sum_{r \in k_f}\left(\frac{\gamma_r - \xi}{\mu}\right) S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \quad \text{(H.12)}
\end{aligned}
$$

By rearranging terms, we obtain the following expression for the optimal quality choice

$$
\phi_f = \left[\sum_{r \in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r - \xi}{\mu}\right)\right]^{\beta} \quad \text{(H.13)}
$$

Assuming that the taste for product quality is homogeneous across markets ($\gamma_r = \gamma$):

$$\phi_f = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma - \xi}{\mu} \right) \right]^{\beta} \tag{H.14}$$

Replacing the optimal local firm sales (F.9) leads to the optimal quality equation (F.10).

H.5 Uniqueness of the Equilibrium

To ensure the uniqueness of equilibrium in prices and quality, we need to verify that the Hessian is negative definite in prices and quality. The Hessian is negative definite if $\frac{\partial^2 \pi_f}{\partial p_{rf}^2} < 0$, $\frac{\partial^2 \pi_f}{\partial \phi_f^2} < 0$, $\frac{\partial^2 \pi_f}{\partial p_{rf}^2} \frac{\partial^2 \pi_f}{\partial \phi_f^2} > \left(\frac{\partial^2 \pi_f}{\partial p_{rf} \partial \phi_f} \right)^2$, and the subsequent conditions on higher-order principal minors: $\frac{\partial^2 \pi_f}{\partial p_{rf}^2} \frac{\partial^2 \pi_f}{\partial p_{lf}^2} \frac{\partial^2 \pi_f}{\partial \phi_f^2} < \left(\frac{\partial^2 \pi_f}{\partial p_{rf} \partial \phi_f} \right)^2 \frac{\partial^2 \pi_f}{\partial p_{rf}^2} + \left(\frac{\partial^2 \pi_f}{\partial p_{lf} \partial \phi_f} \right)^2 \frac{\partial^2 \pi_f}{\partial p_{lf}^2}$, and so forth (where we already imposed $\frac{\partial^2 \pi_f}{\partial p_{lf} \partial p_{rf}} = 0$, which can be easily shown). The proofs in this section closely follow the derivations in Faber and Fally (2021).

H.5.1 Second-Order Conditions in Prices

- $\frac{\partial^2 \pi_f}{\partial p_{rf}^2} < 0$

Recall from (H.10) the first-order condition with respect to price:

$$0 = \frac{\partial \pi_f}{\partial p_{rf}} = \left[(1 - \sigma) + \frac{c(\phi_f)}{a_f} \frac{\sigma}{p_{rf}} \right] {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r$$

Thus,

$$\begin{aligned} \frac{\partial^2 \pi_f}{\partial p_{rf}^2} &= -\left(p_{rf}\right)^{-2} \frac{c(\phi_f)}{a_f} \sigma {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r + \left[(1 - \sigma) + \frac{c(\phi_f)}{a_f} \frac{\sigma}{p_{rf}} \right] (-\sigma - 1) {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma-1} A_r \\ &= -\left(p_{rf}\right)^{-1} (\sigma - 1) {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r < 0 \end{aligned} \tag{H.15}$$

H.5.2 Second-Order Conditions in Quality

- $\frac{\partial^2 \pi_f}{\partial \phi_f^2} < 0$

From (H.12), we have

$$0 = \phi_f \frac{\partial \pi_f}{\partial \phi_f} = \sum_{r \in k_f} \left[\left(1 - \frac{\phi_f^{\xi}}{a_f} \frac{1}{p_{rf}} \right) (\sigma - 1)(\gamma_r - \xi) \right] \phi_f{}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}$$

which implies

$$0 = \frac{\partial \pi_f}{\partial \phi_f} = (\phi_f)^{-1} \left[\sum_{r \in k_f} \left[\left(1 - \frac{\phi_f^{\xi}}{a_f} \frac{1}{p_{rf}} \right) (\sigma - 1)(\gamma_r - \xi) \right] \phi_f{}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}} \right] \quad \text{(H.16)}$$

