Essays in Applied Macroeconomics

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ABSTRACT

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This dissertation combines micro-level empirical analyses and general equilibrium structural analyses to study shock propagation mechanisms and business cycles dynamics, with a particular emphasis on the role played by firms. In the first chapter, we study how regional shocks spill over across U.S. local markets through intra-firm market networks and explore how such spillovers reshape household welfare across regions. We link data on barcode-region-level prices and quantities with producer-level information to exploit variation in firms' initial exposure to differential drops in local house prices in the 2007-09 recession. We show that a firm's local sales decrease in response to not only direct negative local demand shock but also indirect negative local demand shocks originating in its other markets. Intra-firm cross-market spillover effects arise mainly from product creation and destruction, whereas direct local shock operates through the sales of continuing products. Spillover effects occur because (i) firms replace products that have higher value—sales per product, unit price, and organic sales share—with lower-value ones in response to negative demand shocks, and (ii) such product replacements are synchronized across many markets within each firm. Counterfactual analysis using an estimated multi-region model with endogenous quality adjustments shows that our channel works as a novel inter-regional shock transmission mechanism and generates an implicit regional redistribution effect. Such effect is economically sizable and is comparable to the size of transfer policies implemented during the Great Recession.

In the second chapter, we investigate a role of supply chain network in transmitting housing market disruptions during the Great Recession. We build up a unique micro-level data that combines local housing market condition, firms' sales in each local market, and firm-level supply chain network information. Exploiting firm-specific demand shock stemming from cross-market variation in house price changes and an initial difference in firms' local sales, we find that such shock not only affects downstream firms but also transmits to their

suppliers. The estimated supplier-level elasticity is quantitatively large, reflecting larger role of downstream firms with higher elasticity in the network structure. To quantify such propagation at the aggregate level, we build up a parsimonious network model calibrated to match the micro-level data. Our counterfactual analysis shows that approximately 18% of the observed drop in the aggregate output can be attributed to the propagating role of the supply chain network.

In the third chapter, we study the business cycle with a Translog production function. We empirically identify a complementarity between labor and energy that leads to procyclical returns to scale, which is not compatible with the tightly parameterized production function commonly used in the literature (Cobb-Douglas and CES). Therefore, we propose a flexible Translog production function that not only features complementarity-induced procyclical returns to scale but is also consistent with a balanced growth path. A simple calibrated business cycle model with the proposed production function generates strikingly data-consistent dynamics following demand shocks without relying on either nominal rigidities or countercyclical markups.

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Chapter 1

Spillovers and Redistribution through Intra-Firm Networks:

The Product Replacement Channel

Jungsik (Jay) Hyun[1]

1.1 Introduction

How do regional shocks spill over and affect other regions in the economy? What are the distributional consequences across regions of such a spillover? These long-standing questions in the macroeconomics and international trade literature have been extensively studied in an effort to understand the source of business cycle comovements and the relationship between export dynamics and domestic performance (Backus et al. (1992); Kose and Yi (2006); Vannoorenberghe (2012)). Yet, such questions have become equally relevant in *within-country* contexts, especially during and in the aftermath of the Great Recession. As the crisis involved a large *differential* collapse in local housing markets followed by wide disparities in regional economic activity within the United States, seminal papers, such as Mian et al. (2013) and Mian and Sufi (2014), established a large effect of change in local housing market conditions on local consumption and non-tradable employment in those periods exploiting regional variation in the housing net worth shock. The effect of such regional shocks, however, may not be restricted to

[1]This is a collaborated project with Ryan Kim, my former colleague at Columbia University who now joined Johns Hopkins SAIS.

local markets of origination, given that the economy is highly connected across regions through various linkages. Regional shocks could spill over and propagate through various regional linkages and potentially reshape household welfare across regions. Given the importance of such spillovers, previous studies have identified numerous channels that could generate the regional shock spillovers, such as trade, supply chain, and financial networks.

What is particularly not well understood in the literature is the role of spatial networks created by *multi-market firms*—producers selling their products in multiple counties and states who play an important role in US economic activities.[2] Because these firms could make their product supply decisions at the firm-level, the appearance of a negative demand shock in one market can cause them to change their product supply decision in another market. Three outcomes are possible. First, when firms face a negative demand shock and cannot sell their products in one market, they might sell their products in the other market to keep up their firm-level sales. In this case, a decrease in demand and sales in one market leads to an increase in sales in the other market. Second, if firms that face a negative demand shock in one market have trouble financing at the firm-level due to the low cash flow, the increase in financial cost might force these firms to decrease their supply of goods in the other market. Third, it is possible that firms make their decision entirely at the local level and do not spill over the regional shock, as standard international macro and trade models with constant marginal costs predicts (e.g., Backus et al. (1992); Melitz (2003)). In these models, exogenous foreign demand shocks that affect export demand of an exporting company do not affect its domestic sales.

This paper investigates whether and how regional shocks spill over across counties and states through intra-firm spatial networks of multi-market firms, and explores how the identified mechanism reshapes household welfare across local markets. We construct

[2]Based on the calculation from the ACNielsen Retail Scanner database, about 80% of consumer goods producers sell their products in multiple states, and these multi-state firms accounted for more than 99% of total consumer goods expenditures in 2007 (Figure A.1 in Appendix A.2).

a detailed micro data that combines barcode-region-level prices and quantities from ACNielsen Retail Scanner database with various producer-level information from GS1 data and the National Establishment Time-Series (NETS) database. Our combined dataset contains information on barcode-level product prices and quantities sold in each county produced by public and private firms and their establishment-level information in the United States. For example, if Coca-Cola generates sales in Manhattan (New York County) and Brooklyn (Kings County), we observe prices and quantities sold in Manhattan and Brooklyn separately for each barcode level product (e.g., cherry-flavored 500ml diet coke) produced by Coca-Cola as well as Coca-Cola's establishment location, primary industry code, and many other firm-specific characteristics. To generate the variation in local consumer demand condition, we follow the seminal work of Mian et al. (2013) and rely on a sudden differential collapse in local house prices during the Great Recession to generate a sharp differential drop in local consumer demand. To do this, we supplement our dataset with 2007-2009 county- and state-level house prices from the Zillow database.

Armed with the detailed micro-level data, and exploiting the sharp differential drop in local house prices and variation in firms' initial exposure to these local markets, we show that a firm's local sales decrease in response to not only the direct negative local demand shock but also the intra-firm *spillover shock*, which measures the average *indirect* negative local demand shock originating in the firm's other markets. A firm's county-level sales growth *decreases* by 3.5%p when it faces a 10%p average decline in house price growth in other counties connected through its market network, while it only decreases by 0.6%p due to the same percentage points drop of direct county house price growth. This result suggests that the firm-level decision, which is largely affected by overall demand conditions in other markets, is more important in explaining a drop in local sales during this period than the direct local demand condition.[3]

[3]This is intuitive since firms in our sample sell in many markets on average, and the measure of spillover shock captures the average local demand shock a firm face in its all other markets. For example, the median firm in our sample sells in 155 counties, and in looking at the local sales growth for this particular firm, we measure the spillover shock by measuring the average local demand shock this firm faces in the all other 154

To confirm our intra-firm spillover results we conduct a number of robustness checks. We present Placebo tests that demonstrate that the connection to other markets *through the intra-firm market network* is crucial in generating the spillover effects, not other markets in general. Also, we explicitly address concerns related to the possibility of common or geographically clustered regional shocks as well as the possibility of alternative channels. To list some of them, we show (i) that our spillover results are robust to including county-by-industry fixed effects, which absorb both the aggregate shock and any county and/or sectoral shocks, (ii) that the results are robust to constructing the spillover shocks by *excluding nearby counties*, and (iv) that our results are not driven by house price directly affecting production through establishments by measuring the spillover shocks *excluding counties with establishments*. We also (iv) address the endogeneity of house prices by using instrumental variables for local house price changes, and (v) show that our results are not driven by retailers through which firms sell products.

Behind responses of local firm sales to direct and spillover shocks, there exists a stark asymmetry: intra-firm cross-market spillover effects arise mainly from product creation and destruction, whereas direct local shock operates through the sales of continuing products. We show that the identified spillover effects occur because firms replace products that have higher value—sales per product, unit price, and organic sales share—with lower-value ones in response to negative demand shocks, and within each firm, such product replacements are *synchronized* across many markets including those that did not face a direct shock. Therefore, downgrading of products occur even in local markets that are not directly affected by the shocks, which results in a decline of local sales in those markets.

Our result indicates that the *non-localized* firm-level decision, which is affected by the firm's overall demand conditions from many markets, plays an important role in generating within-firm spillovers across local markets. We provide two additional pieces of supporting evidence by investigating heterogeneous treatment effects. First, we show

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markets.

that the identified spillover effects become stronger as firms become more financially constrained, which is consistent with Berman et al. (2015) and Giroud and Mueller (2019). Second, the within-firm spillover effects become stronger as the spillover shock better proxies the firm level average demand shock.

The final part of our paper discusses the aggregate implications of our findings. We develop a stylized multi-region model with endogenous quality adjustments by firms that reflect product replacements. Our model interprets the replacement of high-valued products with low-valued products as quality downgrading because this replacement is associated with a decrease of sales in the market not directly hit by negative demand shock, and at the barcode level, changes in product attribute that directly affect product quality should involve product replacements.[4] In the model, firms that face a negative demand shock decrease their product quality due to (i) the scale effects that reflect lower fixed costs associated with production at the lower quality level and (ii) the nonhomothetic preferences that make consumers who face negative demand shock switch their consumption toward lower quality goods. In this downgrading process, such firms choose the uniform product quality across many markets, including markets that did not experience direct local demand shocks. This generates the intra-firm spillover effect, as in our empirical analysis.

We estimate the model's key parameters and match broad features in the data to perform counterfactual analysis. We show that the identified intra-firm cross-market spillover effect works a novel inter-regional shock transmission mechanism and generates substantial distributional consequences across regions. We measure the state level quality-adjusted real consumption (per capita), which measures regional welfare, by leveraging our estimated model. We compare the measured regional welfare growth in the benchmark economy (characterized by the uniform quality adjustment) with the

[4]Conditional on direct local demand (or alternatively, without direct local negative demand shock), if unit price decline at the extensive margin purely reflects a decrease in markup for a new product relative to the exiting product (without noticeable quality differences), then one should observe an *increase* in sales (and not decrease in sales) because the price elasticity of demand is typically larger than unity (see, e.g., Broda and Weinstein (2010)).

one measured under the counterfactual economy where firms choose market-specific product quality and, thus, do not spill over regional shock through the intra-firm network. The standard deviation of the quality-adjusted real consumption growth across states in consumer packaged goods sectors increases by about 29% in our counterfactual analysis relative to our benchmark economy. A back-of-the-envelop calculation shows that this corresponds to a one-time $400 per-household transfer (tax) on a state that experienced below-average (above-average) house price growth. This is comparable to the tax rebate checks authorized by the US Congress in 2008 (Economic Stimulus Act of 2008), which were also one-time payments that ranged from $300 to $1200 per qualifying household. Therefore, the magnitude of redistribution induced by our identified channel is economically meaningful and compares in size to transfer policies. This highlights the important role that intra-firm spillover through uniform product replacements plays in mitigating the quality-adjusted regional consumption inequality. We then compare the cross-sectional dispersion of the state level welfare (in terms of level). In the counterfactual economy with market-specific quality adjustments the standard deviation of the measured quality-adjusted regional consumption is nearly twice that of the benchmark economy.

These results indicate that the identified intra-firm spillover through uniform product replacements serves as an implicit redistributive (or risk-sharing) mechanism across regions. Firms that introduce uniform product quality across many markets take into account the average demand conditions in all of their markets. Thus regions that were hit by severe negative demand shocks face relatively higher quality than the counterfactual economy due to the existence of regions that were hit by moderate demand shocks and firms that sell in both regions. In contrast, regions that were hit by moderate demand shocks enjoy relatively lower product quality due to the existence of regions hit by severe negative demand shocks. This mitigates the quality-adjusted regional consumption inequality.[5]

[5]In fact, we get similar implication under the model with the scale effect and *homothetic preferences* instead of nonhomothetic preferences. This is because nonhomothetic preferences generate lower welfare for both high

Literature Review

Our paper contributes to several strands of the literature. A growing literature studies how shocks transmit throughout the economy and discuss its macroeconomic implications. This literature focuses on various types of linkages, including trade and supply chain networks (Backus et al. (1992); Frankel and Rose (1998); Kose and Yi (2006); di Giovanni and Levchenko (2010); Acemoglu et al. (2012, 2016); Barrot and Sauvagnat (2016); Carvalho et al. (2016); Stumpner (2019); Caliendo et al. (2018); Adao et al. (2018a); Auerbach et al. (2019)), labor market integration (House et al. (2018)), financial networks (Cetorelli and Goldberg (2012); Acemoglu et al. (2015); Gilje et al. (2016); Cortés and Strahan (2017); Baskaya et al. (2017); Mitchener and Richardson (2019)), and social networks (Bailey et al. (2018)). Our paper adds to this literature by showing whether and through what mechanism regional shocks spill over across regions through intra-firm networks created by multi-market firms. It also demonstrates that the identified channel substantially reshapes household welfare across local markets.

Only a few recent papers have investigated various types of intra-firm spatial networks. At the international level, Cravino and Levchenko (2017) show how multinationals that operate in multiple countries could explain international business cycle comovement, while Berman et al. (2015), Ahn and McQuoid (2017), Almunia et al. (2018), and Erbahar (2019) study how exporters transmit shock across countries.[6] In

demand and low demand regions due to the uniform product quality that is "less appealing" in both regions (i.e., generate "level effect"), but do not affect "dispersion" of welfare across regions that affects regional consumption inequality.

[6]The direction of spillover at the international level is somewhat mixed. Berman et al. (2015) and Erbahar (2019) show a positive association between firm-level exports and domestic sales, while Ahn and McQuoid (2017) and Almunia et al. (2018) show the opposite result. One notable difference between Berman et al. (2015) and Almunia et al. (2018) is that the former investigates the effect of exogenous export demand change on domestic sales while the latter looks at the effect of exogenous domestic sales change on export dynamics. If a firm's export sales is relatively larger than domestic sales, the exogenous export demand shock can be viewed as (proxy of) firm-level demand shock while the exogenous domestic demand shock can be viewed as local shock in firm's perspective. Consistent with this perspective, we show that the better the spillover shock proxies the firm-level demand shock, the positive spillover effect becomes stronger (see Section 1.4.4).

contrast, our paper considers firms that sell in multiple local markets within the United States.

At the domestic level, Giroud and Mueller (2019) show that non-tradable establishment employment is sensitive to consumer demand shocks in other regions in which the parent firm operates establishments. Our paper complements their paper in three important dimensions. First, while they find evidence of spillover for the non-tradable sectors, our firms mainly consist of consumer packaged good producers classified as tradable goods firms. Second, the nature of the network is different because our spatial networks are based firms' markets (i.e., where they sell their products), which are largely decoupled with their establishment locations.[7] Third, we emphasize the role of uniform product replacements across many markets by each firm as the key mechanism behind the spillover.

Contemporaneous work by Gilbert (2017) emphasizes synchronized product entry decision by retailers. In contrast, we emphasize the role played by producers and show that the identified spillover effect exists even after we control for common retailers through which households purchase products (Table A.4), and that the role of retailers behind the extensive margin response is limited relative to the role played by producers (Table OA.1 in Online Appendix B). In addition, while Gilbert (2017) focuses on descriptive correlations, we exploit differential collapse in local housing markets in the 2007-09 recession to generate exogenous variation that allows us to identify the spillover effects, and provide an extensive set of robustness checks that rule out alternative explanations.

Our paper also contributes to the literature that studies the housing market collapse during the Great Recession. Previous studies focused on its implications for consumer spendings (Mian et al. (2013); Stroebel and Vavra (2019); Kaplan et al. (2016)), employments (Mian and Sufi (2014); Giroud and Mueller (2017)), and regional business

[7]The distinction between multi-market firms and multi-establishment firms has also been drawn in studies of international trade since exporters (multi-market firms) and multinationals (multi-establishment firms) have different incentives to trade. See, for example, Antràs and Yeaple (2014). In our sample, an average of less than 5% of the regions in which a firm sells its products also have the firm's establishments.

cycles (Beraja et al. (2019); Giroud and Mueller (2018)). We contribute to the literature by showing that local demand shocks affect firms' product creation and destruction decisions, which, in turn, affect the consumption and welfare of households in other regions. To the best of our knowledge, this channel has not been studied previously in the literature.

Furthermore, our paper contributes to the literature that studies variety and quality adjustments, product turnover, and innovation by firms in the context of economic growth, business cycles, and the measurement of costs of livings and inequality (Broda and Weinstein (2010); Schmitt-Grohé and Uribe (2012); Hottman et al. (2016); Jaimovich et al. (2019); Dingel (2017); Anderson et al. (2017); Argente et al. (2018); Jaravel (2018); Anderson et al. (2018)). We contribute to the literature by showing that product turnover and quality adjustment decisions made at the firm level generate inter-dependency across regions, generating spillover effects.[8]

The implications of our work are relevant to the literature that studies how local shocks are smoothed out within a country and to what extent risks are shared across regions through various channels. The literature typically has focused on either the role of credit markets for risk sharing (e.g., Asdrubali et al. (1996); Lustig and Nieuwerburgh (2005, 2010)) or the role of monetary and fiscal union where multiple regions face common policy instruments (Hurst et al. (2016)). Our paper contributes to the literature by providing a novel mechanism that generates redistributive (or risk-sharing) effect across regions that works through firms' decisions about product replacements and associated product quality choice.

The rest of this paper is structured as follows. Section 2.2 describes the data and summary statistics, Section 2.3 explains the empirical strategy and construction

[8]Another related literature is industrial organization studies that document uniform pricing behavior by retailers (see, for example, DellaVigna and Gentzkow (2017), Cavallo (2018)). While these papers emphasize the role of pricing decisions by retailers (typically at the high frequency level (e.g., weekly) for continuing products for some duration of a time period), we focus on the role of producers' decisions play in product creation/destruction and associated choice of product quality. In Section 1.4.3, we show that our results are not driven by retailers.

of variables, and Section 1.4 presents the main spillover and decomposition results. In Section 1.5, we discuss the mechanism that underlies our results: the channel of uniform product replacements from high- to low-value products. Section 1.6 develops the multi-region model with endogenous quality adjustment by firms and discusses the distributional implications. Section 3.6 concludes.

1.2 Data and Summary Statistics

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

The barcode-level price and quantity information in each county comes from the ACNielsen Retail Scanner database, which was made available by the Kilts Marketing Data Center at the University of Chicago Booth School of Business.[9] The data contain approximately 2.6 million barcode-level product prices and quantities recorded weekly from about 35,000 participating grocery, drug, mass merchandise, convenience, and liquor stores in all U.S. markets. A barcode, a unique *universal product code (UPC)*

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

assigned to each product, is used to scan and store product information. Participating retail stores use the point-of-sale systems that record information whenever product barcodes are scanned during purchases. The data begin in 2006 and end in 2015, covering the period of the Great Recession and the housing market collapse. It mainly includes consumer packaged goods, such as food, nonfood grocery items, health and beauty aids, and general merchandise. According to Nielsen, the Retail Scanner covers more than half the total sales volume of US grocery and drug stores and more than 30 percent of all US mass merchandiser sales volume.

There are two notable advantages to using the ACNielsen Retail Scanner database when studying multi-market firm behavior. First, the database records product sales at the barcode-level, which is likely to be the most granular scale at which the product can be defined. This feature allows us to decompose a firm's local sales growth coming through the intensive margin from continuously existing products and the extensive margin from product creation and destruction. Using a broader product category classification (as definition of product) would not allow us to identify the extensive margin effect emphasized in this paper.[10] Second, use of the database results in fewer measurement error problems. For example, compared to similar data that rely on consumer surveys (Homescan Panel database), the ACNielsen Retail Scanner data directly record expenditures when consumers purchase and scan products at stores. Thus, our data do not suffer from household non-response and misreporting, which is common problem in survey data used in economic research (Meyer et al. 2015). Also, unlike most firm-level international trade and balance sheet data that infer regional (domestic) sales by subtracting other regional (international) sales from total firm sales, Nielsen collects sales information independently across each region. This feature prevents the mechanical regional sales correlation problem raised in Berman et al. (2015) when

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

we conduct the structural regression exercise described in Section 1.6.

We integrate the prices and quantities of each product with its producer information using the GS1 US Data Hub and the National Establishment Time-Series (NETS). GS1 is the only official source of barcodes in the United States and issues barcodes to producers.[11] Their data record the company name and address for each barcode-level product, and we use this information to link barcode-level product information to various producer-level information from the NETS data.[12] NETS is the U.S. establishment-level longitudinal database made available by Walls & Associates. The original source of the data is Dun and Bradstreet (D&B) archival data, which is collected primarily for marketing and credit scoring. The data allows us to identify each firm's establishment location, primary industry code defined at the SIC 4-digit level, and D&B credit and payment rating during the 1990-2014 time period. We use this information to compare firms that operate in the same primary industry, to analyze heterogeneous treatment effects to investigate the mechanism that lies behind the spillover results, and to address concerns related to supply-side or collateral channel. See, e.g., Neumark et al. (2011), Barnatchez et al. (2017), Rossi-Hansberg et al. (2018), and Asquith et al. (2019) for a more detailed discussion on the NETS data.[13]

We supplement our combined database with house price indexes at the county-level from the Zillow database, the housing supply elasticity established by Saiz (2010), and the "nonlocal mortgage lending shock" constructed by García (2018) to capture the local market demand condition.[14] To explore the role played by financial friction in spillovers,

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

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

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

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

Table 1.1: Summary Statistics

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

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

we further augment our data with the industry-level "external financial dependence index" from Rajan and Zingales (1998).

We report the summary statistics of the final sample used in the regression analyses in Table 1.1. Our combined dataset consists of 4171 number of firms and covers 991 US counties from 2007 to 2009.[15] Three features of the data are worth highlighting. First, most of the firms in our sample sell many products in many counties. For example, the average firm in our sample sells 54 products across 513 counties. This feature of our sample, together with the large variation in county-level house price growth, allows us to study spillover effects across counties through intra-firm networks: there is large variation across firms in their initial exposure to different counties, and these counties were differentially hit by local shocks. Second, there is extreme firm heterogeneity, as Hottman et al. (2016) have documented. A firm in the 90th percentile of the distribution has about 3000 times more sales, produces about 55 times more products, and sells in about 160 times more counties than a firm in the 10th percentile of the distribution. In the empirical analysis, we control for these firm-characteristics. Lastly, many firms sell their products in each county. On average, 848 firms sell their products in each county, and even in a county in the 10th percentile of the distribution, 341 firms sell their products. As discussed in more details in Section 1.3.4, this aspect suggests that it is unlikely that an individual firm could affect local economic conditions, due to its small share in each county.

1.3 Empirical Strategy

This section presents the empirical framework we use to identify the spillover effects of regional shocks through intra-firm networks. We start by discussing key variables, and then we present empirical specifications. At the end of this section, we briefly discuss potential threats to identification and how we address those concerns. We use the terms

[15] As discussed in more details in Online Appendix A, our final combined sample covers about 40% of total sales in the Nielsen data. We show the robustness of our results using the full Nielsen sample as well as the Homescan Panel database in Table OA.3 in Online Appendix B and Table A.9 in Appendix A.1, respectively.

"(local) market" and "region" interchangeably. Our baseline definition of the local market is the county, but we also present results that use state for the sake of robustness.

1.3.1 Dependent Variables

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

$$\tilde{\Delta}\text{Sale}_{rf} \equiv \frac{\text{Sale}_{rf,09} - \text{Sale}_{rf,07}}{\overline{\text{Sale}}_{rf}} \tag{1.3.1}$$

where $\overline{\text{Sale}}_{rf} \equiv \frac{1}{2}(\text{Sale}_{rf,07} + \text{Sale}_{rf,09})$ is a simple average sales of firm f in region r in 2007 and 2009. This growth rate, which is a second-order approximation of the log difference growth rate around 0, follows previous papers that measure the employment growth at the establishment-level (e.g., Davis et al. 1996). This growth rate definition provides a symmetric measure around 0 and is bounded between -2 and 2. These features help limit the influence of outliers without arbitrarily winsorizing extreme observations.[16,17]

Given the prevalence of multi-product firms, we investigate the role that product creation and destruction of these firms play in shock spillovers. Following Broda and Weinstein (2010), we decompose the sales growth defined in equation (1.3.1) into two margins: the intensive margin associated with products that exist in both pre- and post-shock periods, and the extensive margin associated with product creation and destruction (i.e., net creation) :

$$\tilde{\Delta}\text{Sale}_{rf} = \tilde{\Delta}\text{Sale}_{rf}^{\text{continue}} + \tilde{\Delta}\text{Sale}_{rf}^{\text{replace}} \tag{1.3.2}$$

where $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}} \equiv \frac{\text{Sale}_{rf,09}^{\text{continue}} - \text{Sale}_{rf,07}^{\text{continue}}}{\overline{\text{Sale}}_{rf}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}} \equiv \frac{\text{Sale}_{rf,09}^{\text{enter}} - \text{Sale}_{rf,07}^{\text{exit}}}{\overline{\text{Sale}}_{rf}}$. $\text{Sale}_{rf,t}^{\text{continue}}$ is the region-firm-time-specific sales from products that continuously existed in region

[16] Another important benefit of using this growth rate is that it can accommodate both the entry and exit of firms at the local market level. Table A.12 in Appendix A.1 shows the result that accommodates these margins.

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

r throughout 2007-09, $\text{Sale}^{\text{exit}}_{rf,07}$ is the sales from products that existed in region r in 2007 but exited in 2009, and $\text{Sale}^{\text{enter}}_{rf,09}$ is the sales from products that did not exist in region r in 2007 but entered in 2009. Note that we use the following identity for the decomposition of the sales growth: $\text{Sale}_{rf,07} = \text{Sale}^{\text{continue}}_{rf,07} + \text{Sale}^{\text{exit}}_{rf,07}$ and $\text{Sale}_{rf,09} = \text{Sale}^{\text{continue}}_{rf,09} + \text{Sale}^{\text{enter}}_{rf,09}$. The products that entered or exited region r account for less than one-fourth of total sales in 2007 and 2009. Despite their relatively small fraction in total sales, these extensive margins in firm's local sales cause most of the spillover effect.

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

1.3.2 The Spillover Shock

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

Following Mian et al. (2013), we leverage the large differential drop in local house prices during the Great Recession to measure local consumer demand shock. Let $\text{HP}_{r,t}$ denote the house price index in region r at time t. Consistent with the measure of sales growth, we define the region-specific house price growth in 2007-09 as

$$\tilde{\Delta}\text{HP}_r \equiv \frac{\text{HP}_{r,09} - \text{HP}_{r,07}}{\overline{\text{HP}}_r} \tag{1.3.3}$$

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

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

$$\tilde{\Delta}\text{HP}_{rf} \text{ (other)} \equiv \sum_{r' \neq r} \omega_{r'f} \times \tilde{\Delta}\text{HP}_{r'} \tag{1.3.4}$$

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

1.3.3 Empirical Specification

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

$$\tilde{\Delta}\text{Sale}^{i}_{rf} = \beta^{i}_{0} + \beta^{i}_{1}\tilde{\Delta}\text{HP}_{r} + \beta^{i}_{2}\tilde{\Delta}\text{HP}_{rf} \text{ (other)} + \text{Controls}_{rf} + \varepsilon^{i}_{rf} \tag{1.3.5}$$

where $i = \{\text{(all), continue, replace}\}$. $\tilde{\Delta}\text{Sale}^{i}_{rf}$ indicates region-firm level sales growth measured by all products (i.e., $\tilde{\Delta}\text{Sale}_{rf}$) that arise from continuously existing products (the intensive margin) and from the net creation of products (the extensive margin), respectively. $\tilde{\Delta}\text{HP}_{r}$, which is our measure of direct local demand shock, is the region-level house price growth, while $\tilde{\Delta}\text{HP}_{rf}$ (other) is the average house price growth in the firm's other markets, measuring the spillover shock. Controls_{rf} is the vector of control variables that include SIC 4-digit sector fixed effects and various region-firm control variables.[18] Standard errors are double clustered at the state and sector level and regressions are weighted by initial region-firm level sales.[19]

[18] These include — (region controls) pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than high school diploma, percentage with only a high school diploma, unemployment rate, poverty rate, percentage urban, and employment share in a county for 2-digit industries — and — (region-firm controls) log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups.

[19] In Table A.10 in Appendix A.1, we report standard errors accounting for the shift-share correlation structure as in Adao et al. (2018b). The standard errors are more or less similar.

Our coefficient of interest is β_2^i, which measures the spillover effect on various margins of the firm's local sales. Specifically, β_2 is the elasticity of the firm's local sales growth with respect to the average local demand shock that originates in the firm's other markets, *conditional on direct local demand*. A priori, β_2 can have any sign. If negative local demand shocks in other regions reduce (increase) the firm's local sales, then the sign of β_2 should be positive (negative). The other coefficient, β_1^i, measures the effect of direct local house price growth on various margins of firm's local sales. As β_1 captures the conventional effect emphasized in Mian et al. (2013) at the region-firm level, we expect β_1 to be positive. Finally, it is worth emphasizing that the effect of any nation-wide shock, including the effect of a common aggregate decline in house prices in all regions, is absorbed by the constant term β_0^i. That is, our estimation of β_2^i exploits a *differential* drop in house prices across regions, not the common aggregate component.

1.3.4 Discussion of the Identification Assumption

The main identifying assumption for the consistent estimation of β_2^i is that any confounding factor that affects the firms' local sales growth is not correlated with house price growth in the firm's other markets. This assumption can be violated if, for example, a particular firm is very influential in a local market that it can influence house prices in that market. But such reverse causality is not a major concern since even the largest firm in a typical county has a sales share less than 5%.[20]

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

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

Table 1.2: Balance Checks

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

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

1.3.4.1 Sorting into Particular Markets by Firms

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

In Table 1.2, we provide a support that this is not a major concern by performing balance test. Specifically, we regress a number of firm-level initial characteristics on the within-firm average of the house price growth across counties (i.e., the firm-specific average shock) and the sector fixed effects.[21] As we can be seen from the table, we

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

do not find a systematic correlation between a firm's average shock and its initial characteristics. This implies that firms that were exposed on average to adverse local housing market conditions during the Great Recession are not systematically different from those exposed to relatively favorable local housing market conditions.[22]

1.3.4.2 Common or Clustered Regional Shocks

The Great Recession was a period of large aggregate shocks that affected the entire economy. Also, it is well known that different industries were differentially affected during the crisis.[23] All our regressions include sector fixed effects, which take care of aggregate and/or sectoral shocks. Moreover, our most conservative specification includes county-by-sector fixed effects (instead of directly controlling county-level observables), which take care of not only sectoral shocks but also potential county-sector-specific shocks. County-by-sector fixed effects allow us to effectively compare the local sales growth of firms *within the same county* among firms in the same industry.

Yet another evident identification threat is the possibility of geographically clustered shocks that simultaneously affect multiple regions in which firms are selling. For example, if a firm had been selling in geographically clustered markets, and if such markets are hit by clustered shocks correlated with house prices, this will lead to a fall in house prices and sales jointly. In this case, such clustered shocks could explain the positive relationship between a firm's local sales growth, $\tilde{\Delta}\text{Sale}_{rf}$, and the house price growth in its other markets, $\tilde{\Delta}\text{HP}_{rf}$ (other). To address these concerns, in Section 1.4, we show the robustness of our result by constructing the spillover shocks by excluding nearby counties and considering only geographically distant counties.

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

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

1.3.4.3 Other Channels

Finally, it is possible that our estimate of β_2^i is confounded by alternative channels or factors other than the spillover of local demand shocks. Such factors include the possibility that house prices could directly affect production facilities (i.e., supply-side or collateral channel), the endogeneity of house prices, common retailer through which households purchase products, and clientele effects. To address these concerns, we provide a number of Placebo tests and robustness analyses in Section 1.4.

1.4 Main Empirical Results

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

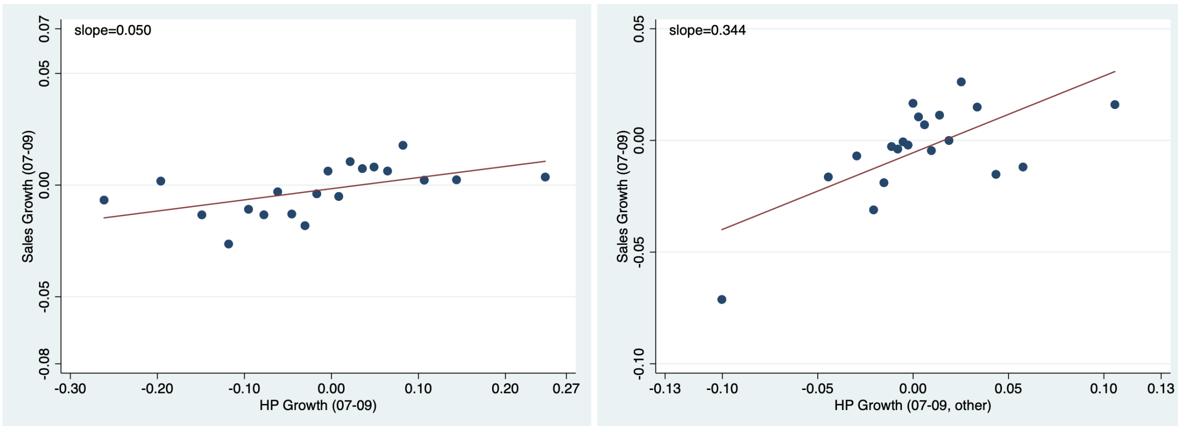
1.4.1 Regional Spillover

We start by presenting the bin scatter plots that visualize the regression in equation (1.3.5). The left panel in Figure 1.1 plots a firm's local sales growth against the direct local demand shock, while the right panel plots it against the spillover shock. As can be seen from the positive slopes in both the left and right panels of the figure, a firm's local sales growth is positively associated with both the direct and the spillover shock.

Table 1.3 presents the formal regression results of equation (1.3.5), in which we measure a firm's local sales growth by including both continuing and replaced products. Column (1) shows that a firm's local sales growth positively respond to both the direct local shock—$\tilde{\Delta}\mathrm{HP}_{(07-09)}(\%)$—and the indirect spillover shock—$\tilde{\Delta}\mathrm{HP}_{(07-09)}(\%)$ (other)—that originates in its other markets. Both coefficients are positive and statistically

Figure 1.1: Local Sales Growth against

(i) Direct Local Shock (Left) & (ii) Spillover Shock (Right) (All Residualized)



Note. These figures show bin scatter plots (20 bins based on ventiles) depicting the relationship between (residualized) county-firm level sales growth, $\tilde{\Delta}\text{Sale}_{(07-09)}$, against (i) (residualized) county-level house price growth, $\tilde{\Delta}\text{HP}_{(07-09)}$ (left panel), and (ii) (residualized) initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, $\tilde{\Delta}\text{HP}_{07-09}$ (other) (right panel). Residualized variables are constructed using regression corresponding to Column (1) of Table 1.3 using Frisch-Waugh theorem. The reported slop coefficients are based on simple linear regression using 20 bins.

significant. Importantly, the estimated elasticity of local sales with respect to the spillover shock, 0.35, turns out to be six times larger than that of the direct local shock. This is intuitive if one recalls that a typical firm sells in more than a hundred of counties. Thus, the spillover shock proxies the (leave-county-out) firm-specific demand shock that arises from the rest of a firm's other counties.

In Column (2), we show the estimation result of equation (1.3.5) in which we include sector-by-county fixed effects instead of directly controlling county-level observables. We obtain a highly significant positive coefficient of 0.40. This indicates that a 10%p decline in a firm's average local demand shock in the other markets reduces its local sales growth by 4%p.

Prior research shows that a decline in regional house prices during the Great Recession caused a drop in local consumer demand (e.g., Mian et al. (2013)). However,

Table 1.3: The Effect of the Direct and the Spillover Shocks on Firm's Local Sales Growth

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

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the county-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, exclude-plant) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales and the firm has no establishments. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, out-of-state) is the initial sales-weighted house price growth between 2007 and 2009 in other counties located in other states. Sectors are defined based on SIC 4-digit. Region controls include pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than high school diploma, percentage with only a high school diploma, unemployment rate, poverty rate, percentage urban, and employment share in a county for 2-digit industries. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

changes in regional house prices could have affected a firm's local sales by directly affecting production rather than through consumer demand. One example is the "collateral channel". Changes in regional house prices could affect a firm's collateral value, which, in turn, could affect production. Also, regional house prices could be correlated with regional productivity shocks, which again could directly affect production. Under these supply-side channels, intra-firm networks still matter, and not because they spill over local demand shocks, but because they spill over local "supply-side" shocks. In Column (3), we provide direct evidence consistent with the local consumer demand channel. Specifically, we construct the spillover shock by *excluding* counties in which the firm's establishments are located. Thus, regional house prices can only affect a firm's local demand and not the collateral value or productivity of its establishments.[24] The estimated coefficient is 0.38, which is highly statistically significant.

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

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

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

A.1, we construct the spillover shocks by excluding nearby counties within a radius of up to 150 miles. The results are robust to these alternative specifications.

In Column (5), we estimate equation (1.3.5) by defining the state as the unit of the local market. By defining the local market at the state-level, we aggregate regional demand shocks within each state (including any clustered regional shock that jointly affects counties within each state) and treat them as a state-level demand shock. We obtain a highly significant positive coefficient of 0.30. This result also indicates that our spillover effect is not particularly driven by firms who sell in multiple counties located within a single state.

Importantly, what matters for the spillover is the connection to other markets *through the intra-firm market networks* and not other markets in general. Table A.2 in Appendix A.1 presents Placebo tests that demonstrate the point. Instead of constructing the spillover shock using the true intra-firm networks, we construct *Placebo spillover shocks* using various Placebo networks. In Column (1) to Column (3) we construct Placebo spillover shocks using alternative weighting schemes (instead of a firm's initial sales share in those markets). As can be seen from the table, we cannot reproduce the spillover effect if we use alternative Placebo weighting schemes, such as equal weights, county level population weights, and county level median household income weights. In Column (4), we generate random intra-firm networks by randomizing each firm's intra-firm market networks.[25] Again, such random intra-firm networks do not generate the spillover effect. These results indicate that to successfully identify spillover effects we must (i) consider markets in which firms generated sales during the initial period *and* (ii) properly measure initial exposure across these markets through initial sales shares. Finally, Column (5) shows that spillover effects cannot be reproduced by identifying a firm's networks on the basis of the location of its establishments.[26]

[25]To be more specific, for each county-firm observation, we replace the firm's other connected counties (i.e., r''s with $\omega_{r'f} > 0$) with randomly selected counties. We then construct the placebo spillover shock based on such random network and estimate equation (1.3.5). We repeat this process 800 times and report the average coefficients and standard errors, respectively.

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

To summarize, Table 1.3 provides strong evidence that regional shocks spill over through intra-firm networks and affect local performance of firms in other regions. We further confirm our result by conducting a number of robustness checks in Section 1.4.3.

1.4.2 Decomposition

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

We first estimate equation (1.3.5) by replacing $\tilde{\Delta}\text{Sale}_{rf}$ with $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}}$, respectively. Columns (1)-(3) in Table 1.4 show the results. Notice that our definitions of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{continue}}$ make the estimated coefficients in Column (1) identical to the sum of coefficients in Columns (2) and (3).[27]

As can be seen in Column (2), net creation does not respond to the direct local shock. Instead, it strongly (and positively) responds to the spillover shock with an estimated coefficient of 0.32. In contrast, sales growth that arises from common products significantly and positively responds to the direct local shock, but it does not significantly respond to the spillover shock. Columns (4)-(6) repeat the analyses using equation (1.3.5). The results are similar. A 1%p decline in the spillover shock reduces the extensive margin by 0.42%p, and largely for this reason local sales respond to the spillover shock. In Table A.3 in Appendix A.1, we repeat the analysis at the state-firm level.

The decomposition results in this section point out that product replacements in local markets is the principal factor through which shock spillover occurs through intra-firm networks. In Section 1.5, we investigate why a firm's product replacements in a local market responds to the spillover shock that originates in its other markets and

[27] We present the result decomposing $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ into creation and destruction in Table A.15 in Appendix A.1.

Table 1.4: Decomposition of Sales Growth: The Extensive vs. Intensive Margins

	(1) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(2) $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	(3) $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$	0.059**	0.009	0.051**
	(0.028)	(0.014)	(0.024)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.345***	0.320***	0.025
	(0.110)	(0.093)	(0.067)
Sector FE	✓	✓	✓
Region Controls	✓	✓	✓
Region-Firm Controls	✓	✓	✓
R^2	0.201	0.284	0.223
Observations	840681	840681	840681

	(4) $\tilde{\Delta}\text{Sale}_{(07-09)}$	(5) $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	(6) $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.398***	0.419***	-0.021
	(0.105)	(0.102)	(0.045)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.392	0.408	0.427
Observations	840681	840681	840681

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ is the county-level house price growth between 2007 and 2009, and $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region controls include pre-recession percentage white, median household income, percentage owner-occupied, percentage with less than high school diploma, percentage with only a high school diploma, unemployment rate, poverty rate, percentage urban, and employment share in a county for 2-digit industries. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

why such response results in decrease of local sales.

1.4.3 Robustness

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

1.4.3.1 Retailer Effects

One potential concern is that our spillover results may have been driven by retailers through which firms sell products. For example, lower sales growth in Coca-Cola of New York county relative to that of Pepsi might reflect the differential performance of retailers selling Coca-Cola's products relative to those selling Pepsi's products. To address this, we show the robustness of our results in Table A.4 by comparing the local sales growth of firms *within* the same retailer. Specifically, we add the retailer margin and construct county-firm (i.e., producer)-retailer level sales growth and run the regression by including sector×county×retailer fixed effects.[28] Thus, any county-retailer specific trend in local sales within SIC 4-digit producer sector will be absorbed by

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

such fixed effects. Column (1) shows the result. our coefficient is 0.53, which is highly statistically significant.

However, it is still possible that, for example, the lower sales growth of Coca-Cola in a particular retailer in New York county relative to that of Pepsi could occur if that retailer faces larger Coca-Cola specific negative shocks from its stores in other regions. Thus, in Column (2), we include the "average producer-specific demand shock" a retailer faces through its stores in other regions (where the producer's products are sold).[29] It turns out that change in county-firm-retailer specific sales is mainly driven by firm-level spillover shock and not the retailer-firm specific spillover shock. In Columns (3) and (4) we show the corresponding decomposition results.

1.4.3.2 Endogeneity of House Prices and IV Regression

Notice that the spillover shock we construct has the Bartik-type property. Thus, the spillover shock can be viewed as exogenous at the firm-level even if local house price change is not purely exogenous at the local market level. However, we also check the robustness of our result by instrumenting the spillover shock with similarly constructed instrumental variables that leverage widely-use instruments for house prices: (i) housing supply elasticity (Saiz (2010)) and (ii) nonlocal mortgage lending shocks (García (2018)).[30]

Table A.5 and Table A.6 in Appendix A.1 present the results using these two instruments. All of the results are robust to these specifications.

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[29]Specifically, we run the following regression:

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

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

[30]Specifically, we replace $\tilde{\Delta}\text{HP}_{r'}$ in (1.3.4) with the county-level housing supply elasticity or nonlocal mortgage lending shocks.

1.4.3.3 Clientele Effects and Common Largest Market

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

In Table A.8 in Appendix A.1, we also show that our results are not driven by comparing the local sales of two firms that have their major markets concentrated in different regions in the US (e.g., east coast vs. west coast).[31] Although such variation is one of the sources of differential demand shocks across firms (which we utilize), we show the robustness of our results by comparing firms that share a common *largest market* (defined at the census division level). The results are robust under the specification with sector-by-largest market fixed effects.

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

We also repeat our analyses using ACNielsen Homescan Panel data and show that using the 2004 sales share to construct the spillover shock and additionally, controlling lagged-dependent variables (i.e., pre-trends in local sales) does not change our results. The ACNielsen Homescan Panel dataset is constructed by Nielsen from a demographically representatitve sample of approximately 33,000 households in the United States.[32] We

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

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

collapse the data into state-firm level and perform the analyses.[33]

Columns (1)-(3) of Table A.9 repeats Columns (4)-(6) in Table 1.4, where the spillover shocks are constructed using firms' 2004 sales share across local markets.[34] We get similar results. In Columns (4)-(6), we additionally control lagged-dependent variables. The results barely changes.

1.4.3.5 Additional Robustness Analyses

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

In Table A.11, we allow the product group dimension, which is a broad product category classification provided by ACNielsen.[35] By performing analyses at the county-firm-product group level, we can additionally include product group-by-county fixed effects. As can be seen in Table A.11, the results are robust to this alternative specification.

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

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

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

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

1.4.4 The Heterogeneous Treatment Effect

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

We measure financial constraint using the initial paydex score provided by the NETS data.[36] For the robustness, we also use the financial constraint measure proposed by Rajan and Zingales (1998) (Table A.14 in Appendix A.1).

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

Table A.13 in Appendix A.1 summarizes the result. As can be seen in the first row, more financially constrained firms (i.e., higher ln(100-paydex)) experience stronger spillover. Notably, such interaction mainly works *through the product replacement channel.*

The second row shows that if a firm's local market has a smaller within-firm market share, the spillover effect becomes stronger. Specifically, we consider a dummy variable that has value one if the firm's local sales share is above the median of the distribution across all observations. We get significant negative coefficients for both the overall

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

sales growth (Column (1)) and the extensive margin of sales growth from product replacements (Column (2)), which indicates that if the local sales share is sufficiently high (low), we will obtain a weaker (stronger) spillover effect.

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

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

We show that the within-firm spillover effect across regions occurs because firms respond to negative demand shocks by replacing products uniformly across many markets, and in doing so, they replace high-valued products with low-valued products.[37] Thus, a region that is not directly hit by the shock also experiences a replacement of products from high- to low-valued products, resulting in a decline of local sales.

1.5.1 Uniform Replacement of Products across Multiple Markets

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

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

[37]We formalize why negative demand shocks result in replacement from high- to low-value products through the lens of the model in Section 1.6. We argue that this reflects a downgrading of product quality that results from scale effect and nonhomothetic preferences. If production at the lower quality level requires lower fixed costs, firms find it optimal to downgrade product quality if they face lower demand shocks. Alternatively, if preferences are nonhomothetic, negative demand shock induces households to switch from high-quality goods to low-quality goods, in which case firms find it profitable to downgrade product quality.

Table 1.5: Product Creation and Destruction Patterns

1. Local Market at the County level

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

2. Local Market at the State level

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

Note. Panel (A) calculates the share of value lost by the destruction of products that is attributed to the products that exited more than 50% (90%) of their initially sold markets in 2007. Panel (B) calculates the share of value generated by the creation of products that is attributed to the products that entered more than 50% (90%) of the firm's overall markets in 2009.

In Table 1.5, we investigate whether product creation and destruction involve the entry and exit of products in a majority of each firm's markets. Specifically, Panel (A) of Table 1.5 calculates the share of value lost by the destruction of products that is attributed to the products that exited more than 50% (90%) of their initially sold markets. As can be seen in Panel (A) of Table 1.5-1, about 90% of the value lost by product destruction arises from products that exit more than half of their initially sold counties. Even if we restrict products to those that exited more than 90% of initially sold counties, these products account for 65% of product destruction. As indicated in Panel (B). the product creation patterns are similar. About 80% of the value generated by product creation can be attributed to products that entered more than half of the firm's overall markets.

Table 1.6: Extensive Margin Decomposition (County-level)

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

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

Table 1.5-2 repeats the analysis by defining the local market at the state level. Again, in the case of both product creation and destruction, about 90% of value created (destructed) can be attributed to products entering (exiting) uniformly across more than half of the firm's markets.

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

To investigate whether the extensive margin response to the spillover shock comes from products replaced in multiple markets, we decompose $\tilde{\Delta}\text{Sale}^{\text{replace}}_{rf}$ into two components: (i) $\tilde{\Delta}\text{Sale}^{\text{replace, multi}}_{rf}$, which captures local sales growth coming from products replaced in multiple markets; and (ii) $\tilde{\Delta}\text{Sale}^{\text{replace, local}}_{rf}$, which captures local sales growth that comes from products replaced in the county only.[38]

Columns (2) and (3) in Table 1.6 show the results from separate regressions that replace $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace}}$ with $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, multi}}$ and $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$ as a dependent variable. Essentially all of the spillover effect comes from the response of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, multi}}$, while the response of $\tilde{\Delta}\text{Sale}_{rf}^{\text{replace, local}}$ is negligible and statistically insignificant. We repeat the analysis by defining the local market at the state-level in Table A.18 in Appendix A.1, in which we get similar results.

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

1.5.2 Replacement from High- to Low-Valued Products

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

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

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

$$\text{Net Entry}_{rf} \equiv \text{Entry}_{rf} - \text{Exit}_{rf} \tag{1.5.1}$$

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

Table 1.7: Response of the Net Number of Varieties

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

Note. Net Entry$_{(07-09)}$ is constructed as in equation (1.5.1). $\tilde{\Delta}\text{HP}_{07-09}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

Table 1.7 summarizes the result. Column (1) shows that the net entry remains unaffected by the spillover shock, as indicated by near-zero coefficient. In Column (2), we restrict the sample to local markets that experienced both positive entry and exit of varieties (i.e., $\text{Entry}_{rf} > 0$ and $\text{Exit}_{rf} > 0$). Again, the response of net entry is not distinguishable from zero, indicating that the number of products entering is more or less similar to the number of products exiting. This shows that our spillover effects are

Table 1.8: Replacement from High- to Low-value products at the Extensive Margin

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

Note. The dependent variables measure the value difference between the newly entering products and exiting products calculated by (1.5.2). Column (1)-(3) defines local market at the county level, while Column (4) defines local market at the state level. $\tilde{\Delta}\text{HP}_{07-09}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other regions where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial region-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by region-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

not driven by simple reductions in the number of varieties supplied in the local market.

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

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

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

$$\tilde{\Delta} v_{rf} \equiv \frac{v^{\text{enter}}_{rf,09} - v^{\text{exit}}_{rf,07}}{\overline{v}_{rf}} \tag{1.5.2}$$

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

Table 1.8 shows the result. Column (1) shows that in response to the negative spillover shock, a firm destroys products that generate higher sales-per-product and introduces those that generate lower sales-per-product. Colunm (2) shows that the average unit price of newly entering products is lower than the price of exiting products. In Column (3) and Column (4), we use unit prices adjusted for product group average and organic product turnover rates, which are a proxy for product quality.[39]

It is worth emphasizing that the replacement from high- to low-valued products in a local market occurs in response to the shocks that originate in other markets (i.e., the spillover shock), *conditional on the direct local demand.* That is, such replacement occurs in the local market that did not face direct local shock. At the same time a firm's local sales decrease in the local market due to such product replacement (in the absence of the direct local shock). This means that even though the newly entered products have lower price on average, they generate relatively lower sales than the exited products in the local market that did not face direct local shock. In Section 1.6, we show that this pattern can be justified by assuming that product replacements in response to the negative shocks are associated with downgrading of product quality.

1.6 The Model

This section presents a multi-region model with endogenous quality adjustments by firms that reflect product replacements in our empirical analyses. Building on Faber

[39] In Appendix A.3 we discuss in detail how we construct these value measures. In Table A.16 and Table A.17 in Appendix A.1, we use an alternative definition of price indexes, which includes applying different weighting schemes and adjusting for package sizes, to check the robustness of the result. In Table OA.8 in Online Appendix B, we also confirm that the results are robust at a more disaggregated level by conducting the analysis at the county-firm-product group level with product group fixed effects.

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

1.6.1 Demand

We consider a static economy with R markets indexed by $r \in \mathcal{R} \equiv \{1, 2, ..., R\}$.[40] Each market is populated by a continuum of mass L_r of individuals, each of whom is endowed with exogenous income I_r and dividends from production sector D_r.[41] We denote the total income of an individual in market r by $y_r \equiv I_r + D_r$. The economy consists of two broad sectors : consumer packaged goods (CPG) and an outside sector.[42] Like Handbury (2013) and Faber and Fally (2017), we consider a two-tier utility in which the upper-tier depends on utility from CPG shopping U and the consumption of an outside good z that will be our numeriare. We assume the constant elasticity of substitution (CES) upper-tier utility given by

$$V_r = \left[(1-\alpha)(z_r)^{\frac{\eta-1}{\eta}} + \alpha(U_r)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{1.6.1}$$

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

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

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

where $\eta > 1$.[43] By defining the share of total income y_r allocated to CPG expenditures as Θ_r, one can easily show that

$$\Theta_r = \frac{\alpha^\eta}{\alpha^\eta + (1-\alpha)^\eta (P_r)^{\eta-1}} \equiv \Theta(P_r) \tag{1.6.2}$$

where P_r is the CPG consumption bundle price index, which is defined below.[44] Note that for a given y_r, increase of P_r decreases CPG expenditure share. We define total CPG expenditures as

$$s_r \equiv \Theta_r y_r \tag{1.6.3}$$

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

$$U_r = \left[\int_{f \in G_r} (q_{rf} \zeta_{rf})^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}} \tag{1.6.4}$$

where f deonotes a firm (i.e., CPG producer), G_r denotes the set of firms selling in market r, q_{rf} is the quantity of product bundle produced by firm f that is consumed by an individual in market r, ζ_{rf} refers to the perceived quality (or appeal, taste) of firm f's product bundle in market r, and σ refers to the elasticity of substitution between product bundles.[45] Following Faber and Fally (2017), we assume that the perceived quality $\log \zeta_{rf}$ depends on an intrinsic quality choice $\log \phi_f$ by firm f and a multiplicative term γ_r :

$$\log \zeta_{rf} \equiv \gamma_r \log \phi_f \tag{1.6.5}$$

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

$$\log \gamma_r \equiv \delta_1 + \delta_2 \log I_r \tag{1.6.6}$$

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

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

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

where $\delta_2 \geq 0$.

Important assumption we make here is that firm f's choice of intrinsic product quality, ϕ_f, does not vary across markets and thus do not have market subscript r. This assumption reflects the synchronized product replacement pattern discussed in Section 1.5.1.[46] We assume that change in the quality of a product bundle involves the replacement of products in the bundle. That is, the quality of product bundle changes due to the exiting of original products and the entry of new products.[47]

Individuals solve for their optimal CPG consumption bundle by maximizing (1.6.4) subject to budget constraints given by

$$\int_{f \in G_r} p_{rf} q_{rf} df \leq \Theta_r y_r \equiv s_r \tag{1.6.7}$$

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

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

$$s_{rf} \equiv p_{rf} q_{rf} \tag{1.6.8}$$

the optimality implies

$$\begin{aligned} s_{rf} &= \frac{\left(\frac{\zeta_{rf}}{p_{rf}}\right)^{\sigma-1}}{\int_{f \in G_r} \left(\frac{\zeta_{rf}}{p_{rf}}\right)^{\sigma-1} df} s_r \\ &= (\zeta_{rf})^{\sigma-1} \left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} s_r \end{aligned} \tag{1.6.9}$$

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

$$P_r \equiv \left[\int_{f \in G_r} (p_{rf})^{1-\sigma} (\zeta_{rf})^{\sigma-1} df\right]^{\frac{1}{1-\sigma}} \tag{1.6.10}$$

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

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

with $s_r = P_r U_r$.

One can easily see how the nonhomothetic preferences provide an incentive for firms to downgrade product quality when they face negative demand shocks. From (1.6.9),

$$\log\left(\frac{s_{rf}}{s_{rf'}}\right) = (\sigma - 1)\left[\gamma_r \log\left(\frac{\phi_f}{\phi_{f'}}\right) - \log\left(\frac{p_{rf}}{p_{rf'}}\right)\right] \tag{1.6.11}$$

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

1.6.2 Outside Good Production and Labor Market

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

1.6.3 CPG Production: Environments

In the economy, there is a continuum measure of N firms that produce differentiated CPG bundles. Each firm simultaneously chooses optimal quality and prices subject to monopolistic competition. We abstract a firm's entry and exit decision to be consistent with our empirical analysis, which only considers existing firms in both pre- and post-shock periods.[48] When we bring the model to the data, we map the set of active firms in the model directly to those in the data.

1.6.3.1 Market Network

We start by defining a firm's *market network*, which we define as the set of markets in which a firm sells its product. Consistent with our empirical analysis, we assume that each firm's market network is given and fixed—an assumption that reflects the historical

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

persistence of firm markets (Bronnenberg et al. (2009, 2012)). We bring each firm's market network directly from the data. We index the market network by k, and when we have to indicate a particular firm f's market network, we use notation k_f. The total measure of firms with market network k is denoted by N^k.

1.6.3.2 Cost Structures

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

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

$$mc(\phi_f; a_f) \equiv \frac{c(\phi_f)}{a_f} \tag{1.6.12}$$

where

$$c(\phi) = \phi^{\xi} \tag{1.6.13}$$

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

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

$$f(\phi) = b\beta\phi^{\frac{1}{\beta}} \tag{1.6.14}$$

with $\beta > 0$.

1.6.4 CPG Production: Price and Quality Choice

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

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

By combining (1.6.8), (1.6.9) and (1.6.5), we have firm f's sales and quantity sold in market r given by

$$\begin{aligned} S_{rf} &\equiv s_{rf} L_r \\ &= \phi_f^{(\sigma-1)\gamma_r} \left(\frac{p_{rf}}{P_r}\right)^{1-\sigma} S_r \end{aligned} \tag{1.6.15}$$

and

$$\begin{aligned} Q_{rf} &\equiv q_{rf} L_r \\ &= \phi_f^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} P_r^{\sigma-1} S_r \end{aligned} \tag{1.6.16}$$

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

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

$$\max_{\phi_f, \{p_{rf}\}_{r \in k_f}} \pi_f = \sum_{r \in k_f} (p_{rf} - mc(\phi_f; a_f))\, Q_{rf} - f(\phi_f) - f_0 \tag{1.6.17}$$

subject to the demand condition in (1.6.16).

As shown in Appendix A.4, the optimal price is

$$p_{rf} = \left(\frac{\phi_f^{\xi}}{a_f}\right) \left(\frac{\sigma}{\sigma-1}\right) (\equiv mc(\phi_f; a_f) \times \mu) \tag{1.6.18}$$

and the optimal quality is

$$\phi_f = \left[\sum_{r \in k_f} S_{rf} \left(\frac{1}{b} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta} \tag{1.6.19}$$

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

By combining (1.6.17), (1.6.14), and (1.6.19), we can derive the optimal profit as

$$\pi_f = \sum_{r \in k_f} \frac{1}{\sigma} \left[1 - \beta(\sigma-1)(\gamma_r - 1)\right] S_{rf} - f_0 \tag{1.6.20}$$

The expression of firm f's local sales, S_{rf}, is derived using (1.6.15), (1.6.18) and (1.6.19) as

$$S_{rf} = \left[\sum_{r\in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r - \xi}{\mu}\right)\right]^{\beta(\sigma-1)(\gamma_r-\xi)} \left[\frac{\mu}{a_f}\right]^{1-\sigma} P_r^{\sigma-1} S_r \tag{1.6.21}$$

The optimal price of firm f's local price is

$$p_{rf} = \left[\sum_{r\in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r - \xi}{\mu}\right)\right]^{\beta\xi} \left[\frac{\mu}{a_f}\right] \tag{1.6.22}$$

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

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

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

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

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

1.6.5 Local Price Index

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

$$P_r = \left[\int_{f\in G_r} \left[\phi_f^{-(\gamma_r-\xi)}\left(\frac{\mu}{a_f}\right)\right]^{1-\sigma} df\right]^{\frac{1}{1-\sigma}} \tag{1.6.23}$$

1.6.6 Profits and Dividends

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

$$\overline{\Pi} \equiv \int_f \pi_f df \tag{1.6.24}$$

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

$$D_r \equiv \frac{I_r}{\sum_{r\in\mathcal{R}} I_r L_r}\overline{\Pi} \tag{1.6.25}$$

which implies

$$y_r = I_r + D_r = I_r\left(1 + \frac{\overline{\Pi}}{\sum_{r\in\mathcal{R}} I_r L_r}\right) \tag{1.6.26}$$

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

The model delivers a structural equation that shows within-firm market interdependency. This equation allows us to structurally interpret our reduced-form empirical analyses. The magnitude of the spillover is determined by four structural parameters that govern the elasticity of market share and the elasticity of fixed costs with respect to the change in product quality. The relationship is derived by expressing the equation (1.6.21) in terms of growth rates. We present the result here and provide the derivation in Appendix A.4.3.

By denoting the initial value of a variable x as x_0 and defining growth rate by $\hat{x} \equiv \log x/x_0$, the equation (1.6.21) implies

$$\hat{S}_{rf} = \Upsilon_{r,0}\sum_{r\in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] + (\sigma-1)\hat{a}_f + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r \tag{1.6.27}$$

where $\omega_{rf,0} \equiv \frac{S_{rf,0}(\gamma_{r,0}-\xi)}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$,[49] $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r'\in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$, $X_{f,0} \equiv \sum_{r\in k_f} S_{rf,0}\left(\frac{1}{b}\frac{\gamma_{r,0}-\xi}{\mu}\right)$, $A_r \equiv (P_r)^{\sigma-1}S_r$, and $\Upsilon_{r,0}$ is defined by

$$\Upsilon_{r,0} = \underbrace{\beta}_{\substack{\text{Inverse-elasticity of}\\ \text{fixed cost w.r.t } \phi}} \times \underbrace{(\sigma-1)(\gamma_{r,0}-\xi)}_{\substack{\text{Elasticity of}\\ \text{market share w.r.t } \phi}} \tag{1.6.28}$$

[49] Note that if $\gamma_{r,0} = \gamma_0$ for all $r \in \mathcal{R}$, $\omega_{rf,0} = \frac{S_{rf,0}}{\sum_{r'\in k_f} S_{r'f,0}}$ becomes the initial sales weight.