From the envelope theorem,

$$\frac{\partial^2 \pi_f}{\partial \phi_f^2} = \frac{\partial}{\partial \phi_f} \left[(\phi_f)^{-1} \left(\phi_f \frac{\partial \pi_f}{\partial \phi_f} \right) \right] = -\phi_f^{-2} \left(\phi_f \frac{\partial \pi_f}{\partial \phi_f} \right) + (\phi_f)^{-1} \frac{\partial}{\partial \phi_f} \left(\phi_f \frac{\partial \pi_f}{\partial \phi_f} \right) = (\phi_f)^{-1} \frac{\partial}{\partial \phi_f} \left(\phi_f \frac{\partial \pi_f}{\partial \phi_f} \right)$$

which implies

$$\begin{aligned}
\frac{\partial^2 \pi_f}{\partial \phi_f^2} =& (\phi_f)^{-1} \frac{\partial}{\partial \phi_f} \left(\phi_f \frac{\partial \pi_f}{\partial \phi_f} \right) \\
=& (\phi_f)^{-1} \frac{\partial}{\partial \phi_f} \left[\sum_{r \in k_f} \left[\left(1 - \frac{\phi_f^{\xi}}{a_f} \frac{1}{p_{rf}} \right) (\sigma - 1)(\gamma_r - \xi) \right] \phi_f{}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}} \right] \\
=& (\phi_f)^{-2} \times \sum_{r \in k_f} \left[-\xi \frac{\phi_f^{\xi}}{a_f} \frac{1}{p_{rf}} (\sigma - 1)(\gamma_r - \xi) \right] \phi_f{}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r \\
& + (\phi_f)^{-2} \times \sum_{r \in k_f} \left[\left(1 - \frac{\phi_f^{\xi}}{a_f} \frac{1}{p_{rf}} \right) (\sigma - 1)(\gamma_r - \xi) \right] (\sigma - 1)\gamma_r \phi_f{}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r \\
& - (\phi_f)^{-2} \times b \frac{1}{\beta} (\phi_f)^{\frac{1}{\beta}} \\
=& (\phi_f)^{-2} \times \left[\sum_{r \in k_f} \left(\frac{\sigma - 1}{\sigma} \right) (\sigma - 1)(\gamma_r - \xi)(\gamma_r - \xi) S_{rf} - b \frac{1}{\beta} (\phi_f)^{\frac{1}{\beta}} \right] \\
=& (\phi_f)^{-2} \times \left[\sum_{r \in k_f} \left(\frac{\sigma - 1}{\sigma} \right) (\sigma - 1)(\gamma_r - \xi)(\gamma_r - \xi) S_{rf} - \frac{1}{\beta} \sum_{r \in k_f} S_{rf} \left(\frac{\sigma - 1}{\sigma} \right) (\gamma_r - \xi) \right] \\
=& (\phi_f)^{-2} \times \left(\frac{\sigma - 1}{\sigma} \right) \left[\sum_{r \in k_f} \left[(\sigma - 1)(\gamma_r - \xi) - \frac{1}{\beta} \right] (\gamma_r - \xi) S_{rf} \right] \qquad \text{(H.17)}
\end{aligned}$$

Thus, under the condition $\beta(\sigma-1)(\gamma_r-\xi)<1$, we have that $\frac{\partial^2\pi_f}{\partial\phi_f^2}<0$ holds.

H.5.3 Joint Second-Order Conditions in Quality and Prices

- $\frac{\partial^2\pi_f}{\partial p_{rf}^2}\frac{\partial^2\pi_f}{\partial\phi_f^2} > \left(\frac{\partial^2\pi_f}{\partial p_{rf}\partial\phi_f}\right)^2$