Equation (1.6.27) shows that even if the shock does not directly hit market r, the shocks that hit other markets $r' \neq r$ could generate spillovers to market r through the firm's internal market network. The key mechanism is uniform quality adjustments across multiple markets. Note that a firm's local sales growth is related to both its average sales growth in all its market, $\sum_{r \in k_f} \omega_{rf,0} \hat{S}_{rf}$, and to the term $\sum_{r \in k_f} \theta_{rf,0} \hat{\gamma}_r$ with the same coefficient $\Upsilon_{r,0}$. These two terms capture different channels in the model that induce quality adjustments when firms face demand shocks. The first term $\sum_{r \in k_f} \omega_{rf,0} \hat{S}_{rf}$ shows the role played by the scale effect. Lower sales that are induced by negative demand shocks cause firms to lower product quality so that they could avoid high fixed costs associated with production at the high quality level. The second term $\sum_{r \in k_f} \theta_{rf,0} \hat{\gamma}_r$ captures the role of the nonhomothetic preferences. Negative demand shocks make consumers switch their consumption toward lower quality products, which induce firms to downgrade product quality to appeal to those consumers.

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

A higher $(\sigma - 1)(\gamma_{r,0} - \xi)$ captures a higher elasticity of market shares with respect to intrinsic quality change.[50] As clear from (1.6.9), $(\sigma - 1)$ captures how the market shares respond to change in a households' perceived quality $\zeta_{rf,0}$ conditional on prices. In turn, $(\gamma_{r,0} - \xi)$ reflects the trade off that arises from changing intrinsic product quality: (i) it increases households' perceived quality, which increases the market share; and (ii) it increases price, which decreases the market share. Specifically, $\gamma_{r,0}$ captures the elasticity of perceived quality $\zeta_{rf} \equiv (\phi_f)^{\gamma_{r,0}}$ with respect to a change in intrinsic quality, while ξ reflects the elasticity of the marginal cost $mc(\phi_f; a_f) \equiv \frac{\phi_f^{\xi}}{a_f}$ which passes through to the price. In sum, a higher $(\sigma - 1)(\gamma_{r,0} - \xi)$ implies a higher sensitivity of the revenue-side of quality change, which causes firms to lower their intrinsic quality

[50]This can be seen from (1.6.21), in which market share in r is $\frac{S_{rf}}{S_r} = \phi_f^{(\sigma-1)(\gamma_r - \xi)} \left[\frac{\mu}{a_f}\right]^{1-\sigma} (P_r)^{\sigma-1}$. Thus the elasticity of market share with respect to quality change is $(\sigma - 1)(\gamma_r - \xi)$.

more sensitively to the same magnitude of negative demand shock.

The estimation of $\Upsilon_{r,0}$ requires recovering $\sum_{r\in k_f}\theta_{rf,0}\hat{\gamma}_r$ and properly instrumenting $\sum_{r\in k_f}\left[\omega_{rf,0}\hat{S}_{rf}+\theta_{rf,0}\hat{\gamma}_r\right]$. We revisit this in Section 1.6.9.1, which provides details of our structural estimation procedure.

1.6.8 Partial Equilibrium Responses to the Exogenous Demand Shocks

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

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

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

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

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

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

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

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

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

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

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

Suppose a negative income shock hits market $r' \in k_f$. Theorem 2 implies that this will induce a firm that is selling in market r' to downgrade quality and experience lower sales in market r'. In turn, Theorem 3 implies that such quality downgrading will result in lower sales in market $r(\neq r') \in k_f$, which is not directly hit by the income shock. This is consistent with our empirical findings in Section 1.5.2 regarding regional spillovers that transpire through downgrading of products (i.e., replacement from high- to low-valued products). For example, a firm's local sales and local price in market $r(\neq r')$ will both decrease because of the lower quality, which is the result of the shock that hit market r'.

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

In Appendix A.5, we present the counterfactual economy in which all firms choose market-specific quality. Unlike the uniform quality choice, the market-specific quality choice generates independence across markets. The independence across markets under market-specific quality choice is summarized by Proposition 7 in Appendix A.5.

1.6.9 Counterfactual Analysis

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

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

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

1.6.9.1 Calibration

In this exercise, we define the local market at the state-level. This allows us to exactly match firm-level spatial networks across states using the data while substantially reducing computational burden. We include both single-market firms and multi-market firms in our analysis, which yields a total of 5186 firms that at most sell in 49 states.[51] Each firm's market network k_f (i.e., intra-firm network) is directly obtained from the data.[52]

[51] The states included in our exercise can be found in Table A.23 in Appendix A.1.

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

Because we are not considering firm-level entry and exit, productivity heterogeneity plays a minor role in our model. Thus, in the numerical exercise, we do not introduce productivity heterogeneity and instead assume $a_f = 1$ for all firms.[53] For the initial I_r in the model, we use the 2007 state level average income obtained from the American Community Survey data. For the L_r, we use the 2007 state level population (in thousands). Since we introduced L_r to reflect the relative size of population across states, we abstract cross-state migration or population growth by assuming fixed L_r across time.

For the exogenous local demand shock, $\hat{I}_r$, we use state level house price growth multiplied by 0.23 as a proxy for exogenous demand shock. 0.23 is the consumption elasticity with respect to the house price shock reported by Berger et al. (2018).[54,55]

For the elasticity of substitution parameter η in the upper-tier utility, we impose the limiting case $\eta \to 1$ which implies the Cobb-Douglas upper-tier utility function. Using a larger η at the end only strengthens the implication that we find (i.e., it generates stronger mitigation of regional consumption and welfare inequality). We set the CPG

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

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

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

expenditure share parameter α to 0.20, which is close to the United States counterpart.[56]

Finally, we bring the elasticity of substitution σ from Faber and Fally (2017), which is $\sigma = 2.2$. One caveat is that the estimate in Faber and Fally (2017) is the elasticity of substitution across firms *within a product module*.[57] Thus, we interpret the elasticity of substitution across firms in our model as proxying the average of the within-module elasticity of substitution across firms.[58]

1.6.9.2 Estimation

The remaining key parameters we need to estimate are β, ξ, δ_1 and δ_2 in $\gamma(\cdot)$. The first equation we use is the expression of $\Upsilon_{r,0}$ in (1.6.28), which can be recovered by estimating the structural equation (1.6.27).

The second equation is derived from (1.6.22). Following steps similar to those used in the derivation of (1.6.27), we obtain

$$\hat{p}_{rf} = \beta\xi \sum_{r\in k_f} \left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] - \hat{a}_f \tag{1.6.29}$$

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

The challenge of estimating $\Upsilon_{r,0}$ and $\beta\xi$ in (1.6.27) and (1.6.29), respectively, lies in the fact that $\gamma_{r,0}$ and $\hat{\gamma}_r$ are not observed. Thus, we must first estimate $\gamma_{r,0}$ and $\hat{\gamma}_r$ and then subsequently estimate $\Upsilon_{r,0}$ and $\beta\xi$.

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

[56] This number is calculated based on the BLS report—*Consumer Expenditures in 2007*. We categorize the following major categories as CPG expenditures: Food, Alcoholic beverages, Apparel and services, Personal care products and services, Tobacco products and smoking supplies.

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

[58] In Online Appendix, we also provide the result using $\sigma = 3.9$ reported by Hottman et al. (2016). However, their method relies more heavily on their own supply-side structure, which differs from our model, and thus we prefer the value $\sigma = 2.2$.

We start with the empirical counterpart of equation (1.6.9) aggregated at the state-firm-year level $S_{rft} = (\zeta_{rft})^{\sigma-1} \left(\frac{p_{rft}}{P_{rt}}\right)^{1-\sigma} S_{rt}$, where r indicates state, f indicates firm, and t indicates year.[59] By taking the log of both sides of the above equation and using the assumption $\log \zeta_{rft} = \gamma_{rt} \log \phi_{ft}$, we get

$$\log S_{rft} = (1-\sigma)\log p_{rft} + (\sigma-1)\gamma_{rt}\log\phi_{ft} + (1-\sigma)\log P_{rt} + \log S_{rt} \qquad (1.6.30)$$

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

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

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

$$\log \Xi_{rft} = \log \gamma_{rt} + \log\left(\Delta' \log \phi_{ft}\right) \qquad (1.6.31)$$

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

With the measured $\log \gamma_{rt}$ in hand, we obtain the "predicted" $\log \gamma_{rt}$, which we denote $\log \gamma_{rt}^{predict}$, by first regressing $\log \gamma_{rt}$ on $\log I_{rt}$ to estimate δ_1 and δ_2 in the equation (1.6.6) and then calculating $\log \gamma_{rt}^{predict} = \hat{\delta}_1 + \hat{\delta}_2 \log I_r$. This allows us to filter out noise contained in γ_{rt} and establish a monotone relationship between $\log I_r$ and $\log \gamma_r$, as in the model.[60]

Table A.19 in Appendix A.1 summarizes the result: we use either the log of state level average income or the log of state level house price as a measure of $\log I_{rt}$.

[59] Recall that (1.6.9) is expressed in per individual units. Thus, we define state-firm level sales as $S_{rf} = s_{rf} L_r$ and state level sales as $S_r = E_r L_r$.

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

Broadly, we find a strong positive association between $\log \gamma_{rt}$ and $\log I_{rt}$ across different specifications, although directly measuring $\log I_{rt}$ using state level average income yields a much clearer association. This may indicate that income (rather than house price per se) is the primary factor that determines the degree of nonhomotheticity.

We use the simplest specification in Column (1) as our benchmark, which is a pooled regression across state and year with year fixed effects. The predicted $\log \gamma_{rt}^{predict}$ obtained from specification Column (1) serves as our measure of $\log \gamma_{rt}$.[61] This also implies $\delta_2 = 0.166$ in (1.6.6).

(2) Estimation of β and ξ

With the $\gamma_{r,0}$ and $\hat{\gamma}_r$ in hand, we can estimate Υ_0 and $\beta\xi$ by estimating (1.6.27) and (1.6.29), respectively, where $\Upsilon_0 \equiv \beta(\sigma-1)(\gamma_0-\xi)$ can be interpreted as the average estimate of $\Upsilon_{r,0}$ across states obtained by running a state-firm level regression. Below we discuss in detail our IV strategy to obtain a consistent estimate of Υ_0 and $\beta\xi$, but first explain how we recover β and ξ using the consistent estimates of Υ_0 and $\beta\xi$.

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

$$\xi = \frac{\sigma-1}{\kappa+\sigma-1}\gamma_0 \tag{1.6.32}$$

obtained by rearranging $\left(\frac{\Upsilon_0}{\beta\xi} \equiv\right) \kappa = \frac{\beta(\sigma-1)(\gamma_0-\xi)}{\beta\xi}$. Since we have values for κ, σ and γ_0 (which is the average $\gamma_{r,0}$ across states), we can recover ξ. Then, β is recovered using $\beta = \frac{\beta\xi}{\xi}$.[62]

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

[62] Note that the calculation of the independent variable $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ requires knowledge of ξ because of $\theta_{rf,0} \equiv \frac{S_{rf,0}\gamma_{r,0}}{\sum_{r' \in k_f} S_{r'f,0}(\gamma_{r',0}-\xi)}$. Thus, in practice, we start with a guess value of ξ, measure $\sum_{r' \in k_f}\left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ and run the regression, and then check if (1.6.32) returns the same value of ξ.

We now discuss how we estimate Υ_0 and $\beta\xi$. A consistent estimate of Υ_0 can be obtained by running a fixed effect regression that is similar to the one used in the reduced-form analysis (1.3.5). The difference is that instead of directly regressing a firm's local sales growth on the spillover shock, we regress a firm's local sales growth on $\sum_{r' \in k_f} \left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$ instrumented by the spillover shock.

Specifically, the state fixed effects that take care of $\hat{A}_r$ (and the common component in $(\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r$), while adding various state-firm level controls and industry fixed effects allows us to compare plausibly similar companies, at least partially taking care of $(\sigma-1)\hat{a}_f + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r$. Most importantly, instrumenting $\sum_{r \in k_f} \left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ using the spillover shock, which measures the leave-out average demand shocks that arise in other markets, allows us to further avoid potential endogeneity associated with unobserved error terms.[63]

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

We can estimate $\beta\xi$ using a similar strategy. We regress a firm's local price index on $\sum_{r \in k_f} \left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right]$ instrumented by the spillover shock. Column (3) of Table A.20 reports an OLS estimate of $\beta\xi$, and Column (4) reports the IV estimate. Our estimate is $\beta\xi = 0.317$.[64]

[63]Our various robustness analyses in Section 1.4.3 make us confident that the spillover shock is not systematically correlated with direct local market factors as well as supply-side factors such as productivity (i.e., $\hat{a}_f$).

[64]In Table A.22 in Appendix A.1, we show the estimation result under the assumption that $\gamma_{rt} = \gamma$ for all r and t. This implies homogeneous utility function across regions with homothetic preferences. Under this assumption, (1.6.27) and (1.6.29) become $\hat{S}_{rf} = \Upsilon\left(\sum_{r \in k_f} \omega_{rf,0}\hat{S}_{rf}\right) + (\sigma-1)\hat{a}_f + \hat{A}_r$ and $\hat{p}_{rf} = \beta\xi\left(\sum_{r \in k_f} \omega_{rf,0}\hat{S}_{rf}\right) - \hat{a}_f$, respectively, where $\Upsilon \equiv \beta(\sigma-1)(\gamma-\xi)$ and $\omega_{rf,0} \equiv \frac{S_{rf,0}}{\sum_{r' \in S_{r'f,0}}}$ is the initial sales weight. The point estimates of Υ and $\beta\xi$ (as well as the precision) are very similar to those in Table A.20 reflecting small variations in $\left(\sum_{r \in k_f} \theta_{rf,0}\hat{\gamma}_r\right)$ relative to $\left(\sum_{r \in k_f} \omega_{rf,0}\hat{S}_{rf}\right)$ (i.e., the ratio of standard deviations of these variables across firms is .5:100, which partially reflects the fact that $\hat{\gamma}_r$ does not vary across firms while $\hat{S}_{rf}$ varies across firms).

Table 1.9: Parameter Values

Parameter	Value	Description	Source
Υ_0	0.62	Elasticity of Local Sales wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$ (avg)	Own Estimation
$\beta \times \xi$	0.32	Elasticity of Local Price wrt $(\tilde{\Delta}Sale + \tilde{\Delta}\gamma)$ (avg)	Own Estimation
σ	2.20	EoS across Firm's Product Bundle	Faber & Fally (2017)
ξ	0.39	Elasticity of Marginal Cost wrt Quality	Derived from Own Estimation
β	0.81	Elasticity of Fixed Cost wrt Quality	Derived from Own Estimation
γ_0	1.03	Elasticity of Perceived Quality wrt Quality	Own Estimation
δ_2	0.17	Elasticity of γ wrt Income	Own Estimation
b (benchmark)	1	Fixed Cost Parameter	Normalize
b (counterfactual)	0.04	Fixed Cost Parameter	Matched s.t. Avg. Quality Equal Benchmark
η	1	EoS across CPG and Outside Goods	Cobb-Douglas
α	0.20	CPG Share Parameter	Matched so that CPG share equals 0.20 under η

We summarize the resulting parameter values in Table 1.9. In Table A.21 in Appendix A.1, we show that the estimated model can successfully replicate the elasticity of firm's local sales growth with respect to both the direct local shock and the spillover shock. We show this by estimating equation 1.3.5 at the state-firm level using the model generated data (i.e., generated by feeding in the observed house price growth as the state-level exogenous shock in the model).

1.6.9.3 Implication: Regional Redistribution

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

This implies that the nonhomotheticity plays a limited role under our estimation.

We start by investigating the dispersion of the quality-adjusted regional consumption growth, which measures regional welfare growth. We use two measures, (i) quality-adjusted real CPG consumption per capita U_r (i.e., "CPG welfare"); and (ii) real (composite) consumption per capita, aggregating CPG goods and the outside good V_r (i.e., "overall welfare"). The results are summarized in Table 1.10. For the purpose of brevity, we only present four states *and* the summary statistics across all states. Results for all states can be found in Table A.23 in Appendix A.1.

The first measure captures the welfare effect that arises through CPG consumption, which is the principal focus of our empirical and theoretical analyses. Yet, households can switch their consumption to other types of goods if they find CPG less appealing because of the quality change. The overall effects that incorporate such substitutions are captured by $\hat{V}_r$. We view our measure of $\hat{V}_r$ as the lower-bound of the welfare effect because we are assuming that our channel exists only in CPG consumption. In reality, a similar mechanism could exist in other types of consumption. Also, we would like to emphasize that our assumption of the Cobb-Douglas upper-tier utility is a conservative choice, and that introduction of a larger elasticity of substitution between CPG and the outside good will strengthen our implication. Like $\hat{V}_r$, which serves as the lower-bound, we view $\hat{U}_r$ as the upper-bound of the welfare effect.

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

While states that have been less affected by negative shocks experience deterioration of welfare due to spillovers from severely hit states, the opposite holds for states that went through severe negative shocks. For example, Arizona (AZ) experienced a 13.67%

Table 1.10: Regional Redistribution across States

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

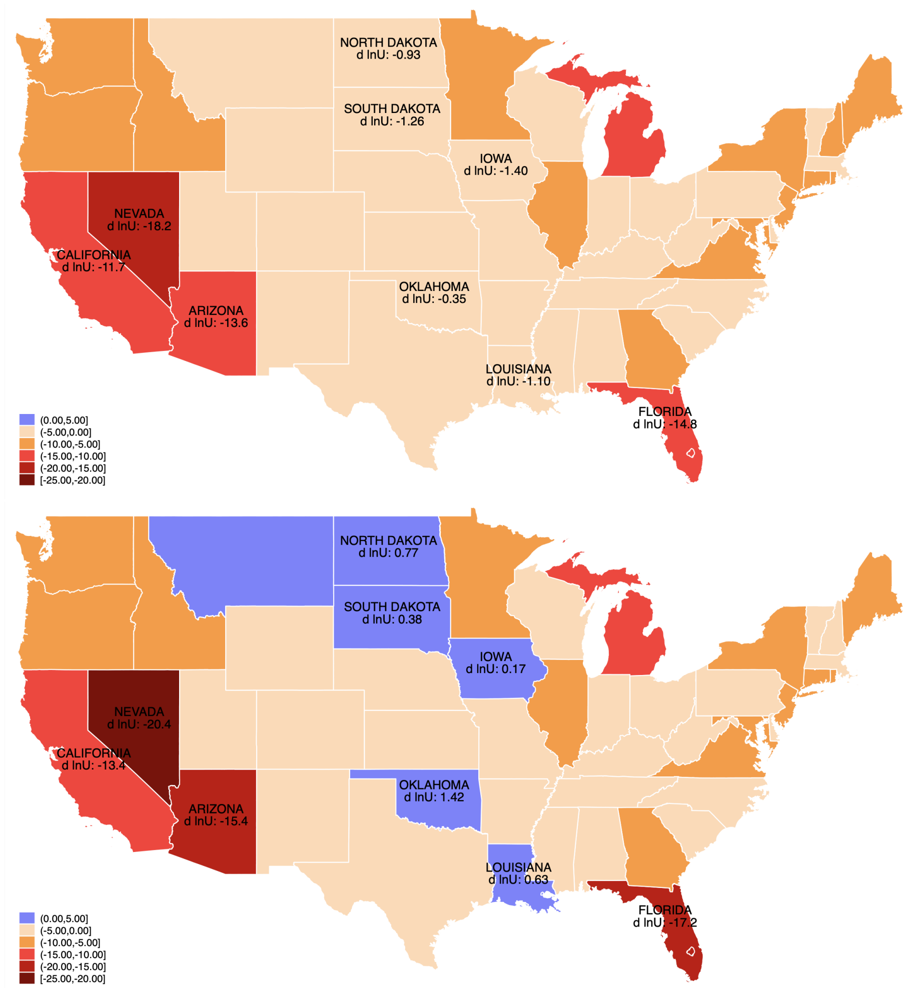
Note. $\hat{HP}_r(\%)$ is the state-level house price growth. $\hat{I}_r(\%)$ is the exogenous regional income growth which is calculated as $\hat{HP}_r(\%) \times 0.23$. Benchmark indicates the model with uniform quality choice in Section 1.6, and counterfactual indicates the model with market-specific quality choice in Appendix A.5. $\hat{U}_r(\%)$ 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.

decline of CPG welfare under the benchmark economy, but under the counterfactual economy it would have fared worse, with a 15.40% loss of CPG welfare. similarly, California (CA) experienced a 11.70% decline of CPG welfare under the benchmark economy, while it could have experienced a 13.40% loss of welfare in the counterfactual economy. This means that states that were hit by severe negative shocks benefit from regions that were less hit because multi-market firms downgrade product quality less under the benchmark than they do under the counterfactual economy.

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

The dispersion of welfare growth across states can be summarized by the standard

Figure 1.2: Regional Redistribution across States: Benchmark (Up) vs. Counterfactual (Down)



Note. This figure plots the state-level CPG welfare growth, $\hat{U}_r(\%)$, in the benchmark and the counterfactual economies. Benchmark indicates the model with uniform quality choice in Section 1.6, and counterfactual indicates the model with market-specific quality choice in Appendix A.5.

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

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

In Figure 1.2, we visualize the state-level CPG welfare growth in the benchmark economy (upper panel) and the counterfactual economy (lower panel). We confirm that the benchmark economy features more equalized welfare growth across states than the counterfactual economy.

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

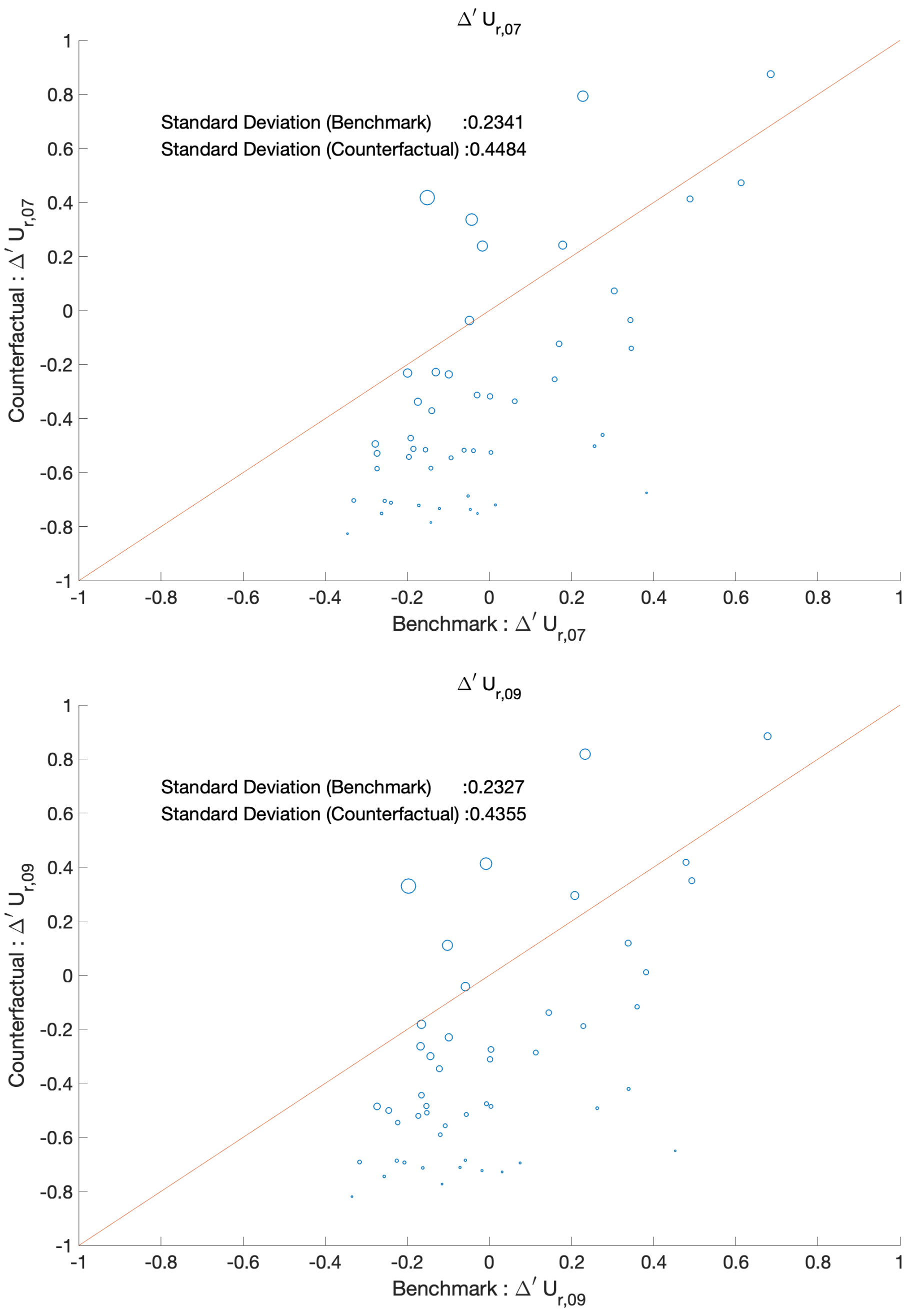
In contrast, Arizona (AZ) and California (CA) could have experienced an overall welfare loss of 10.09% and 8.76%, respectively, yet they actually experienced smaller welfare declines of 9.73% and 8.40%, respectively. The average absolute difference in welfare growth between the two economies is given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

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

Figure 1.3 shows the scatter plot of regional CPG welfare between the benchmark and the counterfactual. We calculate the deviation of regional CPG welfare from its cross-sectional average. The upper panel plots the 2007 snap shot and the lower panel shows that of 2009. In both years, the observations associated with lower welfare (relative to the cross-sectional average) lie below the 45-degree line, while those associated with higher welfare lie above the 45-degree line. This indicates that the counterfactual economy generates a larger dispersion of welfare across states, implying a larger quality-adjusted regional consumption inequality. In both years, the counterfactual economy produces a standard deviation of regional welfare distribution that is almost two times that of the benchmark. In Figure A.2 in Appendix A.2, we show the result using the overall welfare V_r. Similar patterns hold, with the counterfactual economy generating 10% larger standard deviation compared to that of the benchmark.

In summary, the multi-market firms' product replacement decision, which involves uniform quality adjustments, mitigates the regional quality-adjusted consumption and welfare inequality in terms of both growth and level. These results indicate that the identified intra-firm spillover through uniform quality adjustments serves as a

Figure 1.3: Cross-sectional Dispersion of Regional CPG Welfare



Note. $\Delta' U_{r,t} \equiv (U_{r,t} - \text{Avg.}U_{r,t})/\text{Avg.}U_{r,t}$ measures the cross-sectional dispersion of CPG welfare at time t. The size of the circle reflects population weights. The mean, $\text{Avg.}U_{r,t}$, and the reported standard deviations are weighted by state level population.

redistributive (or risk-sharing) mechanism across regions. Given that firms introduce uniform product quality across markets and that they take into account average demand conditions in all their markets to decide product quality choice, regions with higher demand face relatively lower product quality compared to the counterfactual economy because of regions that have lower demand. In contrast, regions with lower demand enjoy relatively higher product quality due to the regions that have higher demand. This mitigates the quality-adjusted regional consumption inequality.[65]

1.7 Conclusion

In this paper, we study whether and how intra-firm spatial networks created by multi-market firms spill over regional shocks across US local markets. We show that a firm's local sales decrease in response to not only the direct negative local demand shock but also the indirect negative local demand shocks that affect its other markets. In particular, the intra-firm spillover effect is mostly attributed to the extensive margin response of local sales that arises from the product creation and destruction. As the key mechanism behind the spillover, we emphasize the role of synchronized product replacements across multiple markets by each firm wherein high-valued products are replaced with lower-valued products in response to the negative shocks. Through

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

the lens of a multi-region model with endogenous quality adjustments by firms that reflect product replacements, We show that the identified intra-firm spillover serves as a redistributive mechanism across local markets and substantially mitigates the quality-adjusted regional consumption inequality.

Chapter 2

Propagation of Housing Market Disruptions during the Great Recession: Supply Chain Network Channel

Jungsik (Jay) Hyun[1]

2.1 Introduction

Among many hypotheses that explain a large drop in aggregate consumption expenditure and employment in the Great Recession, a prominent explanation is a fall in consumer demand arising from a collapse in the housing market. Using cross-region variation, the set of influential papers such as Mian et al. (2013) and Mian and Sufi (2014) establish that a decrease in housing net worth leads to a fall in consumption expenditure and non-tradable sector employment.

What seems underexplored in this study is the role of the firm-level supply chain network. Depending on the firm-level network structure, the effect of housing market disruptions on aggregate dynamics changes dramatically. On the one hand, the firm-level supply chain network could propagate and amplify the shock. A fall in household expenditure would lower firms' sales and their intermediate goods demand, which could further decrease intermediate goods suppliers' sales. An industry-level network study (in

[1]This is a collaborated project with Ryan Kim, my former colleague at Columbia University who now joined Johns Hopkins SAIS.

a different context) reveals about six times larger effect of demand-side shocks on value added growth when they factor in upstream propagation (Acemoglu et al. (2016)).[2] On the other hand, the effect through the firm-level network could be different from the industry-level propagation. If intermediate goods suppliers facing a troubled customer can easily find alternative customers to supply their products, such shock would be absorbed in the economy. Even if the suppliers cannot find alternative customers, if either a share of firms that are deeply involved in supply-chain relationship is small in the economy or such firms are insensitive to the shock, the propagation might have a negligible effect at the aggregate level.

Exploiting a unique micro-level data, we take the first step to investigate the role of firm-level supply chain network in propagating the housing market disruptions during the Great Recession. We combine county-level housing market condition from the Zillow database, firms' sales in each county from the Nielsen Retail Scanner and GS1 database, and firm-level supply chain network information from the Compustat Segment and FactSet Revere database. Our combined dataset contains detailed information on firms' supply chain network and their sales in each local market, as well as local housing market condition during the Great Recession. For example, if households at New York County purchase Coke, we observe New York County housing market condition, Coca-Cola's sales generated from New York County and information on upstream suppliers that Coca-Cola deals with. To the best of our knowledge, this is the first paper that combines firm-location-specific sales with firm-level supply chain network information.

Armed with the detailed micro-level data, we find that the housing market disruption propagates through the inter-firm network by exploiting the difference in firms' initial sales across regions and local variation in house prices. As a first step, we measure a *firm-specific* demand shock by taking an initial sales-weighted average across county-level house price changes within each firm. Using this shock, we show that decrease of household expenditure driven by housing market disruption lowers downstream firm sales,

[2] Using industry-level data, Acemoglu et al. (2016) explore upstream propagation of two different demand shocks: imports from China and federal government spending.

confirming the results in Mian et al. (2013) and Kaplan et al. (2016) at the firm-level.[3] To analyze the propagation, we further utilize initial inter-firm network information to construct the indirect exposure of the demand shock to upstream suppliers through downstream firms. We find that such exposure decreases upstream suppliers' sales growth and employment.