The cross derivative in quality and prices can be calculated by differentiating (H.16) with respect to p_{rf} :

$$\begin{aligned}
&\frac{\partial^2\pi_f}{\partial p_{rf}\partial\phi_f}\\
=&(\phi_f)^{-1}\\
&\times\left[\left(\frac{\phi_f^{\xi}}{a_f}(p_{rf})^{-2}\right)(\sigma-1)(\gamma_r-\xi)\phi_f{}^{(\sigma-1)\gamma_r}p_{rf}^{1-\sigma}A_r+\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)(\gamma_r-\xi)\phi_f{}^{(\sigma-1)\gamma_r}(1-\sigma)p_{rf}^{-\sigma}A_r\right]\\
=&(\phi_f)^{-1}\left[\left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)+\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(1-\sigma)\right](p_{rf})^{-1}(\sigma-1)(\gamma_r-\xi)\phi_f{}^{(\sigma-1)\gamma_r}p_{rf}^{1-\sigma}A_r\\
=&(\phi_f)^{-1}\left[\left(\frac{\sigma-1}{\sigma}\right)+\left(\frac{1-\sigma}{\sigma}\right)\right](p_{rf})^{-1}(\sigma-1)(\gamma_r-\xi)\phi_f{}^{(\sigma-1)\gamma_r}p_{rf}^{1-\sigma}A_r\\
=&0
\end{aligned}\tag{H.18}$$

Since $\frac{\partial^2\pi_f}{\partial p_{rf}^2}<0$ and $\frac{\partial^2\pi_f}{\partial\phi_f^2}<0$ under $\beta(\sigma-1)(\gamma_r-\xi)<1$, we conclude that $\frac{\partial^2\pi_f}{\partial p_{rf}^2}\frac{\partial^2\pi_f}{\partial\phi_f^2}>0=\left(\frac{\partial^2\pi_f}{\partial p_{rf}\partial\phi_f}\right)^2$.

H.5.4 Higher-Order Joint Second-Order Conditions in Quality and Prices

- $\frac{\partial^2\pi_f}{\partial p_{rf}^2}\frac{\partial^2\pi_f}{\partial p_{lf}^2}\frac{\partial^2\pi_f}{\partial\phi_f^2} < \left(\frac{\partial^2\pi_f}{\partial p_{rf}\partial\phi_f}\right)^2\frac{\partial^2\pi_f}{\partial p_{rf}^2}+\left(\frac{\partial^2\pi_f}{\partial p_{lf}\partial\phi_f}\right)^2\frac{\partial^2\pi_f}{\partial p_{lf}^2}$, and etc.

From (H.15), (H.17), and (H.18), it is immediate that $\frac{\partial^2\pi_f}{\partial p_{rf}^2}\frac{\partial^2\pi_f}{\partial p_{lf}^2}\frac{\partial^2\pi_f}{\partial\phi_f^2}<0=\left(\frac{\partial^2\pi_f}{\partial p_{rf}\partial\phi_f}\right)^2\frac{\partial^2\pi_f}{\partial p_{rf}^2}+\left(\frac{\partial^2\pi_f}{\partial p_{lf}\partial\phi_f}\right)^2\frac{\partial^2\pi_f}{\partial p_{lf}^2}$. A similar argument extends to the higher-order joint second-order conditions.

H.6 Properties of Equilibrium

In this section, we show that if $\beta(\sigma-1)(\gamma_r-\xi)<1$, the equilibrium quality ϕ_f, local sales S_{rf}, and profit π_f monotonically increase with firm productivity a_f (i.e. $\frac{\partial\log\phi_f}{\partial\log a_f}>0$, $\frac{\partial\log S_{rf}}{\partial\log a_f}>0$ and $\frac{\partial\log\pi_f}{\partial\log a_f}>0$).

We first show that $\frac{\partial \log \phi_f}{\partial \log a_f} > 0$. By using the expression on the optimal quality (G.28), we have

$$b\phi_f^{\frac{1}{\beta}} = \sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \tag{H.19}$$

which can be written as

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

Differentiation with respect to $\log a_f$ yields

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

or by rearranging terms,

$$\frac{\partial \log \phi_f}{\partial \log a_f} = \beta \sum_{r \in k_f} \omega_{rf} \frac{\partial \log S_{rf}}{\partial \log a_f} \tag{H.20}$$

where $\omega_{rf} \equiv \frac{S_{rf}(\gamma_r - \xi)}{\sum_{r' \in k_f} S_{r'f}(\gamma_{r'} - \xi)}$ with $\sum_{r \in k_f} \omega_{rf} = 1$.

Now, we can express Equation (G.27) as

$$\exp(\log S_{rf}) = \exp[(\sigma - 1)(\gamma_r - 1) \log \phi_f] \mu^{1-\sigma} \exp[(\sigma - 1) \log a_f] A_r$$

where $A_r = P_r^{\sigma-1} S_r$. Differentiation with respect to $\log a_f$ yields

$$\begin{aligned} S_{rf} \frac{\partial \log S_{rf}}{\partial \log a_f} &= \phi_f^{(\sigma-1)(\gamma_r-1)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} A_r (\sigma - 1)(\gamma_r - 1) \frac{\partial \log \phi_f}{\partial \log a_f} + \phi_f^{(\sigma-1)(\gamma_r-1)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} A_r (\sigma - 1) \\ &= S_{rf} (\sigma - 1)(\gamma_r - 1) \frac{\partial \log \phi_f}{\partial \log a_f} + S_{rf} (\sigma - 1) \end{aligned}$$

which implies

$$\frac{\partial \log S_{rf}}{\partial \log a_f} = (\sigma - 1)(\gamma_r - 1) \frac{\partial \log \phi_f}{\partial \log a_f} + (\sigma - 1) \tag{H.21}$$

By combining (H.20) and (H.21), we obtain

$$\begin{aligned}\frac{\partial \log \phi_f}{\partial \log a_f} &= \beta \sum_{r \in k_f} \omega_{rf} \left[(\sigma-1)(\gamma_r - 1) \frac{\partial \log \phi_f}{\partial \log a_f} + (\sigma - 1) \right] \\ &= \sum_{r \in k_f} \omega_{rf} \beta (\sigma-1)(\gamma_r - 1) \frac{\partial \log \phi_f}{\partial \log a_f} + \beta(\sigma-1)\end{aligned}$$

By using $\frac{\partial \log \phi_f}{\partial \log a_f} = \sum_{r \in k_f} \omega_{rf} \left(\frac{\partial \log \phi_f}{\partial \log a_f} \right)$, we can rewrite the above equation as

$$\sum_{r \in k_f} \omega_{rf} \left[1 - \beta(\sigma-1)(\gamma_r - 1) \right] \frac{\partial \log \phi_f}{\partial \log a_f} = \beta(\sigma - 1)$$

By means of contradiction, let us assume that $\frac{\partial \log \phi_f}{\partial \log a_f} \leq 0$. We obtain a contradiction since our assumption $\beta(\sigma-1)(\gamma_r-1) < 1$ implies $\sum_{r \in k_f} \omega_{rf} \left[1 - \beta(\sigma-1)(\gamma_r - 1) \right] \frac{\partial \log \phi_f}{\partial \log a_f} \leq 0 < \beta(\sigma-1)$.

Thus, we conclude that $\frac{\partial \log \phi_f}{\partial \log a_f} > 0$.

Now, it is immediate from (H.21) and $\frac{\partial \log \phi_f}{\partial \log a_f} > 0$ that $\frac{\partial \log S_{rf}}{\partial \log a_f} > 0$. Additionally, from (G.15) and $\frac{\partial \log S_{rf}}{\partial \log a_f} > 0$, we have $\frac{\partial \log \pi_f}{\partial \log a_f} > 0$.

H.7 Structural Equation of Market Interdependency – Derivation

We start with Equation (G.27). 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 $S_{rf,0}$, where the subscript 0 denotes the initial period.