The propagation we find features a larger average indirect effect on upstream suppliers compared to the average direct effect on downstream firms. This reflects heterogeneous response of downstream firms to the shock and its interaction with the network structure. We provide an evidence of downstream-level heterogeneity of elasticity to the shock, and further show that firms with higher elasticity have larger role in the network structure. This interaction results in large supplier-level elasticity to the transmitted shock.[4]

We conduct numerous robustness analyses to confirm our empirical findings are driven by indirect spillover through the supply chain network. By further combining our database with the National Establishment Time-Series (NETS) establishment-level database, we show that our propagation result is not driven by the shocks that directly affect upstream suppliers' establishments located in the same counties. In addition to our main measure of household expenditure shock, we additionally used the housing supply elasticity originated from Saiz (2010) and used in Mian et al. (2013) to corroborate our results. Finally, we perform the Placebo analysis and show that the Placebo network cannot generate the propagation result we find.

To quantify the empirical findings at the aggregate level, we integrate our micro-

[3]Note that this result relies on the fact that firms are region-specific. If firms' initial sales are uniform across regions or firms can easily sell to other regions when they face a negative local demand shock, the firm-specific demand shock we measured might not have any effect on sales at the firm-level. The historical persistence of market shares across firms are well documented in the previous literature (**?**, **?**), and we confirm this persistence with our data in Appendix B.1

[4]There is an interesting question of why firms having more supply chain relationships are also more sensitive to the shock. In our companion paper (Hyun and Kim (2019)), we suggest disproportionate role of multi-market firms in the network structure. Section 2.4.1 also provides a brief discussion on this question.

level empirical evidence into a parsimonious network model to find that the firm-level network channel can explain about 18% of the aggregate output fluctuation during the Great Recession. While our empirical analyses reveal that there is propagation, it is unclear how large the effect will be at the aggregate level as there is a substantial heterogeneity across firms in terms of firm size and network degree. We incorporate this perspective by calibrating to match the share of firms along with other variables in our micro-level data, such as network structure and firm-specific demand shock.

Literature Review

This paper contributes to several strands of literature. First, our work is closely related to the literature that has exploited regional variation of housing market conditions to highlight mechanisms behind the large economic drop during the Great Recession.[5] Mian et al. (2013) and Mian and Sufi (2014) have exploited regional variation of local housing market conditions to investigate the extent to which household leverage has contributed to the Great Recession. They document that local housing market bust led to significant decline in the local economic activities such as consumption and nontradable employment during the Great Recession. Stroebel and Vavra (2019) show a causal response of firms' price-setting and households shopping behavior to the housing market induced local demand shocks. We contribute to this literature by showing that decline of household expenditure induced by housing market bust not only affected directly exposed firms but also indirectly affected suppliers through firm-to-firm linkages.

Recent papers also started to pointed out that implication derived using local variation can be different from that at the aggregate level due to possible general equilibrium forces. Beraja et al. (2019) show that the local and aggregate elasticities to the same type of shocks are quantitatively different, and thus propose a semi-structural methodology that combines regional and aggregate data within a model. Adao et al.

[5] There is also a strand of empirical works that has assessed the differential effect on labor market outcomes stemming from differential shock exposure across local labor markets in the context of Chinese import competition (see for example, Autor et al. (2013))

(2018a) measure the impact of economic shocks on local labor markets in the presence of rich spatial links across markets relying on a structural general equilibrium model. Our paper contributes to this literature by providing a direct reduced-form evidence of firm-to-firm spillover of housing market disruption that could not be properly captured by regional variation analysis.

Another important literature that our paper contributes is the growing literature focusing on the role of production network. Papers in this literature suggest input-output linkages as an important channel that propagates microeconomic shocks generating macroeconomic fluctuations. Acemoglu et al. (2012) show that under sufficient asymmetry of the network structure, intersectoral input-output linkages lead to aggregate fluctuations of microeconomic shocks. Acemoglu et al. (2016) theoretically show that supply-side shocks mainly propagate to the downstream, whereas demand-side shocks propagate to the upstream. They further provide empirical support to their argument using U.S. sectoral input-output matrix. In contrast to their work, our paper provides firm-level evidence of upstream propagation of firm-specific demand shocks, and further investigate aggregate-level implication. Recent papers also started to utilize firm-level network datasets, which have advantage in terms of identification compared to using sector-level data. Using the Compustat Segment dataset, Barrot and Sauvagnat (2016) show the evidence of firm-level propagation of idiosyncratic shocks generated by natural disasters in the location where a company's headquarter is located. They show that input-specificity is important determinant of degree of shock propagation. Carvalho et al. (2016) use the Great East Japan Earthquake as the source of shocks to show propagation effect through supply chain network. However, precisely because these papers exploit natural disasters hitting headquarters of companies, the nature of shocks they utilize are supply-side driven. Hence, whether or not supply chain networks propagate or serve as buffer to demand-side shocks at the firm-level still remains an open question. Up to our knowledge, this paper is the first to provide firm-level evidence of upstream propagation of demand shocks arising from local housing markets.[6] Regarding the recent

[6]Related to our paper focusing on the Great Recession period, there are also interesting recent works that

development of this literature, Carvalho (2014) provides excellent review.

Finally, there are recent papers providing evidence of regional spillover of local demand shocks. **?** shows that interstate trade generated the regional propagation of local consumer demand shocks during the Great Recession. Giroud and Mueller (2019) shows that firms' internal network generated the regional spillover of local housing market shocks. Instead, our paper focuses on inter-firm linkages through supply chain network as a potential source of local demand shock propagation.

The paper is organized as follows. Section 2.2 describes the datasets we use in the analysis. Section 2.3 provides detailed explanation of our empirical strategy and construction of variables. Section 2.4 provides the main empirical results. Section 2.5 contains additional robustness analysis. In Section 2.6, we provide a parsimonious network model and perform a counterfactual analysis to derive aggregate implications. Section 3.6 concludes. All tables and figures are at the end of the paper.

2.2 Data

2.2.1 Scanner Data

To construct firm-specific demand shock stemming from local housing market conditions, we first need to construct a measure that captures firm's relative exposure to different regions. We measure such exposure using firms' initial sales in each local market constructed using Nielsen retail scanner data.[7]

Nielsen retail scanner data consists of weekly pricing, volume, and store merchandising conditions generated by participating retail store point-of-sale systems in all US markets. Data are included from approximately 35,000 participating grocery, drug,

investigate credit shock spillover through supply chain. See, for example, Agca et al. (2017) and Costello (2017).

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

mass merchandiser, and other stores. Products from all Nielsen-tracked categories are included in the data, such as food, non-food grocery items, health and beauty aids, and select general merchandise. The years of coverage are 2006-2015.

However, Nielsen retail scanner data does not directly provide the information of producers of products. We bring producer information from GS1, the single official source of barcodes (i.e. Universal Product Code (UPC)) in the United States. These producers form our downstream companies.

2.2.2 Supply Chain Data

Our supply chain information comes from two sources : (i) FactSet Revere and (ii) Compustat Segment. Previous literature mostly used Compustat Segment as the only source of supply chain information (e.g. Barrot and Sauvagnat (2016)). FactSet Revere, however, provides richer network information relative to Compustat Segment, and thus we believe we are able to capture network effect more precisely compared to the previous empirical literature.[8]

FactSet Revere was built to uncover business relationship interconnections among companies globally. FactSet analysts systematically collect companies' relationship information from primary public sources such as SEC 10-K annual filings, investor presentations, and press releases, and classify them through four normalized relationship types: (i) customers, (ii) suppliers, (iii) competitors, and (iv) strategic partners. We mainly use relationship information categorized as "customers" or "suppliers".[9]

Company information is fully reviewed annually, and changes based on corporate actions are monitored daily. Thus it provides detailed and up-to-date dataset providing information on inter-company relationships.

[8]FactSet Revere is also used in a recent paper by Taschereau-Dumouchel (2017), in a different context with our paper, to evaluate the importance of the firms' decisions to operate in shaping the production network.

[9]According to the data manual, category "customers" includes two subcategories (i) disclosed customers and (ii) out-licensing. Category "suppliers" includes (i) disclosed suppliers, (ii) distribution, (iii) manufacturing, (iv) in-licensing, (v) marketing. We also verified robustness of our analysis restricting the relationship to "disclosed customers" and "disclosed suppliers".

According to the data manual, FactSet Revere supply chain relationships database covers more than 23,000 publicly traded companies around the world, comprising over 325,000 business relationships,[10] with historical data going back as far as 2003. Importantly, FactSet Revere database also includes private firms and less important relationships, which allows us to better capture the complete picture of network structure in the economy. Finally, linkage weight between supplier and customer is disclosed, whenever available, which is measured by percentage of supplier's revenue arising from relationship with that customer.

We first link FactSet Revere relationship database company ID and Compustat Fundamentals company ID (gvkey), using information on Ticker symbol, company name, and company address. As FactSet companies include both listed and unlisted companies, only subset of FactSet companies are linked to Compustat Fundamentals companies. So our initial universe of companies include firms appearing either in FactSet Revere supply chain relationship database or Compustat Fundamentals (or both). We then augment FactSet Revere supply chain information with Compustat Segment based relationship data provided by Barrot and Sauvagnat (2016), which provides Compustat Fundamental company IDs for both customer and suppliers.[11] Specifically, two companies that either appear in FactSet Revere or Compustat Fundamentals (or both) are supplier-customer if either FactSet Revere or Compustat Segment (or both) records that they have such relationship. We then restrict the universe of companies to those who have at least one record of supply chain relationship using our augmented supply chain data.

As a final step, we merge companies in Nielsen-GS1 merged data with downstream companies (customers) in our augmented supply chain data to get our final sample of downstream companies, and for the upstream companies (suppliers) we restrict our sample to listed companies that appear in Compustat Fundamentals. We restrict upstream companies to listed ones since we rely on Compustat Fundamentals to obtain

[10]Coverage status is given as of February 2017.

[11]We thank Jean-Noël Barrot for publicly sharing the Compustat Segment customer-supplier linkage file through his homepage.

basic firm-level variables such as sales and employment. We want to emphasize that, although our upstream level analysis is restricted to listed companies, we include both unlisted and listed companies at the downstream level. As we are mainly interested in upstream propagation of household expenditure shock through supply chain network, it is crucial to capture well the downstream-level exposure to local demand conditions. Our augmented supply chain data combined with Nielsen-GS1 data serves this purpose well as it allows us to include both unlisted and listed companies at the downstream-level.

2.2.3 Other Data

We also use some other datasets in our analysis. We obtain house price indices at the county-level from Zillow database. As well documented in Giroud and Mueller (2019), changes in house prices from 2006 to 2009 based on Zillow are highly correlated with the "housing net worth shock" (Δ Housing Net Worth, 2006-2009) in Mian et al. (2013); Mian and Sufi (2014). The county-level house price growth measure is matched with retail store location information from Nielsen database. Our final sample covers 985 counties, which covers 70% of total US population (based on 2007).

In robustness section, we additionally use establishment location information of firms obtained from the National Establishment Time-Series (NETS) dataset. NETS consists of establishment-level longitudinal microdata covering, in principle, the universe of U.S. businesses.[12] See Neumark et al. (2011) and Barnatchez et al. (2017) for detailed discussion on NETS.

2.3 Empirical Strategy

The main idea is to see whether a supplier who deals with downstream firms that are "more" exposed to household expenditure shocks is relatively more affected compared to

[12]As well documented in Barnatchez et al. (2017), NETS dataset is useful for studying cross-sectional business activity in high detail, although there are some limitations for studying business dynamics. Thus, we only bring cross-sectional pre-recession establishment location information for the analysis, abstaining from using dynamic perspective of the data.

a plausibly similar supplier whose downstream firms are “less” exposed to such shocks. As our main focus is to investigate the upstream propagation of household expenditure shocks arising from the housing market disruption, our empirical analysis involves two types of firms: downstream firms and their suppliers (upstream firms). We refer to firms included in Nielsen sample who directly sell products to households as “downstream firm” or simply “firm”, and their suppliers as “upstream firm” or simply “supplier”.[13]

2.3.1 Direct Effect of Housing Market Disruption to Downstream Firms

We first investigate whether the household expenditure shocks directly affect downstream firms. The downstream-level specification is given by

$$\Delta Sale_i^D = \alpha_1 + \beta_1 \Delta HP_i^D + \gamma_1 X_i^D + \epsilon_i \tag{2.3.1}$$

where i indicates downstream firms, $\Delta Sale_i^D$ is the sales growth rate of downstream firm i from 2007 to 2009, ΔHP_i^D indicates the average household expenditure shock faced by the downstream firm i, X_i^D is the vector of various firm-level controls including fixed effects. The superscript “D”stands for “downstream” to indicate that the variables are in downstream firm-level. Firm-specific demand shock ΔHP_i^D is constructed as a weighted average of county-level house price change between 2006 and 2009, weighted by the firm’s pre-recession county-level sales. We explain construction of variables in detail in Section 2.3.3.

The coefficient of interest is β_1 that captures elasticity of sales growth with respect to firm-specific demand shock, both measured in percentage growth term.[14] Positive β_1 indicates that firms that were initially more exposed to regions that went through larger drop in house price growth during the Great Recession have experienced larger drop in sales growth as well. This means that household expenditure shocks have direct

[13]We abstain from using the terminology “customer” to indicates downstream firm as it can be confused with households.

[14]Interpretation goes as follows: 1pp increase (decrease) of average house price growth rate faced by a firm increases (decreases) its sales growth rate by $\beta_1$pp.

consequence on downstream firms, confirming Mian et al. (2013) and Kaplan et al. (2016) at the firm-level.

2.3.2 Upstream Propagation of Firm-specific Demand Shocks to Suppliers

Our main empirical specification of upstream propagation is given by

$$\Delta Sale_j^U = \alpha_2 + \beta_2 \Delta HP_j^U + \gamma_2 X_j^U + \epsilon_j \tag{2.3.2}$$

where j indicates suppliers, $\Delta Sale_j^U$ is the sales growth rate of supplier j from 2007 to 2009, ΔHP_j^U is the average of downstream firm-specific demand shocks faced by the supplier j, X_j^U is the vector of various firm-level controls including fixed effects. The superscript "U" stands for "upstream" to indicate that the variables are in supplier level. Construction of variables are explained in detail in Section 2.3.3.

We call ΔHP_j^U a *supplier-specific demand shock*. Note that the supplier-specific demand shock originates from regions where the downstream firms (of the supplier) sell products to households. Thus, if we get a positive coefficient β_2, this can be interpreted as a transmission of shocks from the downstream to the upstream.

2.3.3 Construction of Variables

We start with product-location level sales $S_{p,i,r,l,t}$. This indicates sales of a product p produced by a downstream firm i generated at a retail store r in location l at time t. We use county as our baseline location and year as time index. $S_{p,i,r,l,t}$ is directly constructed from Nielsen Retail Scanner dataset by summing up weekly sales of each product in each retail store in a given year. We link product information in Nielsen with its producer information using GS1 data and thus could identify company that produced each product.

With $S_{p,i,r,l,t}$ at hand, we construct firm-county specific sales in a given year by summing up sales of all products produced by the firm arising from all retail stores (covered by Nielsen) in the county in that year:

$$S_{i,l,t} \equiv \sum_{p \in P_i} \sum_{r \in R_l} S_{p,i,r,l,t} \tag{2.3.3}$$

where P_i indicates set of products produced by firm i and R_l indicates set of retailer stores located in county l. We could further move on to construct firm-level sales in a given year by calculating

$$S_{i,t} \equiv \sum_{l} S_{i,l,t} \tag{2.3.4}$$

We calculate growth rate of sales using (2.3.4). Throughout the analysis, we use growth rates in the form suggested by Davis et al. (1996): for any variable X, the growth rate between t_1 and t_2 is defined as $\Delta X \equiv 2\left(\frac{X_{t_2}-X_{t_1}}{X_{t_1}+X_{t_2}}\right)$. That is, the denominator is calculated by the average of the beginning and end period levels, rather than the beginning period level. Davis et al. (1996) recommend using this growth rate because it has a number of attractive properties such as symmetry around 0 and boundedness between -2 and 2.[15] Thus, sales growth of the downstream firm i from 2007 to 2009 is defined by

$$\Delta Sale_i^D = 2\left(\frac{S_{i,09} - S_{i,07}}{S_{i,07} + S_{i,09}}\right) \tag{2.3.5}$$

Now, we move on to construct (downstream) *firm-specific* demand shock: ΔHP_i^D. This is calculated as a weighted average of county-level house price change weighted by firm's initial sales on each county:

$$\Delta HP_i^D \equiv \sum_{l} \omega_{i,l} \times \Delta HP_l \tag{2.3.6}$$

The weight is given by $\omega_{i,l} \equiv \left(\frac{S_{i.l,07}}{S_{i,07}}\right)$, and $\Delta HP_l \equiv 2\left(\frac{HP_{l,09}-HP_{l,06}}{HP_{l,06}+HP_{l,09}}\right)$ is the house price change in county l calculated using the Zillow database. The rationale behind the construction is that each firm is more exposed to household expenditure shocks in

[15]This measure also lends itself to aggregation, and less susceptible to the bias arising from the effects of regression to the mean. We use this measure mainly because of its symmetric property around 0. Our results are robust to using the growth rate defined by $\Delta X \equiv \left(\frac{X_{t_2}-X_{t_1}}{X_{t_1}}\right)$.

counties where its initial sales are large, and thus puts larger weights on house price changes in those counties.

Finally, we construct firm-specific demographic controls by calculating weighted average of county-level variables related to pre-recession demographic properties. Here again, we average across counties with weights corresponding to firm's initial county-level sales.[16] Firm-specific demographic controls capture average demographic properties faced by each company, which may affect demand conditions of households.

After constructing downstream firm-specific variables, we bring supply chain data combined with Compustat Fundamentals to construct supplier-specific variables.[17] Supplier j's sales growth is defined as in (2.3.5), where we use Compustat sales in 2007 and 2009 in place of $S_{j,07}$ and $S_{j,09}$, respectively. We construct *supplier-specific demand shock* as weighted average of its downstream firm-specific demand shocks:

$$\Delta HP_j^U \equiv \sum_{i \in I_j} \lambda_{j,i} \times \Delta HP_i^D \tag{2.3.7}$$

where I_j indicates set of downstream firms of supplier j, and $\lambda_{j,i}$ is the linkage weight.[18] Note that the supplier-specific demand shock originates from regions where downstream

[16] These include median household income and education level (defined by percentage with less than high school diploma).

[17] Recall that we are only using Compustat variables to get informations of the suppliers. Thus, only the suppliers are restricted to listed firms.

[18] Not all links have linkage weight information defined by percentage of supplier's revenue arising from linkage with a particular downstream company. Approximately 10% of all linkages have this information. Thus, following the previous literature using firm-level supply chain network data (e.g. Barrot and Sauvagnat (2016)), we use uniform weight across multiple downstream companies as our benchmark. We confirmed robustness of our result using three alternative weighting schemes. First, we used downstream firms' initial sales as weights, under the premise that relationship with large firms will be more important to suppliers compared to that with small firms. Second, whenever we have information on percentage of supplier's revenue arising from linkage with a particular downstream company, we used that as linkage weight, while for the remaining missing cases, we assigned uniform weight. Finally, we consider linkage weight constructed based on the assumption that each downstream firm puts equal weights across suppliers. The results are robust to these alternative specifications, reflecting the fact that around half of suppliers are connected to a single customer (making linkage weight irrelevant for these firms). The result can be found in Table B.8 in the Appendix B.1.

Table 2.1: Share of the Largest Firm in Each County

variable	N	mean	sd	p10	p50	p90
MaxShare	985	.0519	.0257	.0323	.0444	.0816

Note. This table shows the summary statistics of the share of the largest firm in each county in terms of sales: $MaxShare_l = \frac{\max_i [S_{i,l,07}]}{\sum_i S_{i,l,07}}$, where l indicates a county and $S_{i,l,07}$ is firm i's 2007 sales in county l. We have 985 counties in our samples after combining county-level house price growth measure.

firms sell products to the households. Thus if supplier sale growth is affected by supplier-specific demand shock, this can be interpreted as the evidence of upstream propagation of household expenditure shocks through firm-to-firm linkages. Similarly, we construct supplier-specific demographic controls which capture average demographic properties faced by downstream firms of a given supplier.

In robustness section, we instrument firm-specific demand shock and supplier-specific demand shock using firm-specific and supplier-specific housing supply elasticities (Saiz (2010)), respectively, to tackle potential endogeneity of house price change. These instruments are constructed in similar procedure as in contruction of firm-specific and supplier-specific demand shocks.

2.3.4 Discussion on the Identification

Local house price change, which we use as a measure of local demand shock, is obviously endogenous to local economic conditions. However, we argue that by transforming local house price changes into firm-level, endogeneity concerns arising in cross-region variation analyses largely become irrelevant. The main reason is that the firm-specific demand shock we use features the Bartik-type property as each firm's role in a particular regions is negligible.

Suppose that there is an omitted local factor that jointly affects housing market and consumption in particular county. That is, one might be concerned that both the changes in house price growth and consumption growth at the county-level are driven by the county's more exposure to "recession-prone" industries (see Mian et al. (2013) for detailed discussion). However, as long as local house price change positively comoves with local demand conditions, and as long as each firm's influence on a particular county is negligible, we can interpret our firm-specific house price change as firm-specific "demand" shock. The only caveat is that firm-specific demand shock may not have been entirely driven by local housing market condition per se.[19] Table 2.1 shows a summary statistics of the share of the largest firm ("maximum share") in each county in terms of sales.[20] The mean and median is 5.2% and 4.4%, respectively, with more than 90% of counties in our sample having maximum share less than 9%. Note that these ratios are calculated solely based on Nielsen sales. Thus, these numbers are plausibly overestimated, implying the "actual" role of each firm in a particular county will be even smaller. This verifies that each firm's role in a particular county is negligible.

Also, precisely because of this small role of each firm in each county, our firm-specific demand shock barely suffers from the reverse causality concern: firm's characteristic reversely affecting a particular county, generating comovement of local house price change and firm's sales growth. So we can interpret our firm-specific demand shocks as shocks *arising* from local demand conditions, not the opposite direction.

2.4 Main Results

This section provides the main empirical results. We show that household expenditure shocks affect downstream firms and propagate to their suppliers. More importantly, we show that there is a substantial heterogeneity across downstream firms in terms of elasticity of sales growth to the shock, and that downstream firms that are important in the network structure tend to have larger elasticity to the demand shock. Therefore, our estimated supplier-level elasticity turns out to be quantitatively large, reflecting larger

[19]We show the robustness of our result using the housing supply elasticity (Saiz (2010)) as an instrument in Section 2.5.2.

[20]Formally, maximum share is defined by $MaxShare_l = \frac{\max_i [S_{i,l,07}]}{\sum_i S_{i,l,07}}$, where l indicates a county and $S_{i,l,07}$ is firm i's 2007 sales in county l.

Table 2.2: Direct Effect of Demand Shocks to Downstream Firms

	(1)	(2)	(3)	(4)	(5)
	ΔSale (%)	ΔSale (%)	ΔSale (%)	ΔSale (%)	ΔSale (%)
ΔHP (%)	0.297***	0.338***	0.314***	0.338***	0.459**
	(0.048)	(0.052)	(0.042)	(0.049)	(0.180)
Firm Controls	-	✓	-	✓	✓
Sector FE	-	-	✓	✓	✓
Sample	Full	Full	Full	Full	Matched
Sales Share	100%	100%	100%	100%	39%
R^2	0.003	0.054	0.065	0.109	0.193
Observations	18128	18128	18128	18128	1758

Note. Sectors are defined based on product groups in Nielsen Retail Scanner dataset. Firm controls include log of initial sales and firm-specific demographic controls. Firm-specific demographic controls are weighted average of county-level pre-recession variables averaged across counties with weights corresponding to firm's initial county-level sales (see Section 2.3.3 for details). The "full sample" indicates Nielsen-GS1 sample, and the "matched sample" indicates Nielsen-GS1-Factset merged sample, where we do not restrict firms to have supply chain relationship in 2007. "Sales Share" indicates ratio of total sales between the specified sample and the Nielsen-GS1 sample. All standard errors are clustered at the sector level.

role of downstream firms with high elasticity in the network structure. All the summary statistics can be found in the Appendix B.1.

2.4.1 Downstream-level Analysis

Table 2.2 shows the regression result of (2.3.1), using sample firms in the Nielsen-GS1 dataset. Column (1) shows the result without including firm-level controls and sector fixed effect.[21] There is a significant positive correlation between firm-specific demand shocks and firms' sales growth with estimated coefficient 0.29. In Column (2) and Column (3), we either include firm-level controls such as log of initial sales and firm-

[21] We define sector of the downstream firms based on product groups in Nielsen Retail Scanner dataset. Examples of product groups are "Baby food", "Beer", "Cosmetics", "Glassware, Tableware", "Laundry supplies", "Snacks", "Paper products", etc. If a firm has multiple product groups, we assign product group with the largest sales share (in 2007) as its sector.

Table 2.3: Direct Effect of Demand Shocks to Downstream Firms depending on Sample

	(1)	(2)	(3)
	ΔSale (%)	ΔSale (%)	ΔSale (%)
ΔHP (%)	0.459**	0.673**	1.151**
	(0.180)	(0.313)	(0.546)
Firm Controls	✓	✓	✓
Sector FE	✓	✓	✓
Network Weighted		-	✓
Sample	Matched	Restrict	Restrict
Sales Share	39%	22%	-
R^2	0.193	0.260	0.364
Observations	1758	469	5399

Note. Sectors are defined based on product groups in Nielsen Retail Scanner dataset. Firm controls include log of initial sales and firm-specific demographic controls. Firm-specific demographic controls are weighted average of county-level pre-recession variables averaged across counties with weights corresponding to firm's initial county-level sales (see Section 2.3.3 for details). The "matched sample" indicates Nielsen-GS1-Factset merged sample, where we do not restrict firms to have supply chain relationship in 2007, and the "restricted sample" indicates Nielsen-GS1-Network dataset where we require firms to have supply chain relationship in 2007. "Sales Share" indicates ratio of total sales between the specified sample and the Nielsen-GS1 sample. All standard errors are clustered at the sector level.

specific demographic controls (described in Section 2.3.3), or sector fixed effect. In both specifications, the coefficients only slightly increases and remain highly statistically significant. In Column (4), we include both firm-level controls and sector fixed effect. The estimated coefficient (i.e. elasticity of sales growth with respect to the shock) is given by 0.34, and is highly significant. This implies 1pp drop of average house price change faced by a downstream firm leads to 0.34pp drop of its sales growth.

In Column (5), we run the same regression using the matched sample between Nielsen-GS1 dataset and Factset Revere dataset. Approximately 10% of Nielsen-GS1 firms are matched with firms in the Factset Revere dataset (regardless of whether they have network connections in 2007 or not). The matched sample accounts for 39% of total sales in Nielsen-GS1 sample. When restricting our sample to the matched sample, we get slightly higher elasticity of 4.6.

Not all firms in the matched sample are reported to have network connection in 2007. Table 2.3 shows the regression result further restricting the sample firms to those who have suppliers in 2007 (i.e. those who are appearing in our Nielsen-GS1-Network dataset). These firms are directly connected to suppliers in our upstream-level regression. Although the number of downstream firms in such sample reduces quite substantially, our restricted sample still accounts for 22% of total sales in 2007 (calculated based on the Nielsen-GS1 data), and 56% of total sales in 2007 in the matched sample. Column (1) repeats the main regression result in the matched sample (Column (5) in Table 2.2). Column (2) shows the result using the restricted sample that have suppliers. The estimated elasticity is now 0.67, which is larger than 0.46 in the matched sample and 0.34 in the full sample.

Notice that not all firms in the Nielsen-GS1 dataset as well as those in the matched data have reported network connection in 2007. This is because not all firms who sell products to the households are involved in supply chain relationship, or if involved, such relationship is negligible inside the network structure to be captured by the data. Therefore, we will interpret any un-captured network relationship using our data (if exists) as "unimportant" relationship, in the sense that either the firm is not involved in supply chain relationship, or if involved, such relationship is negligible to be captured by the data.[22]

Results in Table 2.3 shed lights on the possibility of interaction between downstream firm heterogeneity in terms of sensitivity to the demand shock and the network structure. It indicates that firms that are "important" in the network structure tend to be more sensitive to the shock. This is again confirmed by looking at Column (3), where we repeat the analysis imposing frequency weight proportional to the number of suppliers each downstream firm has. That is, if a firm has 5 suppliers, we assume there are 5

[22]Of course, this partially reflects the fact that our network data does not cover the universe of supply chain relationship in the United States. However, even if our network data covered the universe such relationship, firms that are not involved in supply chain relationship will not appear in the network dataset. In this sense, we can interpret Nielsen-GS1 firms not appearing in the network data as firms not important inside the network structure.

Table 2.4: Upstream Propagation

	(1)	(2)	(3)	(4)
	ΔSale (%)	ΔSale (%)	ΔSale (%)	ΔEmp (%)
ΔHP (%)	0.383**	0.618***	0.619***	0.518**
	(0.169)	(0.209)	(0.199)	(0.199)
Firm Controls	-	✓	✓	✓
Sector FE	✓	✓	✓	✓
Network FE	-	-	✓	✓
R^2	0.188	0.214	0.219	0.198
Observations	659	659	659	627

Note. Sectors are defined based on NAICS 4-digit code. Firm controls include log of initial sales (log of initial employment in Columns (5)-(6)), initial short-term liquidity, log of average downstream firms' sales, and supplier-specific demographic controls. Supplier-specific demographic controls are weighted average of firm-specific demographic controls weighted based on linkage weights, and capture average demographic properties faced by a given supplier's downstream companies (see Section 2.3.3 for details). All standard errors are clustered at the sector level.

duplicates of the firm in the economy and run the same regression. We obtain even greater elasticity of 1.15, reflecting the fact that those with more suppliers tend to be more sensitive to the shock.[23] We will further discuss the potential driving factor behind this result in Section 2.4.3.

2.4.2 Upstream Propagation

We now move on to the upstream-level analysis and show that demand shocks propagate to suppliers. Table 2.4 shows the regression result of (2.3.2), where in the last column we replace sales with employment. All four columns include sector fixed effect defined by NAICS 4-digit code. Column (1) shows the result without including supplier-level controls (except sector fixed effect). We find a significant positive correlation between supplier-specific demand shocks and suppliers' sales growth with estimated coefficient

[23]These results are not driven by the fact that we are restricting suppliers to the listed firms. The results are similar even if we do not restrict suppliers to listed ones.

0.38. Column (2) shows our benchmark result adding full set of supplier-level controls.[24] Adding controls strengthen our propagation results with larger and highly significant elasticity of 0.62. This implies 1pp drop of average house price change *indirectly* leads to 0.62pp drop of supplier's sales growth through firm-to-firm linkage with downstream firms. In Column (3) we additionally control the number of downstream firms each supplier has. Specifically, we divide supplier sample into quintiles based on the number of downstream firms, and include this categorical variable as fixed effect. The estimated elasticity to the shock barely changes, reflecting the fact that our results are not driven by difference in the number of downstream firms. Columns (4) repeats the analysis using employment instead of sales. We get statistically significant positive coefficient of 0.52, showing that household expenditure shocks not only affect suppliers in terms of sales, but also affect employment through their effect on the downstream companies.

These results clearly show the existence of strong upstream propagation through supply chain network. In Table B.8 in the Appendix B.1, we show the robustness of our results using various linkage weighting schemes for shock construction in (2.3.7), and also consider more disaggregated sector definition.

2.4.3 Downstream Firm Heterogeneity and the Network Structure: Why Suppliers have Large Elasticity to the Transmitted Shock?

The supplier-level elasticity 0.62 to the transmitted shock turns out to be larger than the average downstream-level elasticity to the direct shock ranging from 0.34-0.46 obtained using the full Nielsen-GS1 sample or the matched sample (Table 2.2). This reflects the fact that relatively more sensitive downstream firms tend to have larger role in the network structure as can be verified in Columns (2) and (3) of Table 2.3. That is, those who have network connection have relatively larger elasticity to the direct shock, and among such firms, those with larger number of suppliers tend to have even higher elasticity to the shock. Column (2) in Table 2.5 formally shows this by including

[24]Supplier-level controls include log of initial sales (log of initial employment in Columns (5)-(6)), initial short-term liquidity, log of average downstream firms' sales, and supplier-specific demographic controls.

Table 2.5: What Make Firms More Sensitive to Shocks?

	(1) ΔSale (%)	(2) ΔSale (%)	(3) ΔSale (%)	(4) ΔSale (%)
ΔHP (%)	0.334***	0.331***	0.367**	0.436***
	(0.050)	(0.050)	(0.146)	(0.150)
Num. Supplier	0.000	0.007	0.007	0.006
	(0.001)	(0.004)	(0.004)	(0.005)
Num. Supplier × ΔHP		0.039*	0.038*	0.036
		(0.022)	(0.023)	(0.023)
I(Mult.Mkt Firm) × ΔHP			0.211**	0.196**
			(0.095)	(0.093)
Log(Sale) 07 × ΔHP			-0.016	-0.025
			(0.015)	(0.016)
Num. County × ΔHP				0.0009**
				(0.000)
Firm Controls	✓	✓	✓	✓
Num. Local Mkt Controls	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
R^2	0.112	0.112	0.112	0.112
Sample	Full	Full	Full	Full
Observations	18128	18128	18128	18128

Note. Sectors are defined based on product groups in Nielsen Retail Scanner dataset. Firm controls include log of initial sales and firm-specific demographic controls. Firm-specific demographic controls are weighted average of county-level pre-recession variables averaged across counties with weights corresponding to firm's initial county-level sales (see Section 2.3.3 for details). All columns additionally control the number of counties firm generates sales and the multi-market indicator. All standard errors are clustered at the sector level.

interaction between the number of suppliers and the firm-specific demand shock.

However, it turns out that it is not the number of suppliers itself that induces higher elasticity of downstream firms involved in supply chain relationship. Instead, We argue that this reflects disproportionately large role of multi-market firms inside the network structure. In our companion paper (Hyun and Kim (2019)), we document a *positive* regional spillover occurring in the economy through multi-market firms.[25] That is, local demand shocks spillover to distant regions through multi-market firms' market-linkage, where negative regional demand shock not only reduces sales in the region of the shock origin, but also reduces sales in distant regions.[26] This interesting finding helps us understand why multi-market firms should have higher elasticity to the shock: in the presence of positive regional spillover, a firm's regional sales complement each other, inducing firm-level sales to react more sensitively to the amount of average demand shock. And it turns out that multi-market firms (i.e. more sensitive firms) have larger role inside the network structure as well.

Columns (3) and (4) in Table 2.5 shows that multi-market firms are indeed more sensitive to the shocks.[27]. In Column (3), we add two interaction terms with firm-specific demand shock: one interacted with multi-market indicator, and the other with log of initial sales. Consistent with the regional spillover story, we get a statistically significant positive coefficient in front of interaction between multi-market indicator and the shock, meaning that multi-market firms have larger elasticity to the shock. In Column (4), we additionally introduce interaction between firm-specific demand shock and the number

[25]In the paper, we document (1) local demand shocks spillover to distant regions through multi-market firms' market-linkage, where negative local shocks not only reduce sales in the origin of shocks but also reduce sales in distant regions, (2) the spillover in sales is fully attributed to the net creation of products, not the existing products, highlighting the role of multi-market firms' product innovation or quality choosing decision.

[26]Recent papers in the Trade literature investigated similar type of spillovers in the context of international trade. The empirical evidences are mixed: Berman et al. (2015) show a positive causal effect of changes in firm-level exports on firm-level domestic sales, while Almunia et al. (2018) show the opposite causal relationship between demand-driven changes in domestic sales and export flows.

[27]We define multi-market firm as a firm that generates sales from more than 5 counties (1st quartile of firms' number-of-local-markets distribution)

of counties firm generates sales. We get positive and statistically significant coefficients in both multi-market indicator$\times$shock interaction and the number of counties$\times$shock interaction terms. These results strongly suggest that the number of local markets is a key factor determining firm-level sensitivity to the shock, with having multiple markets inducing larger sensitivity to the demand shock.

Table B.7 confirms that downstream firms that have supply chain relationship indeed have relatively larger number of local markets. The 1st quartile of the number of local markets in the full sample is 5 (i.e. 25% of downstream firms generate sales in less than 5 counties), while this number is 46 in the restricted sample.

In sum, supplier-level elasticity to the transmitted shock is large in magnitude, reflecting the fact that multi-market downstream firms tend to be more important in the network structure. This has an important implication since small number of influential firms selling in many regions are not only more sensitive to the direct negative demand shock but also has disproportionately large role in the network structure, potentially influencing many upstream suppliers generating non-trivial aggregate effect.

2.5 Robustness Analysis

In this section, we conduct numerous robustness analyses to confirm our empirical findings are driven by indirect spillover through the supply chain network. We first show that our propagation result is not driven by shocks that directly affect upstream suppliers' establishments located in the same counties of the shocks' origin. Also, we show that our results are robust to instrumenting local house price change with the housing supply elasticity (Saiz (2010)). Finally, we perform the Placebo analysis and show that the Placebo network cannot generate the propagation result we find in our empirical analysis

Table 2.6: Robustness (Excluding Regions with Establishments)
- Upstream-level Regression

	(1)	(2)	(3)
	ΔSale (%)	ΔSale (%)	ΔSale (%)
ΔHP (%)	0.628^{**}		0.520^{**}
	(0.247)		(0.233)
ΔHP (Exclude) (%)		0.457^{**}	
		(0.206)	
IV	-	-	✓
First-stage F stat	-	-	1026.5
Firm Controls	✓	✓	✓
Sector FE	✓	✓	✓
Network FE	✓	✓	✓
R^2	0.216	0.213	0.216
Observations	457	457	457

Note. Column (1) provides upstream-level regression based on Nielsen-GS1-Network-NETS dataset using the original shock constructed by *not* excluding regions with establishments. Column (2) shows the regression using the shock constructed by excluding the regions where supplier has establishments. Column (3) instruments the original shock using excluded shock. Sectors are defined based on NAICS 4-digit code. Firm controls include log of initial sales, initial short-term liquidity, log of average downstream firms' sales, and supplier-specific demographic controls. All standard errors are clustered at the sector level.

2.5.1 Excluding Regions with Establishments

One potential concern is that the local house price change, which we use as measure of local household expenditure shock, may affect production of suppliers directly through facilities located in the same regions where the shocks are originating. For example, local house price change can be correlated with regional productivity, or may affect financial condition of firms located in such region.

To tackle this concern, we further combine our dataset with the National Establishment Time-Series dataset (NETS), from which we bring pre-recession establishments location information of each supplier. We construct a supplier-specific demand shock by leaving out regions where the supplier has establishments. Thus, the shock is constructed purely based on the regions where the supplier's downstream firms generate sales and the supplier does not have establishments.

Column (1) in Table 2.6 repeats the main upstream-level regression using suppliers matched with the NETS data, where we use the original supplier-specific shock constructed by *not* excluding regions with establishments. We get similar result as in our main upstream-level analysis. Column (2) shows the regression using the shock constructed by excluding the regions where supplier has establishments. We get estimated coefficient of 0.46, which is slightly smaller but highly significant. Column (3) instruments the original shock using excluded shock, and we get estimated coefficient of 0.52. Thus, we conclude that the propagation result is not driven by shocks directly affecting suppliers through establishments located in the shock origin.

2.5.2 IV specification: Housing Supply Elasticity

Our firm-specific and supplier-specific demand shocks, which are constructed using local house price change, can be endogenous to local economic conditions. However, as we argued in Section 2.3.4, the Bartik-type feature of our shocks largely relieves endogeneity concerns typically arising in regional variation analyses. Still, we verify the robustness of our results by instrumenting firm-specific (and supplier-specific) demand shocks by corresponding firm-specific (and supplier-specific) housing supply elasticity (Saiz (2010)).[28] Unfortunately, the Saiz instrument is not provided for all counties, so we restrict counties to those Saiz instruments are available.[29]

Table 2.7 shows the regression result of (2.3.2), instrumenting firm-specific demand shock with firm-specific Saiz instrument. Columns (1) and (3) show the result *without* using Saiz instrument for respective sample. Interestingly, even restricting the counties

[28]Construction of firm-specific and supplier-specific housing supply elasticities follow the same procedure as in construction of firm-specific and supplier-specific demand shocks.

[29]Nearly half of the counties included in our main analysis in Section 2.4 are dropped if we restrict counties to those with Saiz instruments. This can be potentially problematic especially for our regression, since capturing all demands arising from every region is crucial for constructing firm-specific demand shock. Thus, our result in this section should be interpreted with caution.

Table 2.7: Robustness (IV) - Downstream-level Regression

	(1) ΔSale (%)	(2) ΔSale (%)	(3) ΔSale (%)	(4) ΔSale (%)
ΔHP (%)	0.347***	0.889***	0.429**	0.952*
	(0.046)	(0.104)	(0.170)	(0.497)
IV	-	✓	-	✓
First-stage F stat	-	1668	-	95.4
Firm Controls	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Sample	Full	Full	Matched	Matched
R^2	0.101	0.093	0.183	0.179
Observations	17519	17519	1738	1738

Note. Sectors are defined based on product groups in Nielsen Retail Scanner dataset. Firm controls include log of initial sales and firm-specific demographic controls. Firm-specific demographic controls are weighted average of county-level pre-recession variables averaged across counties with weights corresponding to firm's initial county-level sales (see Section 2.3.3 for details). Firm-specific Saiz instrument, is constructed by the same procedure as firm-specific demand shock and demographic controls. The "full sample" indicates Nielsen-GS1 sample, and the "matched sample" indicates Nielsen-GS1-Factset merged sample, where we do not restrict firms to have supply chain relationship in 2007. All standard errors are clustered at the sector level.

to those with Saiz instrument, the estimated coefficients are stable compared to Table 2.2. Columns (2) and (4) show the IV regression result. The estimated coefficients increases to 0.89 for the full sample, and 0.95 for the matched sample. This may reflect potential measurement error of the shocks, or may come from the fact that the "demand shock" at the firm-level may not have been totally induced by local housing market.[30] We interpret the coefficient as the follows: if we get rid of measurement errors and restrict the source of local expenditure shock to that arising purely from local housing market, then the estimated elasticities become larger with values 0.89-0.95.

Table 2.8 shows the regression result of (2.3.2), instrumenting supplier-specific demand shock with supplier-specific Saiz instrument. Column (1) shows the result

[30]Still, this does not change the fact that we are capturing firm-specific "demand" shock arising from local markets. See the discussion in Section 2.3.4.

Table 2.8: Robustness (IV) - Upstream Propagation

	(1)	(2)
	ΔSale (%)	ΔSale (%)
ΔHP (%)	0.700***	1.182***
	(0.228)	(0.428)
IV	-	✓
First-stage F stat	-	16.3
Firm Controls	✓	✓
Sector FE	✓	✓
Network FE	✓	✓
R^2	0.236	0.230
Observations	612	612

Note. Sectors are defined based on NAICS 4-digit code. Firm controls include log of initial sales, initial short-term liquidity, and supplier-specific demographic controls. Supplier-specific demographic controls are weighted average of firm-specific demographic controls weighted based on linkage weights, and capture average demographic properties faced by a given supplier's downstream companies (see Section 2.3.3 for details). Supplier-specific Saiz instrument is constructed by the same procedure as supplier-specific demand shock and demographic controls. All standard errors are clustered at the sector level.

without instrument, and Column (2) shows the IV result. Again, IV regression generates larger supplier-level elasticity to the shock with estimated coefficient 1.18.

Throughout the analyses, we conclude that our benchmark results in Section 2.4 are at best underestimating the true effect of local expenditure shock *purely arising from local housing market.*

2.5.3 Placebo Test

To further guarantee that our results are capturing network spillover, we perform Placebo test by constructing counterfactual network. Specifically, we randomize connections across downstream and upstream firms, and run the regression in (2.3.2).[31] We repeat the

[31] While performing the Placebo test, we restricted suppliers to those appearing in our main upstream analysis (Section 2.4.2), and downstream firms to those having connections to these suppliers. Then we construct a counterfactual network by randomizing network connections across these downstream and upstream firms.

Table 2.9: Placebo Test - Randomizing Connection

	(1)	(2)
	ΔSale (%)	ΔSale (%)
ΔHP (%) (Randomized)	-0.015	
	(0.221)	
ΔHP (%) (Randomized within Sector)		-0.022
		(0.193)
Firm Controls	Yes	Yes
Sector FE	Yes	Yes
R^2	0.201	0.201
Observations	659	659

Note. Coefficients, standard errors, R^2, and F stat are average of 500 Placebo Regressions. Sectors are defined based on NAICS 4-digit code. Firm controls include log of initial sales, initial short-term liquidity, and supplier-specific demographic controls. Supplier-specific demographic controls are weighted average of firm-specific demographic controls weighted based on linkage weights, and capture average demographic properties faced by a given supplier's downstream companies (see Section 2.3.3 for details). All standard errors are clustered at the sector level.

process for 500 times and report the average coefficients and standard errors, respectively, based on the 500 Placebo regressions in Table 2.9. Column (1) shows that the elasticity of supplier's sales growth with respect to the *Placebo* supplier-specific demand shock is negligible and statistically insignificant.

In Column (2), we additionally perform more demanding Placebo regression. We consider counterfactual network constructed based on randomizing connections across the downstream and upstream firms, where the randomization is performed *within* supplier sector. That is, for each supplier sector, we collect downstream firms that have at least one connection with suppliers in such sector. Then, among these upstream and downstream firms, we randomize connection. This is more conservative in the sense that each upstream firm is randomly assigned with downstream firms that have true connection with some other suppliers in the same sector. That is, the counterfactual network can be thought as a "plausible" network at the sector level. Again, we do not find any evidence of upstream propagation under this counterfactual network.

2.6 Network Model and Counterfactual Analysis

In this section, we incorporate our micro-level data with parsimonious network model to assess the importance of supply chain network in propagating housing market disruption during the Great Recession. The goal is to perform counterfactual analysis. Specifically, we would like to evaluate how much observed decline of the output can be attributed to the network propagation of housing market disruption, by considering counterfactual economy without such propagation channel.

As our propagation occurs purely through firm-to-firm linkage, we abstain from introducing explicit regional markets and regional demand shocks at the household level. Instead, we assume that a representative household consumes N_D different products produced by N_D downstream companies, respectively, and introduce exogenous demand shocks directly to these firms. Then, the structure we impose can be readily mapped to that in Acemoglu et al. (2016), who introduce firm-specific supply shock and firm-specific demand in a static general equilibrium network model. Thus, our structure could be thought as a special case of Acemoglu et al. (2016), with network structure calibrated using our firm-level data. We will repeat the model structure in this section as an illustration, but the detail can be found in Acemoglu et al. (2016).

2.6.1 Production and Network Structure

We start with a static perfectly competitive economy with N firms, where S denotes the set of all firms. Each firm $i \in S$ has a Cobb-Douglas production technology given by

$$y_i = e^{z_i} l_i^{\alpha_i^l} \Pi_{j=1}^{N} x_{ij}^{a_{ij}} \tag{2.6.1}$$

x_{ij} denotes the quantity of goods produced by firm j used as inputs by firm i, l_i is labor, and z_i is a Hicks-neutral productivity shock (representing both technology and other factors affecting productivity). We impose $\alpha_i^l > 0$ and $a_{ij} \geq 0$ for all i, j, where $a_{ij} = 0$ implying j's product not being used in i's production. Also we assume constant returns to scale:

$$\alpha_i^l + \sum_{j=1}^{N} a_{ij} = 1 \tag{2.6.2}$$

and following Barrot and Sauvagnat (2016), assign equal weight across suppliers in the input-output matrix when a firm uses multiple firms' products as factor inputs.[32]

Among N firms, there are N_D number of downstream firms who directly sell products to the households. We assume only the downstream firms directly sell products to the households. Without loss of generality, we index $i = 1, 2, ..., N_D$ as downstream firms and denote the set of downstream firms as S_D. The set of the rest of the firms (who do not sell products directly to the households) is denoted as $S_U \equiv S \backslash S_D$.

As discussed in the beginning, we will not explicitly introduce regional markets and regional demand shocks at the household level, but instead introduce exogenous demand shocks directly to the downstream firms. Specifically, we introduce exogenous demand shock H_i in the form of (downstream) firm-specific government spending (representing household expenditure shocks directly affecting downstream product demand in general, including those arising from housing market disruption). We will use the terminology exogenous demand shock and government spending shock interchangeably. By assumption, only the downstream firms are hit by such shocks, and the market clearing condition for each firm i is given by

$$y_i = c_i + \sum_{j=1}^{N} x_{ji} + H_i \tag{2.6.3}$$

Our assumption implies if $i \in S_D$, $\sum_{j=1}^{N} x_{ji} = 0$, and if $i \in S_U$, $c_i = H_i = 0$.

2.6.2 Households

A representative household has a utility function given by

$$U(c_1, c_2, ..., c_N, l) \equiv \gamma(l)\Pi_{i=1}^{N} c_i^{\beta_i} \tag{2.6.4}$$

[32]That is, if a firm i has n suppliers (i.e. there are n elements in $\{j : x_{ij} > 0\}$), then $a_{ij} = \frac{1-\alpha_i^l}{n}$ for all $j \in \{j : x_{ij} > 0\}$.

where $\beta_i \in [0, 1]$ designates the weight of good i with $\sum_{i=1}^{N} \beta_i = 1$, and $\gamma(l)$ is a decreasing (differentiable) function capturing the disutility of labor supply. Our assumption that only the downstream firms produce products that are directly consumed by the households implies $\beta_i = 0$ if $i \in S_U$.

The government imposes a lump-sum tax, T, to finance its purchases (which is the source of exogenous demand). Denoting the price of the output of firm i by p_i, this implies

$$T = \sum_{i=1}^{N} p_i H_i \tag{2.6.5}$$

where $H_i = 0$ if $i \in S_U$.

Hence, the representative household's budget constraint is given by

$$\sum_{i=1}^{N} p_i c_i + T = wl \tag{2.6.6}$$

where $c_i = 0$ if $i \in S_U$.

2.6.3 Upstream Propagation of Demand Shock

The derivation of equilibrium can be found in the Appendix B.3. We assume $w = 1$ and also shut down the productivity shock, $z = 0$.

Define $\tilde{y}_i \equiv p_i y_i$, $\tilde{c}_i \equiv p_i c_i$, and $\tilde{H}_i \equiv p_i H_i$. Notet that these variables are all in real term as we are imposing $w = 1$. Define $\tilde{V}_i \equiv \tilde{c}_i + \tilde{H}_i$. Then it turns out that

$$\begin{aligned}
\tilde{y} &= (I - A^T)^{-1}(\tilde{c} + \tilde{H}) \\
&= (I - A^T)^{-1}(\tilde{V})
\end{aligned} \tag{2.6.7}$$

where

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix}$$

Table 2.10: Calibration Strategy: Benchmark

parameter	meaning	value	source
w	wage	1	Numeraire
λ	labor disutility	2	$l^{ss} = 0.33$
α_i^l	labor share (have suppliers)	0.45	Acemoglu et al. (2012)
	labor share (not have suppliers)	1	Use only labor
κ	shock normalizing factor	0.41	$\Delta\left(\sum_{i=1}^N \tilde{V}_i\right) = -5\%$

and for $x \in \{y, c, H, V\}$, $\tilde{x}$ is defined as $\tilde{x} \equiv (\tilde{x}_1, ..., \tilde{x}_N)^T$. Note that $\sum_{i=1}^N \tilde{y}_i$ and $\sum_{i=1}^N \tilde{V}_i$ indicate real gross output and real value added, respectively.

Equation (2.6.7) shows the upstream propagating nature of the demand shock. An exogenous demand shock hitting a downstream firm $i \in S_D$ will not only affect firm i's output $\tilde{y}_i$, but will also affect firm j's output $\tilde{y}_j$ (where $j \in S_U$) as long as firm $j \in S_U$ is connected to firm $i \in S_D$ through the input-output structure reflected in $(I - A^T)^{-1}$.

2.6.4 Calibration

We define the steady state of the economy as $H_i = z_i = 0$ for all i. For a given variable x, we denote its steady state as x^{ss}. The structural parameters are calibrated following the existing literature. We summarize our calibration strategy for the benchmark economy that exhibit input-output linkages in Table 2.10, and that for the counterfactual in Table 2.11. We will clarify how we define counterfactual later in detail.

We directly map several components in the model using our micro-level data. First, to better represent the United States economy, our downstream firms include all Nielsen-GS1 firms, regardless of whether they have network connection or not. Those who do not have network connection will simply use labor as the only factor input. In addition, we not only bring suppliers who are directly connected to the downstream firms (i.e. Nielsen-GS1 firms) but also bring suppliers of suppliers and etc. This allows us to capture more complete structure of the network in the economy. At the end, we

Table 2.11: Calibration Strategy: Counterfactual

parameter	meaning	value	source
w	wage	1	Numeraire
λ	labor disutility	2	$l^{ss} = 0.33$
α_i^l	labor share	1	Use only labor
κ	shock normalizing factor	0.41	Same value as in Benchmark

have 18128 downstream firms among which 479 firms have direct linkage to suppliers, and 2782 upstream firms with direct or indirect linkages.[33]

To calibrate the household's weight on each good, $\beta \equiv (\beta_1, ..., \beta_N)$, we use downstream firms' initial sales (normalized to sum up to one) as the weight. This is consistent with what is predicted by the model (see equation (B.3.7) in the Appendix B.3). As we assume only downstream firms sell products to the households, $\beta_i = 0$ if $i \in S_U$.

Finally, we directly map downstream firm-specific demand shocks in the data to the model's downstream firm-specific exogenous demand shock. Define

$$\Delta \tilde{H}_i \equiv 2 \left(\frac{\tilde{H}_i}{\tilde{y}_i^{ss} + (\tilde{y}_i^{ss} + \tilde{H}_i)} \right) \tag{2.6.8}$$

where we assume zero shock at the steady state: $\tilde{H}_i^{ss} = 0$ for all i. We assume $\Delta \tilde{H}_i \propto \Delta HP_i^D$ (Data) for $i \in S_D$, and $\Delta \tilde{H}_i = 0$ if $i \in S_U$. That is, firm i's increase of exogenous demand relative to its steady state output is proportional to the observed firm i's demand shock (where the growth rate is defined in the spirit of Davis et al. (1996)). Formally, we assume $\Delta \tilde{H}_i = \Delta HP_i^D$ (Data) $\times \kappa$, where κ is a normalizing factor chosen so that the model's value added growth under the benchmark matches -5%, which is the observed output growth between 2007-2009 in the aggregate data (measured by real GDP per capita).

[33] The slight difference of the numbers of firms compared to those in our empirical analyses comes from the fact that we are including companies that were dropped during the fixed effect regressions (i.e. in fixed effect regressions, some sectors include a single firm which is dropped during the regression due to singularity.)

2.6.5 Counterfactual Analysis

The counterfactual analysis is performed in the following way. Ideally, we want to sever the network connection while not changing all other components. However, if we sever linkages between downstream firms and the upstream firms (which implies imposing $\alpha_i^l = 1$ for all $i \in S$), then firms in S_U face zero demand and get excluded from the economy. That is, a large number of firms in the economy will be mechanically dropped.

Therefore, in our counterfactual analysis, while severing firm-to-firm linkages, we additionally assume that firms in S_U now sell products directly to the households with sales proportional to those in the benchmark economy. That is, the household's weight on each good, $\beta \equiv (\beta_1, ..., \beta_N)$, is modified so that it equals the vector of steady state sales of all firms, $\tilde{y}^{ss}$, in the benchmark economy (again, normalized to sum up to one). Thus across two economies, each firm's *relative* size (measured by firm sales over the total gross output) at the steady state is identical.

Our objective is to compare the growth rates of the real value added (from its steady state value) across the benchmark and the counterfactual. As in our empirics, we define growth rate as in Davis et al. (1996): $\Delta x \equiv 2\left(\frac{x - x^{ss}}{x^{ss} + x}\right)$.

2.6.6 Results and Interpretation

Table 2.12 shows the results from the counterfactual analysis. In the benchmark economy with the firm-to-firm linkages, the output growth (captured by the value added growth) is matched to be -5%, which corresponds the observed aggregate output growth (real GDP per capita) between 2007-2009 (again calculated based on Davis et al. (1996)). In the counterfactual economy, the output growth becomes -4.1%, which is substantially smaller in magnitude. This shows that approximately 18% of observed output growth can be explained by the supply chain network linkages under demand shocks.

This result is striking if one takes into account that only around 500 firms among 18000 have either direct or indirect network linkages with suppliers. However, these 500 firms are not only "important" in the network structure (in the sense that they are involved in supply chain relationship), but also turn out to be relatively large, accounting

Table 2.12: Counterfactual Analysis

Symbol	Benchmark	Counterfactual	Description
l^{ss}	0.33	0.33	Labor (steady state)
$\sum_{i=1}^{N} \tilde{V}_i^{ss}$	0.33	0.33	Value Added (steady state)
$\left(\sum_{i=1}^{N} \tilde{H}_i\right) / \left(\sum_{i=1}^{N} \tilde{y}_i^{ss}\right)$	-6%	-6%	Average Demand Shock faced by firms
$\left(\sum_{i=1}^{N} \tilde{H}_i\right)$	-2.4%	-2.0%	Total Demand Shock
$\Delta \left(\sum_{i=1}^{N} \tilde{V}_i\right)$	-5%	-4.1%	Value Added Growth
Δl	-5%	-4.1%	Labor Growth

Note. Note that $w = 1$ and thus all expressions above are in real terms. Value added of firm i, $\tilde{V}_i$, is defined by $\tilde{V}_i \equiv p_i c_i + p_i H_i = \tilde{c}_i + \tilde{H}_i$. All growth rates are calculated based on Davis et al. (1996): $\Delta x \equiv 2\left(\frac{x - x^{ss}}{x^{ss} + x}\right)$.

24% of value added in the benchmark economy. This means that small number of large firms that are important in the network structure could play quantitatively large role at the aggregate level.

Also, note that quantitatively larger drop of output growth in the benchmark economy is a direct consequence of larger total demand shock it faces (-2.4%) relative to that of the counterfactual (-2.0%). That is, even though the average size of demand shock each firm faces, $\left(\sum_{i=1}^{N} \tilde{H}_i\right) / \left(\sum_{i=1}^{N} \tilde{y}_i^{ss}\right)$, are identical between the two economy, supply chain network magnifies total demand shock in the benchmark economy. This implies that amplification through supply chain network essentially works through introducing "additional" shocks to (upstream) firms that otherwise would not have experience if there were no firm-to-firm linkages.

2.7 Conclusion

We showed that housing market disruption during the Great Recession transmitted upstream through supply chain network generating quantitatively large effect at the aggregate level. Using a unique micro-level data, we provided direct evidence that household expenditure shock not only affected downstream firms but also transmitted to their suppliers with quantitatively large elasticity at the supplier-level. We showed that large supplier-level elasticity reflects heterogeneous response of downstream firms to the shock and its interaction with the network structure, with downstream firms having higher elasticity tend to have larger role in the network structure. To assess the importance of such propagation, we built a parsimonious network model calibrated to match the micro-level data, and showed that approximately 18% of the observed drop in the aggregate output can be attributed to the propagating role of the supply chain network. Our counterfactual analysis highlights the role of small number of "important firms" in the network structure in generating sizable aggregate effect.

Chapter 3

Business Cycles with Input Complementarity

Jungsik (Jay) Hyun[1]

3.1 Introduction

Standard business cycle models make strong *a priori* structural assumptions about the supply side or the shape of the production function. The most widely used production function in macroeconomics models is the Cobb-Douglas production function. Despite its convenient tractable features, this production function imposes an excessively restrictive structure on how firms substitute their inputs (elasticity of substitution), the productivity of each input (marginal product of input) and the productivity of all inputs together (returns to scale). This production function was often justified with the Kaldor (1957) growth facts, but the recent decline of the labor share (Karabarbounis and Neiman 2014) calls this justification into question. Many researchers acknowledge this limitation and have started to adopt a more general Constant Elasticity of Substitution (CES) production function, but even this production function has important limiting properties: one single constant parameter governs the elasticity of substitution among inputs and returns to scale are assumed to be constant and fixed over time.

[1]This is a collaborated project with Ryan Kim, my former colleague at Columbia University who now joined Johns Hopkins SAIS.

We first empirically assess the plausibility of these restrictions by imposing and estimating a flexible Translog production function (Christensen et al. 1973, 1975). Compared to a CES, this function is another generalization of a Cobb-Douglas production function but allows more flexibility in input substitution, the marginal product of input, and returns to scale. The most important drawback of this production function, however, is that there are too many parameters to estimate with the limited variation in the data, precisely due to its flexible structure.[2] Instead of estimating all parameters in the production function, we utilize the first-order condition of firms for a particular input to estimate part of the production function to avoid this problem. We choose energy input to mitigate concerns related to the estimation and use panel data techniques with detailed industry-level data to recover the efficiency of energy input.

Through our estimation, we find a strong complementarity between energy and labor that leads to *procyclical* time-varying returns to scale, which goes beyond conventional production functions. The idea of time-varying returns to scale sounds striking yet simple. It reflects the idea that in boom periods, when firms employ more of each input, there are synergies among these inputs that lead to larger aggregate returns to scale compared to the periods of recession. A flexible Translog production function allows this complementarity-induced change in returns to scale, especially between labor and energy, as we identified in our framework. Note that the complementarity we found is very different from what is in the Leontief production function, which restricts returns to scale to be constant and invariant.

To integrate our empirical analysis into the business cycle model, we propose a normalized Translog production function that reflects the complementarity-induced procyclical returns to scale we find in the data, and, at the same time, being compatible with the balanced growth path. To capture the essence of the empirical analysis in the model, we only allow one additional parameter in the conventional Cobb-Douglas production function. This single parameter, which is mapped from our empirical analysis,

[2] It is also difficult to calibrate parameters given that there is no previous work that integrates an aggregate Translog production function into the business cycle model.

governs both the degree of complementarity between energy and labor and the cyclicality of returns to scale. To avoid making firms choose their own returns to scale, we introduce these factors as externalities for individual firms' optimization conditions, similar to what has been done in the previous literature that assumes increasing returns to scale.[3]

Armed with our new production function, we find that a simple business cycle model that relies on neither nominal rigidity nor countercyclical markup can generate strikingly consistent aggregate variable dynamics caused by demand shock.[4] It is well-known that a standard neoclassical model without nominal rigidity or countercyclical markups generates countercyclical real wages, capital, investment, and labor productivity with respect to demand shock (e.g., government spending shock), which is inconsistent with the business cycle dynamics if one believes a demand shock is a main source of business cycle fluctuation. Instead of incorporating markup countercyclicality, for which there is mixed empirical evidence,[5] we rely on complementarity-induced procyclical returns to scale to generate strong fluctuation in input demand caused by demand shock. This fluctuation in input demand leads to a favorable dynamic in aggregate variables with respect to all standard demand shocks, including changes in government spending, taste, and impatience.