Take the logarithm on both sides of (G.27):

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

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

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

Linearization with respect to the hat variables implies

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

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

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

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

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

where $\omega_{rf,0} \equiv \frac{S_{rf,0}(\gamma_{r,0}-\xi)}{\sum_{r' \in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$ 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 obtain

$$\hat{S}_{rf} = \Upsilon_{r,0} \sum_{r' \in k_f} \omega_{r'f,0} \left[\hat{S}_{r'f} + \hat{\psi}_{r'} \right] + (\log X_{f,0}) \Upsilon_{r,0} \hat{\Upsilon}_r + \hat{A}_r + (\sigma - 1) \hat{a}_f \tag{H.22}$$

Imposing homothetic preferences, Equation (G.48) becomes

$$\hat{S}_{rf} = \Upsilon \sum_{r' \in k_f} \omega_{r'f} \hat{S}_{r'f} + (\sigma - 1) \hat{a}_f + \hat{A}_r \tag{H.23}$$

which is presented in Equation (F.11) in Section F.1.

H.8 Model Propositions: Proof

Given that the first-order conditions and second-order condition require $\sigma > 1$, $\gamma_r > \xi$, and $\beta(\sigma - 1)(\gamma_r - \xi) < 1$, we always assume these restrictions in proving the following propositions. Note that we prove the propositions in the general case where γ_r can vary across markets, as in the extended model.

H.8.1 Proposition OA.1: Proof

Since we assume that D_r is fixed, $\frac{\partial \log y_r}{\partial \log I_r} = \frac{I_r}{I_r + D_r} > 0$ holds. Therefore, differentiation of a variable with respect to $\log y_r$ yields the same sign as the differentiation with respect to $\log I_r$. For the sake of exposition, we lay out the proof using differentiation with respect to $\log y_r$ instead of $\log I_r$.

Define

$$\Gamma_r \equiv (\sigma - 1)(\gamma_r - \xi) \tag{H.24}$$

Claim 1: $\frac{\partial \log \phi_f}{\partial \log I_r} > 0$.

By using the expression on the optimal quality (G.28), we have that

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

where we used $\frac{1}{\mu-1} = \frac{1}{\frac{\sigma}{\sigma-1}-1} = \sigma - 1$. Then, we can rewrite the above equation as

$$b \exp(\frac{1}{\beta} \log \phi_f) = \sum_{r \in k_f} \left(1 - \frac{1}{\mu}\right) \exp(\log(\Gamma_r)) \exp(\log(S_{rf}))$$

Now, differentiation of the above equation with respect to $\log y_r$ yields

$$b\phi_f^{\frac{1}{\beta}} \frac{1}{\beta} \frac{\partial \log \phi_f}{\partial \log y_r} = \sum_{r' \in k_f} \left(1 - \frac{1}{\mu}\right) \Gamma_{r'} S_{r'f} \left(\frac{\partial \log \Gamma_{r'}}{\partial \log y_r} + \frac{\partial \log S_{r'f}}{\partial \log y_r}\right) \tag{H.25}$$

where $\frac{\partial \log \Gamma_r}{\partial \log y_r} = \left(\frac{\partial \log \gamma_r}{\partial \log y_r}\right)\left(\frac{\gamma_r}{\gamma_r - \xi}\right) \geq 0$ – which is immediate from the Equations H.4 and H.8 and the assumption that P_r and D_r are fixed – and $\frac{\partial \log \Gamma_{r'}}{\partial \log y_r} = \left(\frac{\partial \log \gamma_{r'}}{\partial \log y_r}\right)\left(\frac{\gamma_{r'}}{\gamma_{r'} - \xi}\right) = 0$ if $r' \neq r$ – which is again immediate because we are holding regional aggregate variables P'_r and D'_r.