[3]The assumption that individual firms take returns to scale of the economy as a given makes our model similar to internal increasing returns to scale models with monopolistic competition. See Benhabib and Farmer (1994) for a detailed explanation of internal and external increasing returns to scale.

[4]We assume monopolistic competition without nominal rigidity or countercyclical markup (Blanchard and Kiyotaki (1987); Benhabib and Farmer (1994)), similar to what has been done in the increasing returns to scale literature. Our results do not change if we make a perfect competition assumption with mild decreasing returns to scale at the steady state. Either monopolistic competition or decreasing returns to scale (at the steady state) is needed to make our model internally consistent. We assume only a negligible degree of price-cost markup (2%) in our model, so our benchmark monopolistic competitive economy with a normalized Translog technology can be interpreted as an "approximated" perfect competitive economy, and is thus directly comparable to a standard RBC model with a conventional Cobb-Douglas technology.

[5]The countercyclicality of markup plays a central role in New Keynesian models. Some papers find that the markups are countercyclical (e.g., Rotemberg and Woodford (1991, 1992); Christiano et al. (2005); Smets and Wouters (2007); Ravn et al. (2006); Bils et al. (2014)) while others find that markups are procycylical (e.g., Nekarda and Ramey (2013); Hall (2013); Kim (2016); Stroebel and Vavra (2019)).

To the best of our knowledge, this is the first paper to investigate the role of time-varying returns to scale in a business cycle framework. Our paper contributes to a growing literature that generalizes a conventional Cobb-Douglas production function (Antras (2004); Chrinko (2008); Karabarbounis and Neiman (2014); Oberfield and Raval (2014); Raval (2015); Atalay (2017); Koh and Santaeulàlia-Llopis (2017)). Most of this literature rejects a Cobb-Douglas production functional form assumption and finds complementarity among inputs.[6] Our empirical analysis complements this literature by generalizing a Cobb-Douglas production function and finds complementarity among inputs. One key difference is that we use a Translog production function that allows time-varying returns to scale. To the best of our knowledge, we are the first to build up a dynamic stochastic general equilibrium (DSGE) model with a Translog production function.

Our modeling techniques and results are closely related to the literature that incorporates increasing returns to scale in business cycle analysis (Benhabib and Farmer (1994, 1996); Schmitt-Grohé (2000); Benhabib and Wen (2004)). One of the biggest challenge in this literature is the weak empirical support (Basu and Fernald (1997, 2001); Basu and Kimball (1997)). Our empirical analysis and theoretical model do not violate the returns to scale results in Basu and Fernald (1997) as our production function features constant returns to scale on average (i.e. at the steady state), and is fully consistent with Basu and Kimball (1997) emphasis on the role of capital utilization since one interpretation of the energy input is a capital utilization.[7] The main conclusion is similar to that of Bai et al. (2012), who integrate product-market search friction into standard neoclassical model and generate plausible business cycle dynamics with respect to demand shocks.

The remainder of this paper is structured as follows. Section 3.2 discusses the empirical analysis, data, and results. Section 3.3 presents the normalized Translog

[6]One notable exception is Karabarbounis and Neiman (2014), who find that labor and capital are substitute; however, in estimating their parameters, they study long-term trends rather than business cycle movements.

[7]Energy or electricity is often used as a proxy for capital utilization. See, e.g., Burnside et al. (1995).

production function used in our business cycle models and illustrates the key mechanisms. Section 3.4 presents a simple neoclassical model with our proposed production function and shows the business cycle dynamic following demand shocks. Section 3.6 concludes.

3.2 Empirical Analysis

In this section, we estimate production function coefficients under the Translog production functional form assumption. We first present the data we use to estimate parameters, followed by our framework to recover the parameters and our estimated results.

3.2.1 Data

This paper uses annual six-digit North American Industry Classification System (NAICS) industry-level data from the NBER-CES Manufacturing Industries Database. This database records detailed information on 473 manufacturing industries from 1958 to 2009. The information is compiled from the Annual Survey of Manufacturers and the Census of Manufacturers. The variables in this database include gross output (value of shipment), value added, and 5-factor inputs (production worker, non-production worker, capital, material, and energy) for each industry over time. These data also records deflators for output, material, energy, investment, and wage bills for production workers and total employees. We report our summary statistics in Appendix B.1, and a more detailed explanation of this database can be found in Bartelsman et al. (2000).

The biggest advantage of these data over the aggregate data is that they allow us to exploit both time-series and cross-sectional variation, along with corresponding panel data techniques, to estimate production function parameters. This feature is especially important to estimate a Translog production function, which has excessive parameters to estimate. These data covers more than 50 years with five different disaggregated inputs, suitable for studying business cycle dynamics than are more detailed micro-level data with shorter time spans.

3.2.2 Empirical Framework

Estimating the production function with a Translog production is a key challenge for this project. Because of its flexible structure, there is an excessive number of parameters to estimate in this production function. For example, for the five input variables available in our data, we must estimate five parameters with a Cobb-Douglas production function and, six parameters with a CES production, but twenty parameters with a Translog production function. Even with our detailed industry-level data for many years, it is difficult to consistently estimate all twenty parameters in the Translog production function.

To overcome this challenge, we exploit a firm's first order condition to estimate key parameters that we can consistently estimate rather than estimating a full Translog production function.[8] Firms' optimization conditions deliver the relationship between the marginal product of a particular input and its price. Using this relationship, one can allow the flexible form for the efficiency of this input to estimate parameters using the limited variation in the data. The remainder of this section discusses how we implement this approach.

For simplicity, consider a following Translog production function with only two inputs, labor and capital:

$$\ln(Y) = \underbrace{\ln(A) + \beta_l \ln(L) + \beta_k \ln(K)}_{\text{Cobb-Douglas}} + \underbrace{\beta_{kl} \ln(L)\ln(K) + \beta_{ll} \ln(L)\ln(L) + \beta_{kk} \ln(K)\ln(K)}_{\text{second-order terms}} \tag{3.2.1}$$

where Y is output, A is productivity, L is labor, and K is capital. The first part of the production function is an entirely conventional Cobb-Douglas function. One can view this function as a first-order approximation of a general production function. A Translog

[8]The other way to proceed is either to reduce the number of inputs or to impose more structure on the production function. Reducing the number of inputs would worsen the problem of identification, as we are likely to omit the important variables that could be correlated with our regressors. Imposing more structure on the production function is inconsistent with our original motivation to relax the heavy parameterization of the production function.

production function is a simple extension, allowing both first- and second-order terms. Thus, a Translog production function can be thought of as a second-order approximation of a general production function. One can see that assuming $\beta_{lk} = 0, \beta_{ll} = 0, \beta_{kk} = 0$ recovers a Cobb-Douglas production function.

One can rewrite the above production function with five different inputs available in our data:

$$\ln(Y) = \underbrace{\ln(A) + \sum_{i=1}^{5} \beta_i \ln(V^i)}_{\text{Cobb-Douglas}} + \underbrace{\sum_{i=1}^{5} \sum_{j \leq i} \beta_{ij} \ln(V^i) \ln(V^j)}_{\text{second-order terms}} \tag{3.2.2}$$

where V^i is one of five different inputs indexed by i (production worker, non-production worker, capital, material, and energy).

The simplest way to recover the parameters in the above equation is to run a regression based on equation (3.2.2), treating productivity as a residual. This approach, however, has two key problems. First, there are too many parameters to estimate, which is extremely demanding in terms of the variation in the data. Second, flexible inputs are likely to be correlated with productivity, generating inconsistent estimates of the parameters.[9]

To avoid the two concerns listed above, we exploit a firm's first-order condition. Without loss of generality, all firms choose a particular input V^1 to solve the following cost-minimization problem with a Translog production function:

$$\begin{aligned} \min_{V^1} \; & W^1 V^1 + \sum_{i=2}^{5} W^i V^i \\ \text{s.t.} \; & \ln(Y) = \ln(A) + \sum_{i=1}^{5} \beta_i \ln(V^i) + \sum_{i=1}^{5} \sum_{j \leq i} \beta_{ij} \ln(V^i) \ln(V^j) \end{aligned}$$

where W^i is the nominal price of input V^i. The problem is written such that we suppress the expression that does not have a particular input V^1 for the cost function. Forming

[9] Despite these problems, we still run a regression based on equation (3.2.2) with various methods, including demeaning and Olley and Pakes (1996). Our results are generally consistent with our main results that use first-order condition. The results are available upon request.

a Lagrangian, taking derivatives with respect to V^1, and dividing both sides by output price yields the following first order condition:

$$\underbrace{\frac{W^1}{P}}_{\text{real input price}} = \frac{1}{\mu}\underbrace{\left[\beta_1 + 2\beta_{11}\ln(V^1) + \sum_{i=2}^{5}\beta_{i1}\ln(V^i)\right]\frac{Y}{V^1}}_{\text{marginal product of input}} \tag{3.2.3}$$

where μ is a wedge between real input price and the marginal product of input. Note that assuming $\beta_{i1} = 0$ for all $i = 1, ..., 5$ recovers the conventional first-order condition under the Cobb-Douglas production function. From now on, we simplify the notation by using the $\beta'_{11} \equiv 2\beta_{11}$ and $\beta'_{1i} \equiv \beta_{1i}$ for all $i = 2, ..., 5$.

By multiplying $\frac{V^1}{Y}$ on both sides and rearranging terms, we get the following expression:

$$s^1 = \frac{\left[\beta_1 + \sum_{i=1}^{5}\beta'_{i1}\ln(V^i)\right]}{\mu} \tag{3.2.4}$$

where $s^1 \equiv \frac{W^1V^1}{PY}$. The left-hand side is the input share out of total sales, and the right-hand side is the efficiency of input V^1 divided by the wedge, μ. The term $\left[\beta_1 + \sum_{i=1}^{5}\beta'_{i1}\ln(V^i)\right]$ is an output elasticity with respect to input V^1, which is a unit-free measure of the marginal product of input.

In the next section, we utilize equation (3.2.4) to estimate parameters associated with the Translog production function. Our goal is to estimate β'_{i1} for all i to better understand substitutability and complementarity among inputs.

3.2.3 Estimation

To take the equation (3.2.4) to the data, we allow input share (s^1), wedge (μ), and all inputs (V^i) to vary across industry and time:

$$s^1_{jt} = \frac{\left[\beta_1 + \sum_{i=1}^{5}\beta'_{i1}\ln(V^i_{jt})\right]}{\mu_{jt}}$$

where j is industry and t is time. To make the above equation linear in parameters, we log-linearize the above equation around the steady state to recover the following equation:

$$\hat{s}^1_{jt} = \sum_{i=1}^{5} \left\{ \frac{\beta'_{i1}}{\mu s^1} \right\} \hat{V}^i_{jt} - \hat{\mu}_{jt} \tag{3.2.5}$$

where $\hat{x}$ denotes the log-deviation from the steady-state value of variable x, and $\mu s^1 = \beta_1 + \sum_{i=1}^{5} \beta_{i1} \ln(V^i)$. We assumed that the steady-state values of μ and s^1 do not depend on the industry. The empirical counterpart of the above equation we use is the following:

$$\ddot{s}^1_{jt} = \sum_{i=1}^{5} \delta_{i1} \ddot{V}^i_{jt} - \ddot{\mu}_{jt} \tag{3.2.6}$$

where $\ddot{x}_{jt} = \ln x_{jt} - \frac{1}{J} \sum_{j=1}^{J} \ln x_{jt}$ for variable x. We exploit the panel data to detrend each variable by subtracting the time-specific component across the industry.

Because s^1_{jt} and V^i_{jt} are observed in the data, we can use the above equation to run a regression. The idea of estimating parameters β_{i1} is to regress $\hat{s}^1_{jt}$ on all five inputs $\hat{V}^i_{jt}$ and to treat wedges $\hat{\mu}_{jt}$ as residual based on equation (3.2.6). Based on the above equation, we can identify $\delta_{i1} \equiv \frac{\beta_{i1}}{\mu s^1}$ and recover β_{i1} by calibrating μs^1. Given that minimizing with respect to each input delivers equation (3.2.6) for each input, we can, in principle, run a regression for five different equations that corresponds to five different input shares.

There are two crucial problems, however, with running a regression based on the above equation. First, the wedge might contain components that are possibly correlated with the inputs we allow in the equation above, generating the confounding relationship. For example, the wedge term may reflect adjustment costs or price-cost markup, which are possibly correlated with the input variables. Second, since the left-hand side variable has input V^1 in s^1, there is a mechanical correlation between the left-hand side variable and the right-hand side variable. This will induce the estimated coefficient to be positive mechanically.

To address the first concern about the confounding relationship, we only choose energy input as a choice variable (V^1) and estimate using just this particular input. The utilization of energy input is less likely to suffer from concerns such as adjustment cost and monopsony. In addition, we demean our variable across time within industry to get rid of any industry-specific component in our variables that could potentially correlate with the wedge component. The demeaning leads to the following empirical model:

$$\dddot{s}^{1}_{jt} = \sum_{i=1}^{5} \delta_{i1} \dddot{V}^{i}_{jt} - \dddot{\mu}_{jt} \tag{3.2.7}$$

where $\dddot{x}_{jt} = \ddot{x}_{jt} - \left(\frac{1}{T} \sum_{t=1}^{T} \ddot{x}_{jt} \right)$ for variable x. Finally, we use lagged double-demeaned input prices as instrumental variables to generate plausibly exogenous variation across inputs that are unlikely to be correlated with the remaining wedges, $\dddot{\mu}_{jt}$. Our instrumental variable strategy also addresses the second concern, as it will generate variation that does not lead to a mechanical correlation of variables.

It is useful to discuss identification with equation (3.2.7) to understand what variation in the data identifies β_{i1}. Ideally, we need random variation in inputs that affect the share of energy. For example, if the share of energy input increases with an exogenous increase in labor input, we interpret this relationship as an increase in energy efficiency due to the labor input under the Translog production functional form assumption. In this case, energy and labor input are complements, and the coefficient β_{i1} captures this complementarity. The exogenous variation in inputs stem from lagged input prices, and with demeaning, we only need to assume that last year's idiosyncratic input prices affect this year's input share through this year's idiosyncratic input usage, not through this year's idiosyncratic wedge to identify the parameters of interest.

3.2.4 Estimation Results

Table 3.1 presents the estimated parameters based on equation (3.2.7), highlighting the complementarity between energy and production worker. Based on column (1), we find that energy input follows the law of diminishing returns and that most other inputs, especially production workers, are complements to energy. First, the coefficient in front of energy, β_1, is negative. This states that energy input becomes less efficient as a firm uses more energy, thereby capturing the law of diminishing returns to energy. Second, coefficients in front of inputs other than non-production workers are positive, implying that energy becomes more efficient as a firm uses more of these inputs. This

Table 3.1: Elasticity (θ^{e}_{jt}) estimation based on equation (3.2.7)

	Dependent Variable: $\ddot{\ddot{s}}^{e}_{jt}$				
	IV ($\ddot{\ddot{W}}^{k}_{j,t-1}, \ddot{\ddot{W}}^{k}_{j,t-2}$)			OLS	
	(1)	(2)	(3)	(4)	(5)
energy	-0.56^{**}	-0.4^{**}	-0.4^{**}	0.85^{***}	0.85^{***}
	(0.23)	(0.16)	(0.16)	(0.03)	(0.03)
material	0.17	0.32^{**}	0.29^{*}	-0.41^{***}	-0.42^{***}
(- energy)	(0.22)	(0.15)	(0.16)	(0.03)	(0.03)
labor (p)	1.69^{***}	1.41^{***}	1.33^{***}	-0.33^{***}	-0.33^{***}
	(0.45)	(0.31)	(0.29)	(0.03)	(0.03)
labor (np)	-0.59^{*}	-0.45^{*}	-0.39	-0.12^{***}	-0.12^{***}
	(0.33)	(0.26)	(0.26)	(0.02)	(0.02)
capital	0.51			-0.03	
	(0.44)			(0.02)	
output price			-0.03		
(lagged)			(0.1)		
obs	23,220	23,220	23,220	24,166	24,166
J-test	6.04	6.76	8.73		
(p-value)	(0.3)	(0.34)	(0.19)		

Note. The regression result based on equation (3.2.7): $\ddot{\ddot{s}}^{e}_{jt} = \sum_{k=1}^{K} \beta_k \ddot{\ddot{V}}^{k}_{jt} - \ddot{\ddot{\mu}}_{jt}$. Columns (1), (2) and (3) show the regression result with instrumental variables, and (4) and (5) show the OLS result. Five different inputs are used in this regression: energy, material that excludes energy, non-production worker, production worker, and capital. All inputs and lagged input prices are logged and then double-demeaned across industries and across time. Standard errors in parentheses are clustered on the NAICS industry code. J-test refers to Hansen's J-statistics for overidentifying restriction. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

states that these inputs are complements to energy. In particular, the coefficient in front of production worker is economically and statistically significant, implying that it is a strong complement to energy input.[10] Non-production worker is a substitute since the coefficient of a non-production worker is negative, but the result is marginally statistically significant with a t-statistics of 1.79.

Controlling the lagged output price does not change the result as shown in column (3). In particular, the coefficient in front of the lagged output price is negligible and not statistically significant, implying that potential persistency in wedges is unlikely to cause inconsistency in our estimates.[11] Columns (1) and (4) include capital in the regression, whereas (2) and (5) exclude capital; however, the estimated coefficient of capital is neither economically nor statistically significant. Finally, notice that all coefficients are statistically significant except the capital input coefficient. This result implies that we reject constant θ^e_{jt}, or a Cobb-Douglas production functional form assumption with respect to energy input.

3.2.5 Returns to Scale Cyclicality

The estimated coefficients inform us about the returns to scale of the United States production. Formally, returns to scale with our production function is defined as follows:

$$\begin{aligned}\gamma(V^1_{jt},...,V^5_{jt}) &\equiv \left.\frac{\partial \ln(Y(\lambda V^1_{jt},...,\lambda V^5_{jt}))}{\partial \ln(\lambda)}\right|_{\lambda=1} \\ &= \sum_{k=1}^{5}\left[\beta_k + \sum_{i=1}^{5}\beta_{ik}\ln(V^i_{jt})\right]\end{aligned}$$

where $\gamma(V^1_{jt},...,V^5_{jt})$ measures the percentage increase in output from one percent increase in all inputs.[12] Under the conventional Cobb-Douglas production function, γ_{jt} is constant

[10] If we only allow labor input instead of both production worker and non-production worker, we still find that labor input is a strong complement to energy input.

[11] We treat lagged output price as a control in our regression, but making the lagged output price endogenous and using lagged input prices as instruments does not change the result.

[12] Consistent with the previous section, we redefined $2\beta_{kk}$ as β_{kk} for notational simplicity.

across industry j and time t and equal to $\sum_{k=1}^{5} \beta_k$. In this case, $\gamma > 1$ refers to increasing returns to scale, $\gamma = 1$ refers to constant returns to scale, and $\gamma < 1$ refers to decreasing returns to scale. Once we allow a more flexible production function such as a Translog production function, γ_{jt} need not be constant and depends on inputs.

The insight from Hall (1990) and Basu and Fernald (1997) allows our parameter estimates to inform on the cyclicality of returns to scale. Suppose we derive equation (3.2.4) for all five inputs: $s_{jt}^k = \frac{\left[\beta_k + \sum_{i=1}^{5} \beta_{ik} \ln(V_{jt}^i)\right]}{\mu_{jt}}$ for all k. Rearranging the equation and summing up across k, we have $\gamma_{jt} \equiv \sum_{k=1}^{5} \left[\beta_k + \sum_{i=1}^{5} \beta_{ik} \ln(V_{jt}^i)\right] = \mu_{jt} \sum_k s_{jt}^k$.[13] Because $\sum_k s_{jt}^k$ is observed in the data and $\ln(\mu_{jt})$ can be recovered as a residual from our main regression, we can assess the cyclicality of returns to scale parameter.[14] Table **??** presents the regression result based on $\Delta \widehat{\ln(\gamma_{jt})} = \lambda_j + \lambda_t + \gamma_1 \Delta \ln(vship_{jt}) + \epsilon_{jt}$.

Column (1) presents regression results based on γ_{jt} recovered from markups estimated in the previous section. The coefficient is positive, and it is both economically and statistically significant, implying that returns to scale is strongly procyclical.

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[13]We are assuming that the wedge μ_{jt} does not depend on particular factor inputs k. This is a common assumption in macroeconomic literature and consistent with canonical DSGE models without adjustment costs. If we introduce factor-specific adjustment cost, the formula becomes

$$\begin{aligned} \gamma_{jt} &\equiv \sum_{k=1}^{5} \left[\beta_k + \sum_{i=1}^{5} \beta_{ik} \ln(V_{jt}^i)\right] \\ &= \mu_{jt} \sum_k \left(s_{jt}^k + \phi_{jt}^k\right) \end{aligned}$$

where now μ_{jt} is the common component of wedge and ϕ_{jt}^k is the factor-specific component of wedge. As discussed before, energy input ($k = 1$) is less likely to suffer from concerns such as adjustment cost, and thus we can still recover the common wedge μ_{jt} from a residual of our main regression under the assumption of $\phi_{jt}^1 = 0$. Therefore, as long as ϕ_{jt}^k for $k \geq 2$ has tendancy to be procyclical (or at least acyclical), our procyclical returns to scale result will be strengthened. This turns out to be the case for the labor input adjustment as discussed in Rotemberg and Woodford (1999).

[14]We can only assess cyclicality γ_{jt} and cannot recover γ_{jt} parameters because wedges (or residuals) are only identified up to constant.

Table 3.2: Returns to Scale Cyclicality

	(1)	(2) NR (2013)	(3) BKM (2014)	(4)	(5)
			$\widehat{\ln(\gamma_{jt})}$		
$\ln(\theta_{jt})$	1st order poly	constant	constant	constant	CES
V^1_{jt}	energy	labor	material	energy	energy
$\Delta\ln(vship_{jt})$	1.08	0.29	-0.11	0.40	0.31
	[1.01, 1.14]	[0.26, 0.31]	[-0.13, -0.10]	[0.36, 0.43]	[0.28, 0.33]
industry FE	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes
R^2	.3238	.3157	.1629	.1813	.2021
obs	23,693	23,694	23,694	23,694	23,694
$\rho_{\gamma,y}$	0.49	0.49	-0.35	0.26	0.24
	[0.46, 0.51]	[0.47, 0.52]	[-0.38, -0.32]	[0.24, 0.29]	[0.22, 0.27]

Note. The regression result based on the following equation: $\Delta\widehat{\ln(\gamma_{jt})} = \lambda_j + \lambda_t + \gamma_1\Delta\ln(vship_{jt}) + \epsilon_{jt}$. Column (1) shows the regression result based on γ_{jt} constructed from the estimated wedges. Column (2) recovers γ_{jt} by assuming that the wedges are equal to the inverse labor shares as in Nekarda and Ramey (2013). Column (3) recovers γ_{jt} by assuming that the wedges are equal to the inverse material share as in Bils et al. (2014). Column (4) shows the result based on the wedges equal to the inverse energy shares assumption and column (5) shows the result based on the estimated wedge with a CES production function assumption. The wedges based on the CES production function are estimated using constrained regression and double-demeaning techniques with lagged double-demeaned input prices as instruments. The 95% confidence intervals are constructed with the standard errors that are cluster bootstrapped based on the industry with 5000 repetitions. $\rho_{\gamma,y} = Corr(\Delta\widehat{\ln(\gamma_{jt})}, \Delta\ln(vship_{jt}))$ is reported separately.

3.3 Normalized Translog Production Function

This section proposes a production function, the normalized Translog production function, that captures the key insight in our empirical analyses. The proposed production function exhibits input complementarity that leads to procyclical returns to scale as in our empirical analyses in the short run, f^{SR}, while it collapses into the conventional constant returns to scale in the long run, f^{LR}.[15]

Reflecting the important role of energy input in our empirical analysis, we explicitly consider energy as third factor input in addition to capital service and labor. We denote capital service, labor, and energy inputs as K^s, L, and E, respectively, where we use subscript "ss" to indicate steady state of those variables. The productivity is denoted by ε^a, where we normalize its steady state level to unity ($\varepsilon^a_{ss} = 1$). We use lowercase letters to indicate variables normalized by their steady state values : $k^s_t \equiv \frac{K^s_t}{K^s_{ss}}$, $l_t \equiv \frac{L_t}{L_{ss}}$, $e_t \equiv \frac{E_t}{E_{ss}}$.

Our production technology is defined by

$$\begin{aligned} \text{Short-run}: \ Y_t \ &= f^{SR}\left(k^s_t, l_t, e_t; \Phi_t\right) \cdot f^{LR}\left(K^s_{ss}, L_{ss}, E_{ss}; \Phi\right) \\ \text{Long-run}: \ Y_{ss} &= f^{LR}\left(K^s_{ss}, L_{ss}, E_{ss}; \Phi\right) \end{aligned} \tag{3.3.1}$$

where

$$\begin{aligned} & f^{SR}\left(k^s_t, l_t, e_t; \Phi_t\right) \equiv \varepsilon^a_t \cdot (k^s_t)^{\alpha_k} \cdot l_t^{\alpha_l + \beta_{el} \log \tilde{e}_t} \cdot e_t^{\alpha_e + \beta_{el} \log \tilde{l}_t} \left(= \frac{Y_t}{Y_{ss}} \equiv y_t\right) \\ & f^{LR}(K_{ss}, L_{ss}, E_{ss}; \Phi) \equiv (K^s_{ss})^{\alpha_k} L^{\alpha_l}_{ss} E^{\alpha_e}_{ss} \end{aligned} \tag{3.3.2}$$

with

$$\begin{aligned} \Phi_t &\equiv [\alpha_k, \alpha_l + \beta_{el} \log \tilde{e}_t, \alpha_e + \beta_{el} \log \tilde{l}_t]' \\ \Phi &\equiv [\alpha_k, \alpha_l, \alpha_e]' \end{aligned} \tag{3.3.3}$$

Here, $\tilde{l}_t$ and $\tilde{e}_t$ indicate cross-sectional average of l_t and e_t, respectively, which individual firms take as given.

[15] Distinguishing short-run and long-run production functions could also be found in Cantore et al. (2015) and Koh and Santaeulàlia-Llopis (2017) in the context of CES technology.

As in Cantore et al. (2015), the short-run production function, f^{SR}, is expressed as a deviation from the long-run (i.e. steady state) production function, f^{LR}. In the function, Φ_t is a vector of *endogenous* parameters that governs potentially time-varying short-run returns to scale of the economy. We say "endogenous" parameters because the time-varying components are endogenously determined in equilibrium, although individual firms take these values as given.[16] Φ is a vector of strictly exogenous parameters that govern (time-invariant) long-run returns to scale of the economy.[17]

In the equilibrium, $\tilde{l}_t = l_t$ and $\tilde{e}_t = e_t$ hold. If we evaluate Φ_t at the steady-state (or, at the long-run horizon), we have $\Phi_{ss} = \Phi$ since $\log \tilde{e}_{ss} = \log\left(\frac{\tilde{E}_{ss}}{E_{ss}}\right) = 0$ and $\log \tilde{l}_{ss} = \log\left(\frac{\tilde{L}_{ss}}{L_{ss}}\right) = 0$.

By unifying the short-run and long-run production functions, we get the following expression:

$$Y_t = \varepsilon_t^a \left[(K_t^s)^{\alpha_k} L_t^{\alpha_l} E_t^{\alpha_e}\right] \cdot \left[\left(\frac{L_t}{L_{ss}}\right)^{\beta_{el} \log\left(\frac{\tilde{E}_t}{E_{ss}}\right)} \left(\frac{E_t}{E_{ss}}\right)^{\beta_{el} \log\left(\frac{\tilde{L}_t}{L_{ss}}\right)}\right] \tag{3.3.4}$$

3.3.1 Properties of the Normalized Translog Production Function

In this section, we discuss properties of the normalized translog production function.

(i) The complementarity between energy input and labor input is reflected by a single parameter $\beta_{el} > 0$. If $\beta_{el} > 0$, our model features complementarity-induced procyclical returns to scale in the short-run, provided that the dynamics of $\log \tilde{e}_t$ and $\log \tilde{l}_t$ are procyclical.

(ii) If we evaluate the production function (3.3.1) in the equilibrium (i.e., if we impose $e_t = \tilde{e}_t$ and $l_t = \tilde{l}_t$), then the short-run production function has the Translog

[16] Because the time-varying components in Φ_t are endogenously determined in equilibrium, the terminology "parameter" can be somewhat misleading. Still, we call it a (endogenous) parameter because it characterizes returns to scale of the economy individual firms take as exogenous. The long-run value of Φ_t, Φ, is a vector of strictly exogenous parameters in the sense that it consists only of deep structural parameters. We will discuss these properties in more detail in Section 3.3.1.

[17] We assume constant returns to scale in the long-run.

expression (which is why we call it normalized "Translog") :

$$\log y_t = \log \varepsilon_t^a + \alpha_k \log k_t^s + \alpha_l \log l_t + \alpha_e \log e_t + \beta_{el} \cdot 2 \log(l_t) \log(e_t)$$

(iii) The bracket term in the right hand side of (3.3.4) consists of variables normalized by their steady state values (which is why we call the production function as "normalized" Translog). This is the result of defining the short-run production function, as a deviation from the long-run production function. This kind of normalization can be also found in Koh and Santaeulàlia-Llopis (2017), who also distinguish between the short-run and long-run production functions to allow time-varying CES parameter in the short run. As in that paper, the normalization of inputs with their steady state counterparts makes the production function collapse into a conventional Cobb-Douglas at the steady state.

There are two important advantages to doing so. First, it facilitates the calculation of the steady state of the economy, as the steady state is identical to that of the model without complementarity-induced procyclical returns to scale. This also makes our model directly and easily comparable to the version without procyclical returns to scale, since the steady state is identical across two models.

Second, and more importantly, such normalization makes the model compatible with balanced-growth path.[18] In this sense, the normalization implies that the input complementarity we introduce (and the resulting procyclical returns to scale) is a short-run characteristic that does not affect the long-run growth of the economy.

(iv) Despite procyclical returns to scale, the production function becomes *scale-free* up to the first order because log-linearizing the production function yields exactly identical form as the log-linearized Cobb-Douglas production function. To see this, consider the equilibrium where we have $\tilde{E}_t = E_t$ and $\tilde{L}_t = L_t$. The first-order approximation of our production function is given by

$$\hat{Y}_t = \hat{\varepsilon}_t^a + \alpha_k \hat{K}_t^s + \alpha_l \hat{L}_t + \alpha_e \hat{E}_t$$

where for arbitrary variable X, $\hat{X}_t \equiv \log \frac{X_t}{X_{ss}} \equiv \log x_t$.