Additionally, from (G.28) and (G.27), for any r'

$$S_{r'f} = \phi_f^{\Gamma_{r'}} \left[\frac{\mu}{a_f}\right]^{1-\sigma} A_{r'}$$

where $A_{r'} \equiv (P_{r'})^{\sigma-1} S_{r'} \equiv (P_{r'})^{\sigma-1}(\Theta_{r'} y_{r'} L_{r'})$. This can be rewritten as

$$\log S_{r'f} = \exp(\log \Gamma_{r'}) \log \phi_f + (1 - \sigma) \log \frac{\mu}{a_f} + \log A_{r'}$$

Differentiation with respect to $\log y_r$ yields

$$\frac{\partial \log S_{r'f}}{\partial \log y_r} = \Gamma_{r'} \log \phi_f \frac{\partial \log \Gamma_{r'}}{\partial \log y_r} + \Gamma_{r'} \frac{\partial \log \phi_f}{\partial \log y_r} + \frac{\partial \log A_{r'}}{\partial \log y_r} \tag{H.26}$$

By combining (H.25) and (H.26), we have

$$b\phi_f^{\frac{1}{\beta}}\frac{1}{\beta}\frac{\partial \log \phi_f}{\partial \log y_r} = \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\left((1+\Gamma_{r'}\log\phi_f)\frac{\partial \log \Gamma_{r'}}{\partial \log y_r} + \Gamma_{r'}\frac{\partial \log \phi_f}{\partial \log y_r} + \frac{\partial \log A_{r'}}{\partial \log y_r}\right)$$

which implies

$$\frac{1}{\beta}\left[b\phi_f^{\frac{1}{\beta}} - \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\cdot\beta\Gamma_{r'}\right]\frac{\partial \log \phi_f}{\partial \log y_r} = \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\left[(1+\Gamma_{r'}\log\phi_f)\frac{\partial \log \Gamma_{r'}}{\partial \log y_r} + \frac{\partial \log A_{r'}}{\partial \log y_r}\right] \tag{H.27}$$

By using the expression on the optimal quality (G.28), we know that $b\phi_f^{\frac{1}{\beta}} = \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}$. Under $\beta\Gamma_r \equiv \beta(\sigma-1)(\gamma_r-\xi) < 1$ for all $r\in k_f$, we have

$$b\phi_f^{\frac{1}{\beta}} = \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f} > \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\cdot\beta\Gamma_{r'}$$

implying $\frac{1}{\beta}\left[b\phi_f^{\frac{1}{\beta}} - \sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\cdot\beta\Gamma_{r'}\right] > 0$ appearing on the left-hand side of equation (H.27).

Finally, fixing P_r, we can easily see that $\frac{\partial \log A_r}{\partial \log y_r} = 1$ and $\frac{\partial \log A_{r'}}{\partial \log y_r} = 0$ if $r' \neq r$, which implies

$$\sum_{r'\in k_f}\left(1-\frac{1}{\mu}\right)\Gamma_{r'}S_{r'f}\left[(1+\Gamma_{r'}\log\phi_f)\frac{\partial \log \Gamma_{r'}}{\partial \log y_r} + \frac{\partial \log A_{r'}}{\partial \log y_r}\right]$$
$$= \left(1-\frac{1}{\mu}\right)\Gamma_r S_{rf}\left[(1+\Gamma_r\log\phi_f)\frac{\partial \log \Gamma_r}{\partial \log y_r} + 1\right] > 0$$

where $\frac{\partial \log \Gamma_r}{\partial \log y_r} \geq 0$.

Thus, we conclude that $\frac{\partial \log \phi_f}{\partial \log y_r} > 0$ (which implies $\frac{\partial \log \phi_f}{\partial \log I_r} > 0$).[40]

Additionally, note that due to continuity, this the argument can be extended to the case with varying P_r, as long as such variations are sufficiently small. For example, suppose that we allow a general equilibrium adjustment in P_r due to a change in y_r. Then,

$$\frac{\partial \log A_r}{\partial \log y_r} = \left[(\sigma-1) + \frac{\partial \log \Theta_r}{\partial \log P_r}\right]\frac{\partial \log P_r}{\partial \log y_r} + 1$$

where we know from (G.3) that $\frac{\partial \log \Theta_r}{\partial \log P_r} = -\frac{(1-\alpha)^\eta (P_r)^{\eta-1}}{\alpha^\eta + (1-\alpha)^\eta (P_r)^{\eta-1}}(\eta-1) = -(1-\Theta_r)(\eta-1) < 0$.

[40] Recall that we restrict the model parameters to ensure that $\phi_f > 1$ in equilibrium.

We can see that as long as $(1+\Gamma_r \log\phi_f)\frac{\partial \log \Gamma_r}{\partial \log y_r} + 1 > -\left[(\sigma-1) + \frac{\partial \log \Theta_r}{\partial \log P_r}\right]\frac{\partial \log P_r}{\partial \log y_r}$, we have $\frac{\partial \log \phi_f}{\partial \log y_r} > 0$ (which implies $\frac{\partial \log \phi_f}{\partial \log I_r} > 0$).[41]

Claim 2: $\frac{\partial \log S_{rf}}{\partial \log I_r} > 0$.
Since we already showed that $\frac{\partial \log A_r}{\partial \log y_r} = 1$ and $\frac{\partial \log \Gamma_r}{\partial \log y_r} \geq 0$, it is immediate from (H.26) that $\frac{\partial \log S_{rf}}{\partial \log y_r} > 0$ (which implies $\frac{\partial \log S_{rf}}{\partial \log I_r} > 0$).

Claim 3: $\frac{\partial \log S_{r'f}}{\partial \log I_r} = (\sigma-1)(\gamma_r - \xi)\frac{\partial \log \phi_f}{\partial \log I_r} > 0$.
In the proof of Proposition OA.1, we already showed that $\frac{\partial \log \Gamma'_r}{\partial \log y_r} = \left(\frac{\partial \log \gamma'_r}{\partial \log y_r}\right)\left(\frac{\gamma'_r}{\gamma'_r - \xi}\right) = 0$ if $r' \neq r$ and $\frac{\partial \log A'_r}{\partial \log y_r} = 0$ if $r' \neq r$ – which are immediate because we are holding regional aggregate variables P'_r and D'_r fixed.

Therefore, (H.26) implies

$$\frac{\partial \log S_{r'f}}{\partial \log y_r} = \Gamma_r \frac{\partial \log \phi_f}{\partial \log y_r} > 0 \tag{H.28}$$

where the inequality comes from Claim 1. This implies that $\frac{\partial \log S_{r'f}}{\partial \log I_r} = \Gamma'_r \frac{\partial \log \phi_f}{\partial \log I_r} > 0$.

[41] If all firms are symmetric in market r (i.e., all firms have the same productivity $a_f = a$ and market network $k_f = k$ and thus the same $\phi_f = \phi$), which implies $P_r = \phi_f^{-(\gamma_r - \xi)}\left(\frac{\mu}{a_f}\right)(N_r)^{\frac{1}{1-\sigma}}$ (where N_r is the number of firms in market r), and if we further assume that $\frac{\partial \log \Theta_r}{\partial \log P_r} = 0$, we can show that $\frac{\partial \log \phi_f}{\partial \log y_r} > 0$ always holds even if we allow P_r to vary with y_r. This is because

$$\frac{\partial \log A_r}{\partial \log y_r} = \left[(\sigma-1) + \frac{\partial \log \Theta_r}{\partial \log P_r}\right]\frac{\partial \log P_r}{\partial \log y_r} + 1 = \left[(\sigma-1) + \frac{\partial \log \Theta_r}{\partial \log P_r}\right](-1)(\gamma_r - \xi)\frac{\partial \log \phi_f}{\partial \log y_r} + 1 = -\Gamma_r \frac{\partial \log \phi_f}{\partial \log y_r} + 1$$

which implies

$$\frac{\partial \log \phi_f}{\partial \log y_r} = \frac{\left(1-\frac{1}{\mu}\right)\Gamma_r S_{rf}\left[(1+\Gamma_r \log \phi_f)\frac{\partial \log \Gamma_r}{\partial \log y_r} + 1\right]}{\frac{1}{\beta}\left[\left(1-\frac{1}{\mu}\right)\Gamma_r S_{rf} + \sum_{r' \in k \& r' \neq r}\left(1-\frac{1}{\mu}\right)\Gamma_{r'} S_{r'f}\left[1-\beta\Gamma_{r'}\right]\right]} > 0$$

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