[18] Although we do not consider growth explicitly in the model in Section 3.4, it is straightforward to incorporate growth into the model.

Hence, the procyclicality of returns to scale does not generate any additional fluctuation of output by itself and behaves exactly the same as conventional Cobb-Douglas up to the first order. All the interesting dynamics arise through the first-order condition of the firm. This *scale-free* characteristic is one of the distinguishing features of the model with normalize Translog production function compared to the models with conventional increasing returns to scale.

(v) The short-run and long-run returns to scale of the economy is given by

$$\begin{aligned} &\text{Short-Run Returns to Scale } (RTS_t) = \alpha_k + \alpha_l + \alpha_e + \beta_{el} \left[\log \tilde{e}_t + \log \tilde{l}_t \right] \\ &\text{Long-Run Returns to Scale } (RTS_{ss}) = \alpha_k + \alpha_l + \alpha_e = 1 \end{aligned} \tag{3.3.5}$$

Reflected by the cross-sectional average variables $\tilde{e}_t$ and $\tilde{l}_t$, individual firms take the returns to scale of the economy as given.

This assumption reflects the idea that the returns to scale is more of an economy- or industry-wide characteristic than a firm-specific characteristic. Hence, a single firm's change of input does not affect the returns to scale, but when all firms jointly increase (decrease) labor and energy inputs, then the returns to scale parameter changes toward IRS (DRS).

Also, this assumption is technically required to guarantee that firms' optimizing behavior is well-characterized by the first-order conditions. If an individual firm can internalize the change in returns to scale of the economy, then by choosing larger amount of labor and energy inputs, each firm can make the returns to scale it faces arbitrarily large. This induces firms to choose infinite amount of labor and energy inputs. By assuming individual firms do not internalize the change in returns to scale, this issue no longer arises.[19]

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[19]This assumption makes our model similar to an internal increasing returns to scale (IRS) model. In contrast to an external IRS mode, an internal IRS model requires some degree of market power of individual firms. Following Benhabib and Farmer (1994), we also assume a monopolistic competitive model, but with a negligible amount of constant markup (2% markup). Hence, our model can be considered an "approximation" of a perfect competitive model.

3.3.2 Business Cycle Implications: Intuition of the Mechanism

Before building up a business cycle model with our proposed production function to derive macroeconomic implications, we illustrate the key predictions of the model and provide intuition behind them in this section. An important feature of the complementarity-induced procyclicality of returns to scale is that it generates procyclical dynamics of real wage under positive demand shock without relying on nominal rigidities or countercyclical markups. Canonical neoclassical business cycle models have difficulties in generating such behavior. Also, our proposed production function generates strong cyclical movement of input demand, inducing amplification of shocks.

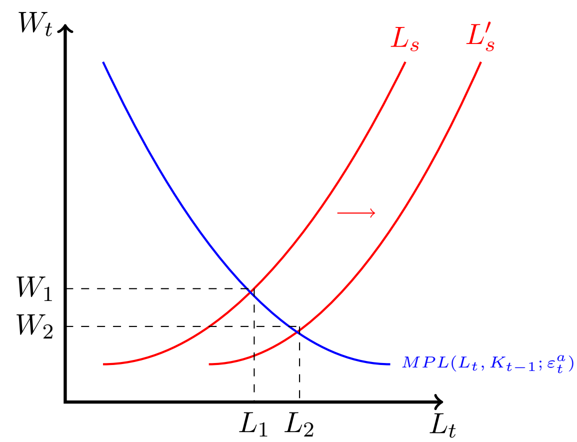
In Figure 3.1, we shows how both traditional countercyclical markup and complementarity-induced procyclical returns to scale explain an increase in wage and labor when firms face a positive demand shock. As a benchmark, Figure 3.1a shows the labor market under the standard RBC model with constant returns to scale technology. Because the production function only depends on labor, capital, and productivity, the marginal product of labor only depends on labor, capital and productivity. When firms experience a positive demand shock, they can only adjust labor input since the capital input is a predetermined variable and productivity is not correlated with positive demand shock. In other words, they cannot shift the labor demand schedule. Only the labor supply schedule shifts to the right which results in increased employment.[20] However, this effect leads to a decrease in wages and an increase in labor input because of a positive demand shock, which cannot be reconciled with empirical evidence.[21]

Markup countercyclicality has been proposed to reconcile this seemingly contradictory prediction as in Figure 3.1b. In models with nominal price rigidity, for example,

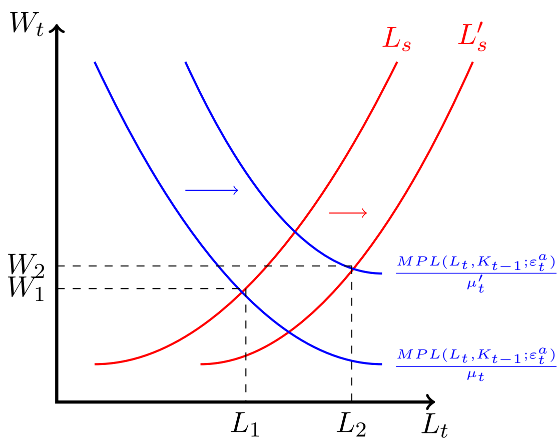
[20] The labor supply shifts to the right with respect to demand shock for various reasons (Rotemberg and Woodford 1991). For example, the labor supply can shift to the right because of an increase in the marginal utility of wealth resulting from an increase in government spending.

[21] Real wage procyclicality with respect to demand change follows the argument in Rotemberg and Woodford (1991, 1992). There is evidence of weakly countercyclical real wages conditional on government spending (Nekarda and Ramey 2011), but we are not aware of any paper that finds strong countercyclical real wages conditional on demand change predicted by conventional models with a perfectly competitive market.

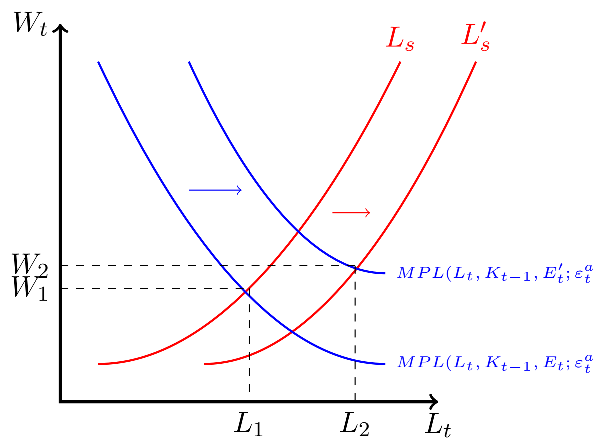
Figure 3.1: Labor Market: Input Complementarity vs. Markup Countercyclicality



(a) Standard RBC with CRS



(b) Markup Countercyclicality with CRS



(c) Complementarity-induced Procyclical RTS

Note. Y-axis is real wage and x-axis is labor. The figures show how the labor market reacts to positive demand shock (a) in a standard RBC model with constant returns to scale, (b) in a model with markup countercyclicality with constant returns to scale, and (c) in a model with complementarity-driven procyclical returns to scale.

markups fall when firms face positive demand shocks because of rigid prices and increases in marginal cost. The decrease in markups allows the labor demand schedule to shift to the right, capturing both the increase in labor and the increase in wages (or constant wages) at the equilibrium.

Input complementarity that induces procyclical returns to scale, however, can also shift the labor demand schedule when firms face positive demand shock as shown in Figure 3.1c. Suppose we allow other flexible inputs such as energy, which has strong complementarity with the labor input, in the production function. In that situation, the marginal product of labor depends not only on labor, capital, and productivity but also on energy. Now consider a positive demand shock. First, this shifts the labor supply schedule as in a standard RBC model, which increases labor input (movement along the labor demand curve). This initial increase of labor increases the marginal productivity of energy, which induces firms to hire more energy. This increase of energy input increases the marginal productivity of labor, which eventually shifts the labor demand schedule (shift of the labor demand curve). This interaction between energy input and labor input is strong enough to make real wages increase when complementarity between these two inputs generates the procyclicality of returns to scale.[22] This also generates larger movements of equilibrium labor, which induces amplification of the shock.[23]

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[22]We emphasize complementarity-induced "procyclical returns to scale" because neither the complementarity itself nor allowing capital utilization is sufficient to generate procyclical real wage with respect to demand shock. For example, a model with capital utilization (or energy input as in our specification) with constant returns to scale cannot generate procyclical returns to scale (regardless of using Cobb-Douglas or more general CES production function). Only under very restrictive environments, such as inelastic labor supply or utility function without negative wealth effects, could potentially generate procyclical real wage dynamics under pre-specified cases. This is why we propose a flexible production function that is not restricted to constant returns to scale such as the widely used CES production function. In the Appendix C.3.2, we compare the impulse response of the normalized Translog, Cobb-Douglas with energy input, and Cobb-Douglas with capital utilization (without energy input).

[23]Such amplification is not a result of introducing energy input. It comes from interaction between energ and labor inputs induced by strong complementarity. This will be clear in our numerical exercise in Section 3.4.

3.4 The Model with Input Complementarity

In this section, we present a simple dynamic stochastic general equilibrium model with the normalized Translog production function. We make three deviations from the canonical real business cycle models: (i) we use the normalized Translog production function that generates complementarity-induced procyclical returns to scale ; (ii) we explicitly consider energy as an input and allow complementarity with labor to reflect our empirical findings ; (iii) we cast the model in a monopolistic competitive framework (as in conventional internal increasing returns to scale model) in which final goods firms aggregate differentiated intermediate goods and sell them to households.[24]

In Figure 3.2, we plot the time series of labor and energy inputs in the United States. There is a strong positive comovements of these variables. Positive comovement of labor and energy, combined with our complementarity parameter $\beta_{el} > 0$ will induce procyclical returns to scale under the normalized Translog production function.

3.4.1 Households

The economy is populated by a large number of identical infinitely lived households. The representative household chooses sequence of consumption C_t, labor supplied L_t, investment I_t, capital stock K_t, and borrowing B_t to solve

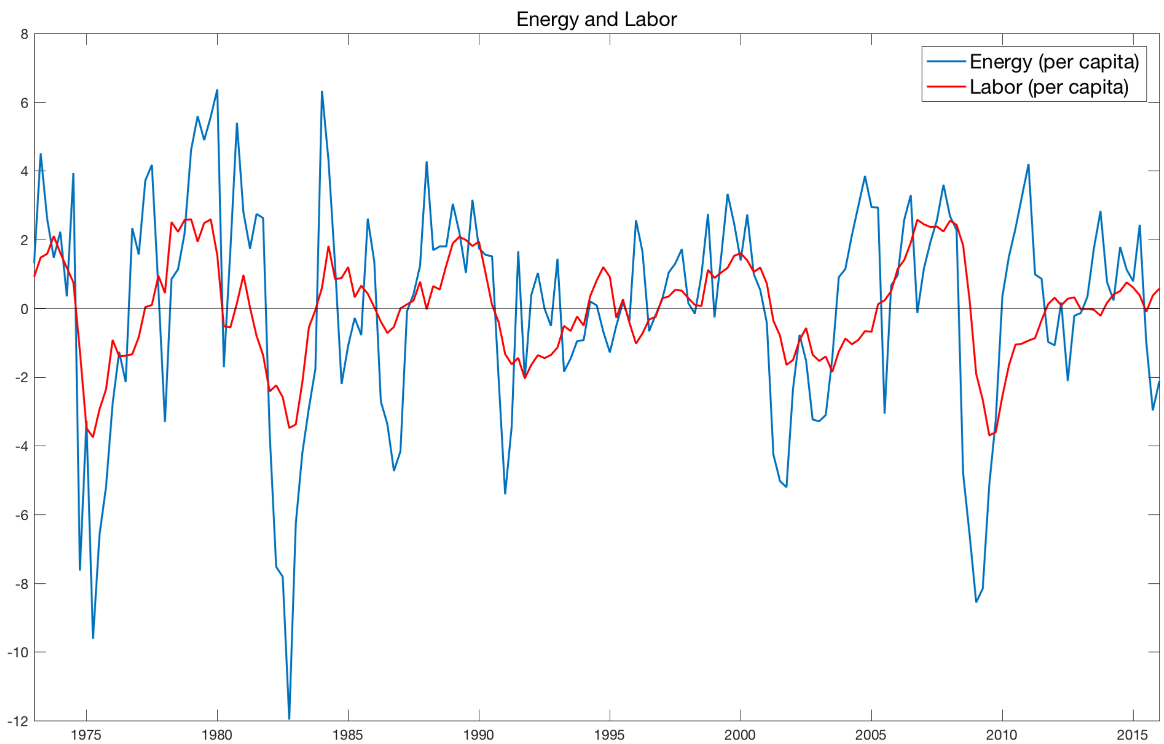
$$\max_{C_t, L_t, I_t, K_t, B_t} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_t)$$

subject to the following budget constraint

$$C_t + I_t + \frac{B_t}{R_t} + T_t = R_t^k K_{t-1} + B_{t-1} + W_t L_t + \Pi_t + \Pi_t^e$$

[24] Since the returns to scale is procyclical, the production function could feature increasing returns to scale (in the boom periods). Thus, as in internal increasing returns to scale model, we need to have some mild degree of markups to make the model well-defined. Alternatively, we could cast the model in perfect competition with additional assumption that the production function features decreasing returns to scale at the steady state. Then as long as the returns to scale parameter (which is determined endogenously) has value less than one, the model is well-defined.

Figure 3.2: Positive Comovement of Labor and Energy (HP filtered



Note. Data source : FRED and US Energy Information Administration. Labor is measured by log of hours per captia, and energy input is measured by log of total energy consumed by the industrial sector (measured in Btu) divided by population. We plot the HP filtered variables at the quarterly level. Y axis represents a percent deviation from the trend defined by the HP filter.

and the law of motion of capital

$$K_t = I_t + (1-\delta) K_{t-1} \tag{3.4.1}$$

where R is a (gross) risk-free rate, R^k is real rental rate of capital, W is real wages, T is tax paid by the household in terms of consumption units, Π is the dividend paid to the households by the intermediate goods firms, and Π^e is the dividend paid by the energy firms. We assume $U_{C,t} > 0$, $U_{CC,t} \leq 0$, $U_{L,t} \leq 0$, $U_{LL,t} \leq 0$.

The FOCs are given by

$$U_C(C_t, L_t) = \beta E_t \left[\, U_C(C_{t+1}, L_{t+1}) \left\{ R^k_{t+1} + 1 - \delta \right\} \right] \tag{3.4.2}$$

$$W_t = -\frac{U_L(C_t, L_t)}{U_C(C_t, L_t)} \tag{3.4.3}$$

$$U_C(C_t, L_t) = \beta R_t E_t \left[U_C(C_{t+1}, L_{t+1}) \right] \tag{3.4.4}$$

3.4.2 Final Goods Producers

The final goods producers purchase differentiated intermediate goods products and aggregate them using the Dixit-Stiglitz CES technology. We assume that the final goods sector is perfectlyd competitive. Each final goods producer solves

$$\max_{Y_t, Y_{it}} Y_t - \int_0^1 P_{it} Y_{it} di$$

subject to

$$Y_t = \left[\int_0^1 Y_{it}^{\lambda} di \right]^{1/\lambda}$$

where Y_t, Y_{it} are the final and intermediate goods, respectively, and P_t^i is intermediate goods price. λ is the inverse of markup.

The optimality implies

$$Y_{it} = Y_t \cdot P_{it}^{1/(\lambda-1)} \tag{3.4.5}$$

3.4.3 Intermediate Goods Producers

We assume a monopolistic competitive intermediate goods sector. The intermediate goods producers have technology characterized by the normalized Translog production function characterized by (3.3.1) and (3.3.4):

$$Y_{it} = \varepsilon_t^a \left[(K_{it}^s)^{\alpha_k} L_{it}^{\alpha_l} E_{it}^{\alpha_e}\right] \cdot \left[\left(\frac{L_{it}}{L_{ss}}\right)^{\beta_{el} \log\left(\frac{\tilde{E}_t}{E_{ss}}\right)} \left(\frac{E_{it}}{E_{ss}}\right)^{\beta_{el} \log\left(\frac{\tilde{L}_t}{L_{ss}}\right)}\right] \tag{3.4.6}$$

Here, Y_{it} is intermediate goods output, K_{it}^s is capital services used in production, L_{it} is labor input, and E_{it} is energy input. $\tilde{L}_t$ and $\tilde{E}_t$ are the aggregate labor and energy, which individual firms take as given. In the equilibrium, $\tilde{L}_t = L_t$ and $\tilde{E}_t = E_t$ hold. Total factor productivity ε_t^a follows

$$\log \varepsilon_t^a = \rho_a \log \varepsilon_{t-1}^a + \eta_t^a, \ \eta_t^a \sim N(0, \sigma_a^2) \tag{3.4.7}$$

Each intermediate goods producer's periodic profit is given by

$$\Pi_{it} = P_{it} Y_{it} - W_t L_{it} - R_t^k K_{it}^s - P_t^e E_{it} \tag{3.4.8}$$

where W_t, R_t^k, and P_t^e are the aggregate real wage, the real rental rate of capital, and real energy price, respectively. Note that because there is no price rigidity, we are using the final good as a numeraire.

Each intermediate goods producer maximizes (3.4.8) subject to the demand for its output (3.4.5) and the technology (3.4.6). The FOCs, after dropping subscript i's, are given by

$$\lambda \frac{Y_t}{L_t}\left[\alpha_l + \left\{\beta_{el} \log\left(\frac{E_t}{E_{ss}}\right)\right\}\right] = W_t \tag{3.4.9}$$

$$\lambda \frac{Y_t}{K_t^s} \alpha_k = R_t^k \tag{3.4.10}$$

$$\lambda \frac{Y_t}{E_t}\left[\alpha_e + \left\{\beta_{el} \log\left(\frac{L_t}{L_{ss}}\right)\right\}\right] = P_t^e \tag{3.4.11}$$

Although we explicitly introduce energy as a factor inputy, we abstract from modeling the energy sector separately, following Rotemberg and Woodford (1996). In other words, there are no resource costs associated with energy production. As in

Rotemberg and Woodford (1996), energy is freely available at no cost to the oligopolistic firms that sell it, and the exogenous variations in P_t^e represent variations in the degree to which they succeed in colluding to keep the price of energy where they want it (here taken as given rather than modeled). Thus, the intermediate goods producers pay P_t^e to get energy input $E_t(i)$, and

$$\Pi_t^e \equiv P_t^e \int_0^1 E_{it} di = P_t^e E_t$$

directly becomes the profit of (implicit) energy firms. These profits are distributed to the shareholders, who are representative households in our model. We assume that energy price follows an exogenous process

$$\log P_t^e = (1-\rho_e)\log P_{ss}^e + \rho_e \log P_{t-1}^e + \eta_t^e,\ \eta_t^e \sim N(0,\sigma_e^2) \tag{3.4.12}$$

In the Appendix C.2, we provide a model with the energy producing sector and make the energy price endogenous.[25] The results are robust to this alternative specification.

3.4.4 Government

The government budget constraint is given by

$$G_t + B_{t-1} = T_t + \frac{B_t}{R_t} \tag{3.4.13}$$

where G_t is government spending, T_t is lump-sum taxes (or subsidies). We define $g_t = \frac{G_t}{Y_{ss}}$, where Y_{ss} is the steady-state value of output, and assume g_t follows an exogenous process

$$\log g_t = (1-\rho_g)\log g_{ss} + \rho_g \log g_{t-1} + \eta_t^g,\ \eta_t^g \sim N(0,\sigma_g^2) \tag{3.4.14}$$

In the model, the government spending shock will be the source of exogenous demand shock. Yet, the implications hold to other types of demand shocks such as preference shock affecting marginal utility of consumption or shock on discount factor.

[25]See Kilian (2008) for discussion on energy price endogeneity.

3.4.5 Resource Constraints

The market clearing of capital implies $K_t^s = K_{t-1}$. Additionally, the social resource constraint can be written as

$$Y_t = C_t + K_t - (1-\delta)K_{t-1} + G_t$$

The full description of the equilibrium conditions can be found in Appendix C.1.

3.4.6 Functional Form

To simulate the model, we impose the following functional form of the utility function, which is widely used in the literature.

$$U(C,L) = \frac{1}{1-\sigma_c} C^{1-\sigma_c} - \psi \frac{L^{1+\sigma_l}}{1+\sigma_l} \tag{3.4.15}$$

3.4.7 Calibration

Following the existing literature, we calibrate the model by setting the time interval as a quarter. We set the discount factor $\beta = 0.99$ and the degree of relative risk aversion $\sigma = 1$. We let the labor share $\alpha_l = 0.7$, the capital share $\alpha_k = 0.24$, and the energy share $\alpha_e = 0.06$, which are within the range of widely used values in the literature.[26] Additionally, we set the steady state government spending to output ratio as $g = 0.2$, which is consistent with post-war U.S. data. The parameter governing labor disutility ψ is calibrated so that the steady state of L matches 1/3, which means that people work approximately one-third of the time. We calibrate $1/\phi = 3.31$, which is the average Frisch elasticity used in the RBC literature (Chetty et al. (2013)).

To calibrate the input complementarity parameter between labor and energy, β_{el}, we bring the value from our micro-estimate. The first order condition with respect to energy input can be written as follows:

$$\lambda \frac{Y_t}{E_t} \left[\alpha_e + \beta_{el} \log \left(\frac{L_t}{L_{ss}} \right) \right] = P_t^e$$

[26] Depending on the data source and the definition of value added, the energy share varies from 0.04 to 0.08. We use an average of these values.

Defining the energy share as $\Theta_t^e \equiv \frac{P_t^e E_t}{Y_t}$ and log-linearizing the above equation yields:

$$\hat{\Theta}_t^e = \tilde{\beta}_{el} \hat{L}_t \tag{3.4.16}$$

where $\tilde{\beta}_{el} \equiv \beta_{el}/\alpha_e$. Note that the equation (3.4.16) is the theoretical counterpart of equations (3.2.5) and (3.2.7) in our empirical analysis. Thus, our micro-estimate $\tilde{\beta}_{el} = 1.69$ implies $\beta_{el} = 0.10$, given the energy share $\alpha_e = 0.06$.

Recall that individual firms take the returns to scale of the economy as given. This means that under boom (bust) periods, individual firms face increasing (decreasing) returns to scale as long as labor and energy inputs are procyclical and $\beta_{el} > 0$. As individual firms face increasing returns to scale in periods outside the steady state (especially during the boom), this requires positive markups as in typical internal increasing returns to scale model with monopolistic competition. We impose minimal degree of markup that makes the model well-defined, given the historical fluctuation of labor and energy which in turn affects the returns to scale defined by (3.3.5). As can be seen in Figure 3.2, the observed fluctuation of energy and labor inputs around long-run trend in the United States economy is in general less than 10%.[27] Thus, by combining $\beta_{el} = 0.10$ and the expression of returns to scale RTS_t in (3.3.5), we get the maximal returns to scale plausible in the US economy as $RTS_t = 1 + 0.10 \times (0.10 + 0.10) = 1.02$. Thus, 2% of markup is sufficient to make our model well-defined, which implies $1/\lambda = 1.02$. Quantitatively, this makes no difference in a perfect competitive model. Thus we can interpret our calibrated model as an approximation of a perfect competitive economy, making the model directly comparable with standard RBC models.

We summarize our calibration strategy in Table 3.3.

3.5 Dynamics of the Economy

In this section, we compare our benchmark model that has the normalized Translog technology with the counterfactual model that has Cobb-Douglas production function (with

[27]Note that inputs going below the trend poses no problem since it induces decreasing returns to scale.

Table 3.3: Calibration Strategy

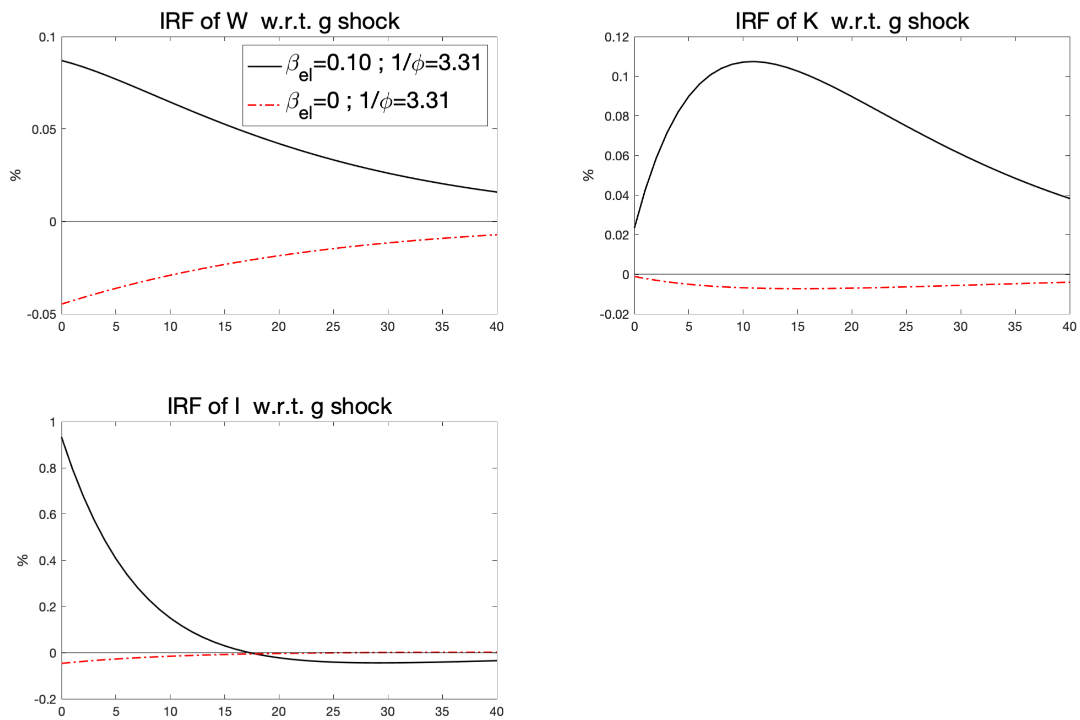
parameter	meaning	value
α_k	capital share	0.24
α_l	labor share	0.70
α_e	energy share	0.06
λ	inverse of markup	$1/\lambda = 1.02$
β	discount factor	0.99
σ_c	intertemporal elasticity	1
δ	depreciation of capital	0.025
ψ	labor disutility	$L_{ss} = 1/3$
P^e_{ss}	energy price	$E_{ss} = 1$

energy input for fair comparison). These are done by setting $\beta_{el} = 0.10$ (benchmark) versus $\beta_{el} = 0$ (counterfactual). We assume a 2% markup in the benchmark model with the normalized Translog, while we assume perfect competition in the counterfactual model with the Cobb-Douglas function. Hence, the model with Cobb-Douglas is identical to the standard RBC model except that firms use energy as a factor input.[28] Quantitatively, 2% markup (in the benchmark model) is nearly indistinguishable from zero markups (i.e., perfect competition), so this model can be regarded as an approximation of a perfect competitive economy.

Below, we present the impulse response of selected variable. The results for all variables can be found in Appendix C.3.

[28]Under the Cobb-Douglas production function, whether firms use energy as a factor input has minor effect on the model's performance. Thus, it is not the inclusion of energy input *per se* that is important but the existence of complementarity-induced procyclical returns to scale that is crucial. In Appendix C.3 we also include impulse responses of the standard RBC model without energy input.

Figure 3.3: Procyclicality: Increase in government spending by 1 %



Note. Y-axis represents a percent deviation from steady state. The solid black lines represent the model with a normalized Translog production function. The red Dashed lines represent the model with a Cobb-Douglas production function.

3.5.1 Procyclical Wage, Capital, Investment with respect to the Government Spending Shock

We begin our analysis by investigating the impulse response of key variables following the government spending shock.[29] Figure 3.3 shows the dynamics of real wage W, capital stock K, and investment I after a 1% increase in government spending. The solid black lines depict the dynamics of these variables under the normalized Translog production function. We find a procyclical real wage, capital, and investment, which is consistent with the data.

In contrast, the red dashed lines depict the responses of these variables in the model with the Cobb-Douglas production function. Under conventional Cobb-Douglas technology, demand shock generates countercyclical movement of these variables. Countercyclicality of these variables with respect to the demand shocks are well-known feature of canonical real business cycle models as documented in Romer (2006). Introducing the normalized Translog production function successfully generates data-consistent dynamics with respect to the demand shock without relying on countercyclical markup or nominal rigidity.

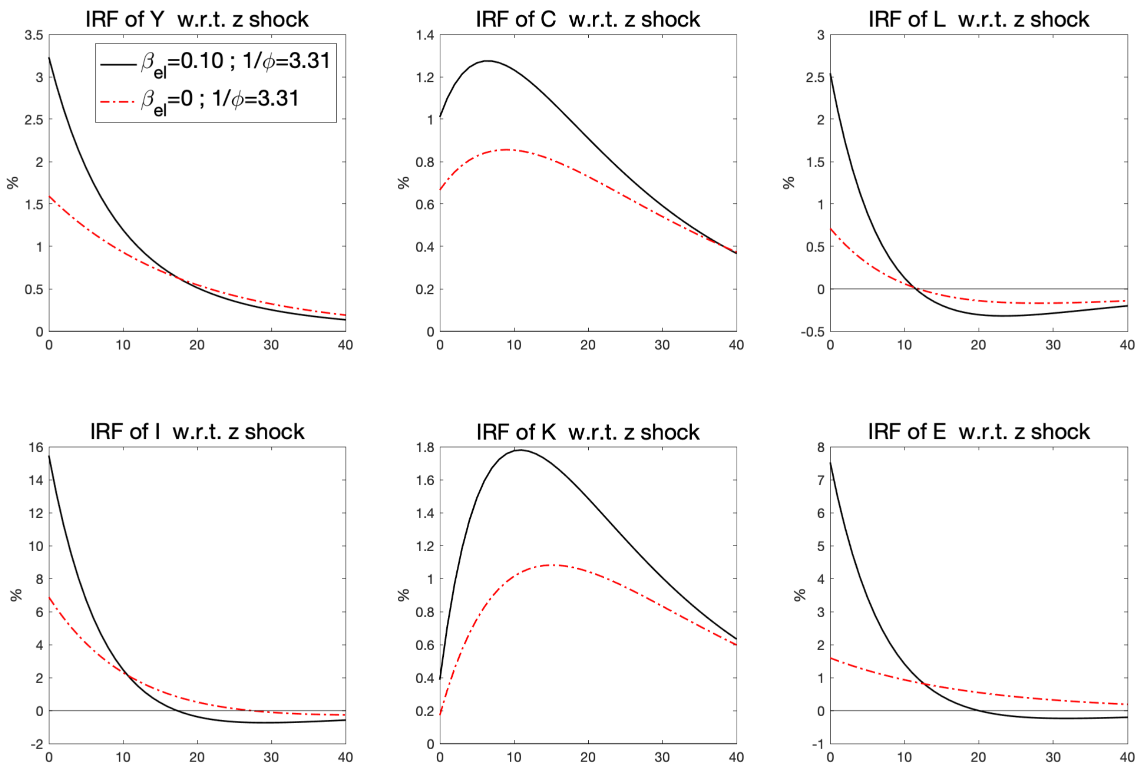
3.5.2 Strong Amplification

Complementarity-induced procyclical returns to scale generate strong amplification with respect to both supply and demand shocks. This is because the interaction between energy and labor does not depend on a particular type of shock: any shock that induces firms to increase factor inputs generate interactions between energy and labor, which turn into strong propagation.

Figure 3.4 and Figure 3.5 show the impulse response of output, consumption, labor, investment, capital, and energy with respect to a 1% positive productivity shock and a 1% positive government spending shock, respectively. Again, solid black lines depict

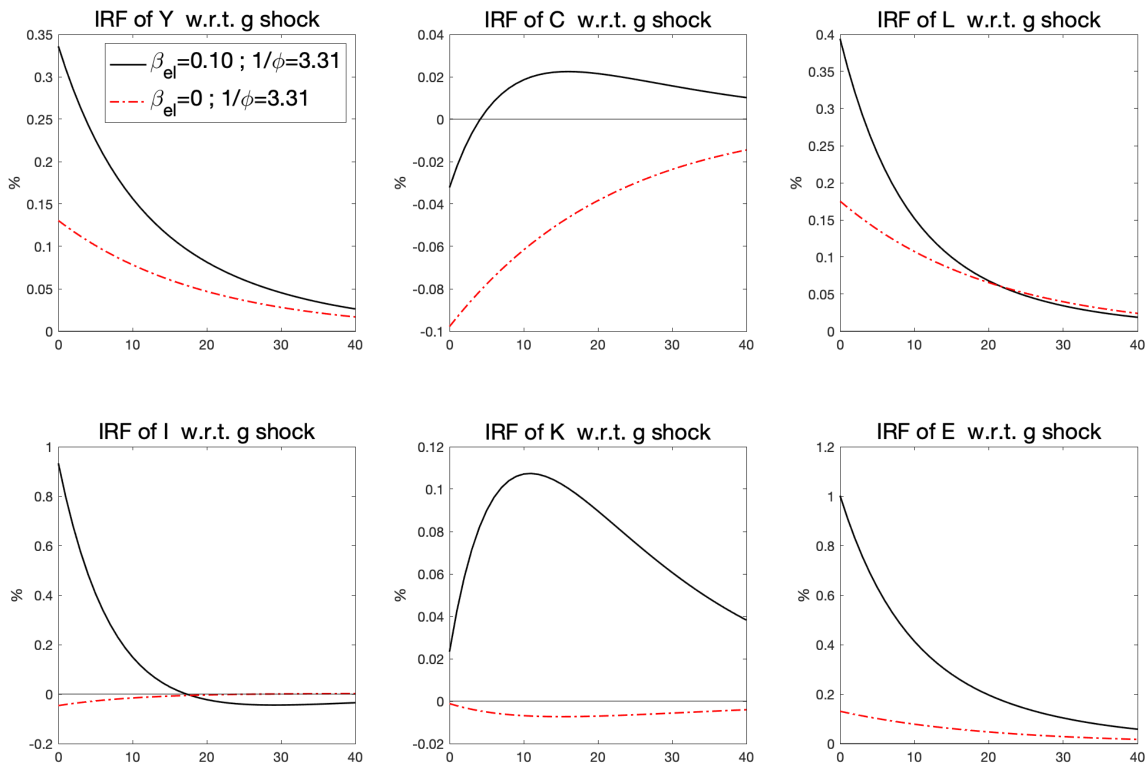
[29]We only considered a government spending shock here, but the implication holds generally under other types of demand shocks, such as preference shock affecting marginal utility of consumption or shock on discount factor.

Figure 3.4: Amplification: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. The solid black lines represent the model with a normalized Translog production function. The red Dashed lines represent the model with a Cobb-Douglas production function.

Figure 3.5: Amplification: Increase in government spending by 1 %



Note. Y-axis represents a percent deviation from steady state. The solid black lines represent the model with a normalized Translog production function. The red Dashed lines represent the model with a Cobb-Douglas production function.

dynamics of the model with normalized Translog, and the red dashed lines depict the model with Cobb-Douglas. In both shocks, the model with a normalized Translog generates stronger amplification than the model with the Cobb-Douglas function. In this sense, complementarity-induced procyclical returns to scale can be thought as having a similar role as capital utilization. However, as can be seen in Figure C.5 and Figure C.6 in the Appendix C.3.2, the amplification effect is much stronger under complementarity-induced procyclical returns to scale since our production function is not restricted to constant returns to scale.

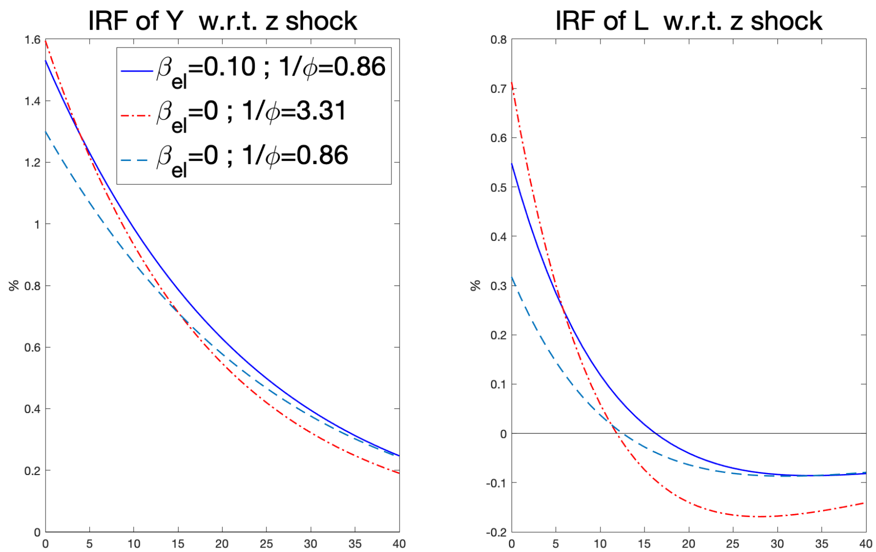
3.5.3 Using Micro-consistent Frisch Elasticity

Our proposed production function provides new insight on the micro versus macro Frisch elasticity debate. Conventionally, the macroeconomic literature has used a large Frisch elasticity to match labor market moments observed in aggregate data. However, this approach has been criticized by several papers, which argue that micro-evidence indicates much lower Frisch elasticity compared to the conventional values used in the macroeconomic literature (see, e.g., Chetty (2012); Chetty et al. (2013)).

Complementarity-induced procyclical returns to scale has potential to reconcile such debate by generating large movement in labor demand even under a small Frisch elasticity. This movement generates larger fluctuation of labor even with micro-consistent value of Frisch elasticity in equilibrium.

Figure 3.6 illustrates this point. We use 0.86 as the micro-consistent Frisch elasticity reported by Chetty et al. (2013) and use 3.31 as the macro-consistent Frisch elasticity which is also reported in Chetty et al. (2013) as an average value used in the RBC literature. We assume a 1% positive productivity shock and compare the responses of output and labor in three different models : (i) a model with normalized Translog with a micro-consistent Frisch elasticity of 0.86 (blue solid lines); (ii) a model with Cobb-Douglas with a micro-consistent Frisch elasticity of 0.86 (green dashed lines); and (iii) a model with Cobb-Douglas with a macro-consistent Frisch elasticity of 3.31 (red dotted-dashed lines).

Figure 3.6: Frisch elasticity: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. Blue solid lines represent the model with a normalized Translog with micro-consistent Frisch elasticity of 0.86. Green dashed lines represent the model with a Cobb-Douglas with micro-consistent Frisch elasticity of 0.86. Red dotted-dashed lines represent the model with a Cobb-Douglas with macro-consistent Frisch elasticity of 3.31.

By comparing the blue solid lines and the red dotted-dashed lines, one can verify that the behavior of the model with normalized Translog with micro-consistent Frisch elasticity closely mimics the model with Cobb-Douglas with macro-consistent Frisch elasticity. Considering the parsimonious structure of the model, we find this as an interesting result.

3.5.4 Indeterminancy and Possibility of Multiple Equilibria

Finally, under certain parametrization, our simple model induces indeterminancy. Under the benchmark calibration in Table 3.3 with Frisch elasticity of 3.31, the threshold for the indetermiancy is given by $\bar{\beta}_{el} = 0.12$.[30] Although $\beta_{el} = 0.12$ is slightly larger than our benchmark value of $\beta_{el} = 0.10$, it is quite surprising that our simple model could closely mimick desirable features of the increasing returns to scale models. Importantly, our empirical analysis and theoretical model do not violate the returns to scale results in Basu and Fernald (1997) as our production function features constant returns to scale on average (i.e. at the steady state), and is fully consistent with Basu and Kimball (1997), which emphasizes the role of capital utilization if one interprets energy as a capital utilization.

3.6 Conclusion

In this paper, we studied the business cycle with a Translog production function, featuring complementarity-induced procyclical returns to scale. Through our empirical study, we identified a complementarity between labor and energy that leads to procyclical returns to scale, which is not compatible with the tightly parametrized production functions commonly used in the literature. Reflecting our empirical analysis, we introduced the normalized Translog production function and showed that a simple calibrated business cycle model with the proposed production function generates strikingly data-consistent dynamics following demand shock without relying on either nominal rigidities or countercyclical markups: (i) procyclical real wage, investment, and capital with respect to demand-side shock, (ii) stronger amplification effect with respect to both supply-side and demand-side shocks than the model without complementarity, (iii) sizable labor fluctuation under calibration based on micro-consistent Frisch elasticity that is comparable to that generated by conventional neoclassical model with macro-consistent Frisch elasticity, and (iv) indeterminancy under certain parametrization. We believe our study underscores the insight of the increasing returns to scale literature, while reconciling empirical challenge it faces.

[30] The parameter region of β_{el} that generates indeterminancy, however, is not monotonic. Under the benchmark calibration, the region is given by $\beta_{el} \in [0.12, 0.22]$. Note, however, that β_{el} larger than 0.22 is way beyond the reasonable parameter range under our micro-estimate.

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Appendix A

Appendix to Chapter 1

A.1 Additional Tables

Table A.1: Excluding Nearby Regions

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

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, out-of-state) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, where we exclude "other counties" that are located in the same state (by assigning zero weights on them and re-normalizing the remaining weights to one), $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, $\geq$"N"mi) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales, where we exclude "other counties" within "N" mile radius around the county (by assigning zero weights on them and re-normalizing the remaining weights to one). Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Placebo Tests

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

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

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

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

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

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

	(1)	(2)	(3)	(4)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (firm, other)	0.533***	0.520***	0.537***	-0.017
	(0.007)	(0.022)	(0.022)	(0.041)
$\tilde{\Delta}\text{HP}_{(07-09)}$ (firm-retailer, other)		0.071	0.055	0.016
		(0.130)	(0.142)	(0.071)
Region-Firm Controls	✓	✓	✓	✓
Sector x Region x Retailer FE	✓	✓	✓	✓
R^2	0.506	0.506	0.451	0.515
Observations	1691268	1691268	1691268	1691268

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

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

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

Note. This table presents variants of the specification in Columns (4)-(6) of Table 1.4 by instrumenting $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) using similarly constructed IV. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are three-way clustered at state, sector, and "other state" level, where "other state" indicates state containing each county-firm observation's largest other county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

Note. This table presents variants of the specification in Columns (4)-(6) of Table 1.4 by instrumenting $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) using similarly constructed IV. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are three-way clustered at state, sector, and "other state" level, where "other state" indicates state containing each county-firm observation's largest other county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Control Firms' Customer Types

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.637**	0.598***	0.039
	(0.258)	(0.150)	(0.244)
Income (other)	-0.004	0.002	-0.006*
	(0.003)	(0.002)	(0.003)
Educ (other)	-0.016***	-0.001	-0.015***
	(0.005)	(0.004)	(0.002)
White (other)	-0.003	0.003	-0.006
	(0.006)	(0.003)	(0.003)
Owner (other)	0.005	-0.007**	0.012**
	(0.004)	(0.003)	(0.005)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
R^2	0.395	0.409	0.429
Observations	840681	840681	840681

Note. This table presents a variant of the specification in Columns (4)-(6) of Table 1.4 with additional demographic controls constructed in a similar way as in $\tilde{\Delta}\text{HP}_{(07-09)}$ (other). These include pre-recession median household income, percentage with high school diploma or less, percentage white, and percentage owner-occupied. All regressions are weighted by county-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.8: Control Largest Market

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other)	0.423^{***}	0.349^{***}	0.073
	(0.121)	(0.070)	(0.114)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Sector x Largest.Mkt FE	✓	✓	✓
R^2	0.502	0.521	0.500
Observations	840681	840681	840681

Note. This table presents variants of the specification in Columns (4)-(6) of Table 1.4, where we add Sector-by-Largest Market fixed effects. We define a firm's largest market as the census division that has largest within-firm sales share. All regressions are weighted by county-firm specific initial sales. Standard errors (parentheses) are double clustered at state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

Note. We constructed state-firm level observations using ACNielsen Homescan Panel database. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009 arising from continuing products. $\tilde{\Delta}\text{Sale}_{04-06}$, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{04-06}$, and $\tilde{\Delta}\text{Sale}^{\text{continue}}_{04-06}$ are corresponding growth rates between 2004 and 2006. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the lagged-initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. The weights are constructed using 2004 state-firm specific sales. We group companies by their three largest product groups and classify them operating in the same sector. Region-Firm controls include log of 2004 state-firm specific sales, log of 2004 firm-level sales, log of the 2004 number of local markets a firm has, and log of the 2004 number of product groups a firm has. All regressions are weighted by state-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

Note. This table repeats Columns (4)-(6) of Table 1.4 under alternative definitions of markets (county and state) using shift-share robust standard error proposed by Adao et al. (2018b). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

	(1)	(2)	(3)
	$\tilde{\Delta}\text{Sale}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$	$\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$
$\tilde{\Delta}\text{HP}_{(07-09)}$ (other, firm)	0.173^{**}	0.306^{***}	-0.133
	(0.070)	(0.033)	(0.099)
Region-Firm Controls	✓	✓	✓
Sector x Region FE	✓	✓	✓
Prod.Group x Region FE	✓	✓	✓
R^2	0.420	0.485	0.475
Observations	1592287	1592287	1592287

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the county-firm-product group specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ is the county-firm-product group specific sales growth between 2007 and 2009 arising from product replacements, $\tilde{\Delta}\text{Sale}^{\text{continue}}_{(07-09)}$ is the county-firm-product group specific sales growth between 2007 and 2009 arising from continuing products, $\tilde{\Delta}\text{HP}_{(07-09)}$ (other, firm) is the initial "county-firm specific sales"-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales (i.e., same shock as in the main county-firm level analyses). Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm-product group specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm-product group specific initial sales. Standard errors (in parentheses) are clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

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

Table A.13: The Heterogeneous Treatment Effects

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

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

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

Table A.15: Creation and Destruction

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

Note. $\text{Creation}_{(07-09)}$ is the county-firm specific sales generated by products that didn't exist in region r in 2007 but existed in 2009 (i.e., $\frac{\text{Sales}^{\text{enter}}_{rf,09}}{\text{Sales}_{rf}}$), and $\text{Destruction}_{(07-09)}$ is the county-firm specific sales generated by products that existed in region r in 2007 but no longer exist in 2009 (i.e., $\frac{\text{Sale}^{\text{exit}}_{rf,07}}{\text{Sale}_{rf}}$). $\tilde{\Delta}\text{Sale}^{\text{replace}}_{(07-09)}$ in Column (5) of Table 1.4 is identical to $\text{Creation}_{(07-09)}$-$\text{Destruction}_{(07-09)}$. $\tilde{\Delta}\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by county-firm specific initial sales. Standard errors (in parentheses) are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.16: Price Response at the Extensive Margin

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

Note. $\tilde{\Delta}\text{Price}^{\text{replace}}_{(07-09)}$ is the county-firm specific price growth at the replacement margin between 2007 and 2009 defined in Appendix A.3, and $\Delta\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A.17: Quality Response at the Extensive Margin

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

Note. $\tilde{\Delta}\text{Price (Avg. Adj.)}^{\text{replace}}_{(07-09)}$ is the county-firm specific quality growth at the replacement margin between 2007 and 2009 defined in Appendix A.3, and $\Delta\text{HP}_{(07-09)}$ (other) is the initial sales-weighted house price growth between 2007 and 2009 in the other counties where the firm generates sales. Sectors are defined based on SIC 4-digit. Region-Firm controls include log of initial county-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

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

Table A.19: Relationship between γ_{rt} and Log of State Income Level

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

Note. $\ln(\text{Income}_{rt})$ is the log of state level average income in year t, and $\ln(\text{HP}_{rt})$ is the log of state level house price in year t. The regression pools 2007 and 2009 observations with year dummy (Year FE) and either Census Division fixed effects or state fixed effects. All regressions are weighted by market size measured by state level sales. Robust standard errors are reported in parentheses. weighted by state level sales. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Price}_{(07-09)}$ is the state-firm specific price growth between 2007 and 2009 defined in Appendix A.3, and $(\tilde{\Delta}\text{Sale}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)}$ (avg) is the measure of $\sum_{r' \in k_f} \left[\omega_{r'f,0}\hat{S}_{r'f} + \theta_{r'f,0}\hat{\gamma}_{r'}\right]$. In Column (2) and Column (4), we instrument $(\tilde{\Delta}\text{Sale}_{(07-09)} + \tilde{\Delta}\gamma_{(07-09)}$ (avg) using $\Delta\text{HP}_{(07-09)}$ (other), which is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. State-Firm controls include log of initial state-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

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

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

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

Note. $\tilde{\Delta}\text{Sale}_{(07-09)}$ is the state-firm specific sales growth between 2007 and 2009, $\tilde{\Delta}\text{Price}_{(07-09)}$ is the state-firm specific price growth between 2007 and 2009 defined in Appendix A.3, and $(\tilde{\Delta}\text{Sale}_{(07-09)})$ (avg) is the measure of $\left(\sum_{r' \in k_f} \omega_{r'f,0} \hat{S}_{r'f}\right)$ where $\omega_{rf,0}$ is the initial sales weight. In Column (2) and Column (4), we instrument $(\tilde{\Delta}\text{Sale}_{(07-09)})$ (avg) using $\Delta\text{HP}_{(07-09)}$ (other), which is the initial sales-weighted house price growth between 2007 and 2009 in the other states where the firm generates sales. Sectors are defined based on SIC 4-digit. State-Firm controls include log of initial state-firm specific sales, log of initial firm-level sales, log of firm's initial number of local markets, log of firm's initial number of product groups. All regressions are weighted by state-firm specific initial sales. Standard errors are double clustered at the state and sector level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

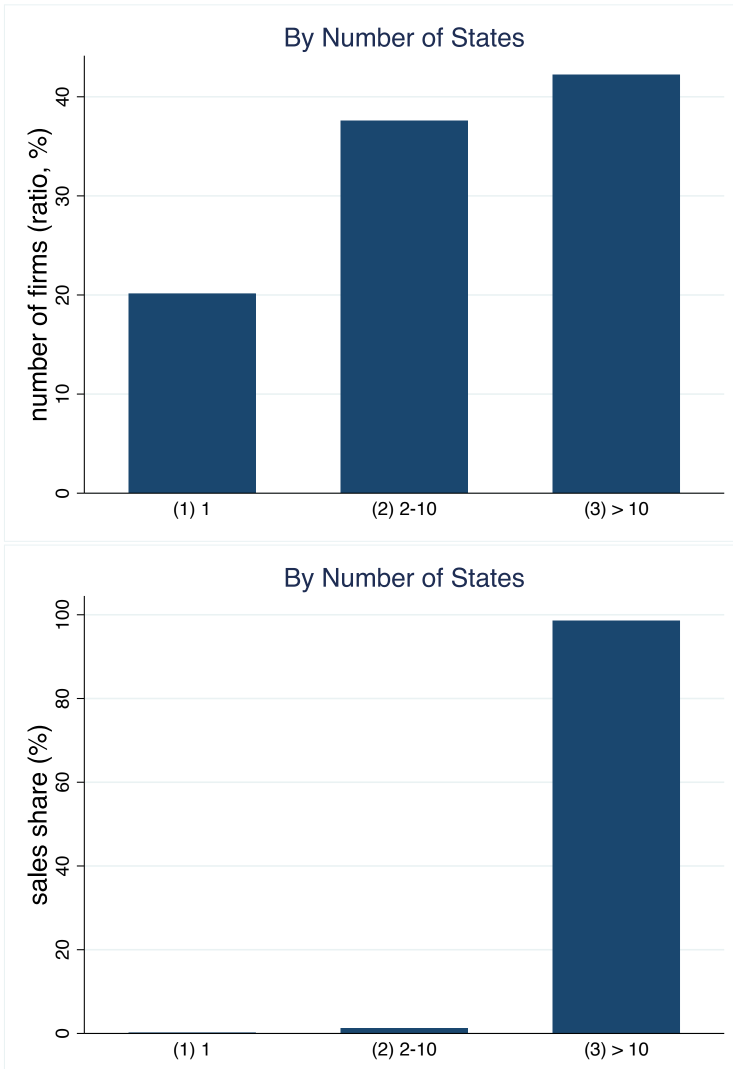
Table A.23: Regional Redistribution across States - All States

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

Note. $\hat{HP}_r(\%)$ 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 1.6, and counterfactual indicates the model with market-specific quality choice in Appendix A.5. $\hat{U}_r(\%)$ 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.

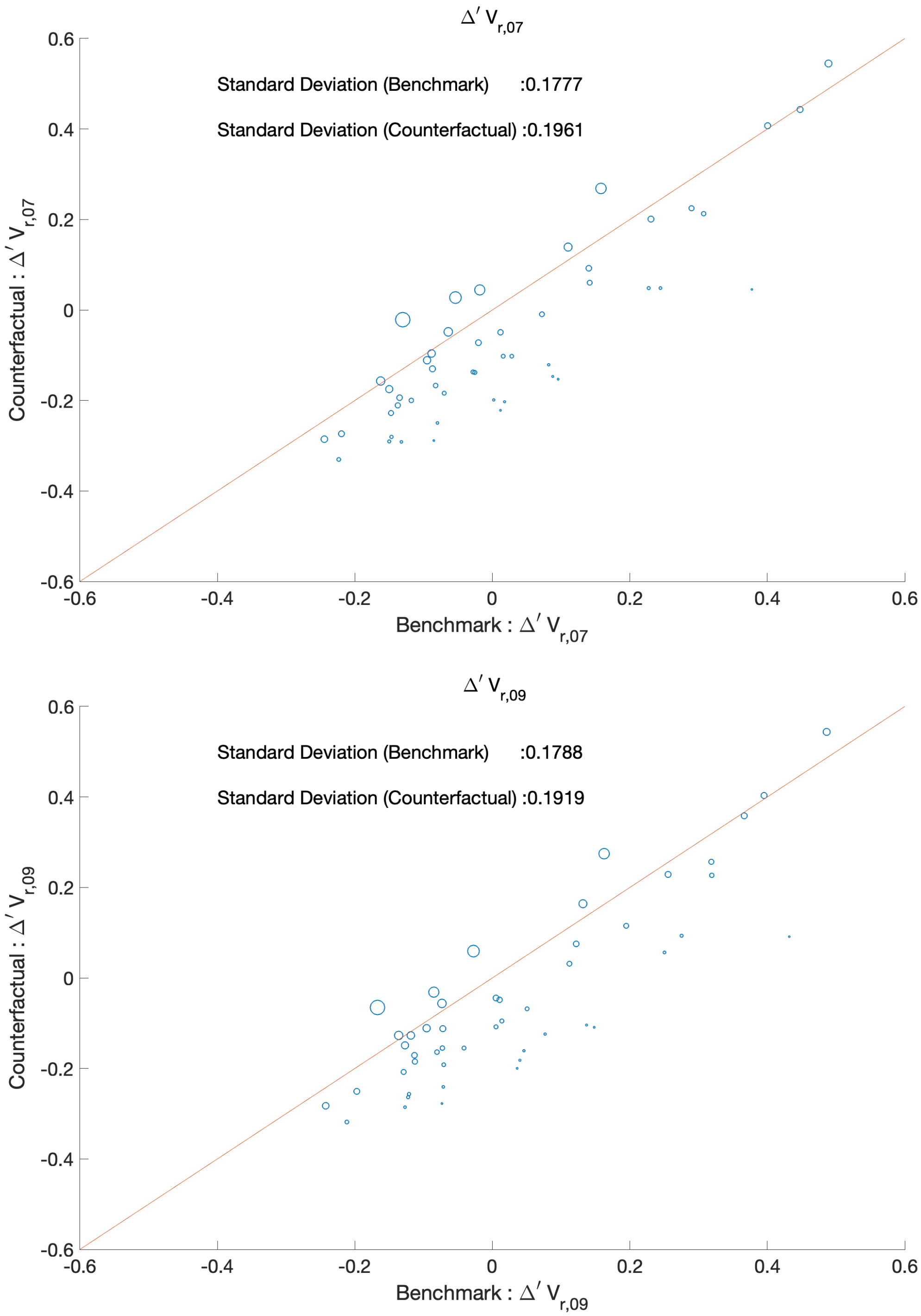
A.2 Additional Figures

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



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

Figure A.2: Cross-sectional Dispersion of Regional Overall Welfare



Note. $\Delta' V_{r,t} \equiv (V_{r,t} - \text{Avg.}V_{r,t})/\text{Avg.}V_{r,t}$ measures the cross-sectional dispersion of regional overall welfare at time t. The size of the circle reflects population weights. The mean, $\text{Avg.}V_{r,t}$, and the reported standard deviations are weighted by state level population.

A.3 Measuring Values : Price and Quality

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

$$p^i_{r,g,f,t} \equiv \Pi_{u\in\Omega_{i,r,t}} \left(p_{r,u,g,f,t}^{\omega_{u,i}^{r,g,f,t}} \right) \tag{A.3.1}$$

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

$$p_{r,g,f,t} \equiv \Pi_i \left(p^i_{r,g,f,t}\right)^{\omega_i^{r,g,f,t}} \tag{A.3.2}$$

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

$$p_{r,g,t} \equiv \Pi_f \left(p_{r,g,f,t}^{\omega_f^{r,g,t}} \right) \tag{A.3.3}$$

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

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

$$\phi^i_{r,g,f,t} \equiv \frac{p^i_{r,g,f,t}}{p_{r,g,t}} \tag{A.3.4}$$

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

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

$$p^i_{r,f,t} \equiv \Pi_g \left(p^i_{r,g,f,t}\right)^{\omega^{r,f,t}_{g,i}} \tag{A.3.5}$$

$$\phi^i_{r,f,t} \equiv \Pi_g \left(\phi^i_{r,g,f,t}\right)^{\omega^{r,f,t}_{g,i}} \tag{A.3.6}$$

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

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

$$p_{r,f,t} \equiv \Pi_i \left(p^i_{r,g,f,t}\right)^{\omega^{r,f,t}_{i}} \tag{A.3.7}$$

$$\phi_{r,f,t} \equiv \Pi_i \left(\phi^i_{r,g,f,t}\right)^{\omega^{r,f,t}_{i}} \tag{A.3.8}$$

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

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

A.4 Derivation of Optimal Prices and Quality

From the profit function (1.6.17), we have

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

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

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

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

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

A.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

$$\begin{aligned}
0 = \frac{\partial \pi_f}{\partial p_{rf}} =& (1-\sigma){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r + \frac{c(\phi_f)}{a_f} \sigma {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma-1} A_r \\
=& \left[(1-\sigma) + \frac{c(\phi_f)}{a_f} \frac{\sigma}{p_{rf}} \right] {\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{-\sigma} A_r
\end{aligned} \tag{A.4.1}$$

This implies optimal price

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

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

A.4.2 First-order Conditions in Quality

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

$$
\begin{aligned}
0 = \frac{\partial \pi_f}{\partial \phi_f} &= \sum_{r\in k_f} \frac{\partial S_{rf}}{\partial \phi_f} - \frac{1}{a_f}\frac{\partial c(\phi_f)}{\partial \phi_f}\sum_{r\in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r\in k_f}\frac{\partial Q_{rf}}{\partial \phi_f} - \frac{\partial f(\phi_f)}{\partial \phi_f} \\
&= \sum_{r\in k_f} (\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r - 1} p_{rf}^{1-\sigma} A_r - \frac{1}{a_f}\xi(\phi_f)^{\xi-1}\sum_{r\in k_f} Q_{rf} - \frac{c(\phi_f)}{a_f}\sum_{r\in k_f}(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&= \sum_{r\in k_f}\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r {\phi_f}^{(\sigma-1)\gamma_r-1} p_{rf}^{1-\sigma} A_r - \sum_{r\in k_f}\xi\left(\frac{\phi_f^{\xi-1}}{a_f}\frac{1}{p_{rf}}\right){\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}-1} \\
&=(\phi_f)^{-1}\left[\sum_{r\in k_f}\left[\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\xi\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \\
&=(\phi_f)^{-1}\left[\sum_{r\in k_f}\left[\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)(\gamma_r-\xi)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}}\right] \qquad \text{(A.4.2)}
\end{aligned}
$$

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

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

$$
\begin{aligned}
0 =& \sum_{r\in k_f}\left[\left(1-\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)(\sigma-1)\gamma_r - \xi\left(\frac{\phi_f^{\xi}}{a_f}\frac{1}{p_{rf}}\right)\right]{\phi_f}^{(\sigma-1)\gamma_r} p_{rf}^{1-\sigma} A_r - b(\phi_f)^{\frac{1}{\beta}} \\
=& \sum_{r\in k_f}\left(\frac{\sigma-1}{\sigma}\right)(\gamma_r-\xi)S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \\
=& \sum_{r\in k_f}\left(\frac{\gamma_r-\xi}{\mu}\right)S_{rf} - b(\phi_f)^{\frac{1}{\beta}} \qquad \text{(A.4.3)}
\end{aligned}
$$

By rearranging terms, we get the optimal quality choice

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

A.4.3 Structural Equation of Market Interdependency - Derivation

We start with the equation (1.6.21). Define $\Upsilon_r \equiv \beta(\sigma-1)(\gamma_r-\xi)$, $B(a_f) \equiv \left[\frac{\mu}{a_f}\right]^{1-\sigma}$, $X_f \equiv \left[\sum_{r\in k_f} S_{rf}\left(\frac{1}{b}\frac{\gamma_r-\xi}{\mu}\right)\right]$, and $A_r \equiv (P_r)^{\sigma-1}S_r$. Denote a firm's initial local sales as $S_{rf,0}$.

Put logarithm in both side of (1.6.21):

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

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

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

Linearization with respect to the hat-variables imply

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

Now lets derive $\hat{X}_f$. Denote the initial state as

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

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

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

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

Thus, we get

$$\hat{S}_{rf} = \Upsilon_{r,0}\sum_{r\in k_f}\left[\omega_{rf,0}\hat{S}_{rf} + \theta_{rf,0}\hat{\gamma}_r\right] + (\log X_{f,0})\Upsilon_{r,0}\hat{\Upsilon}_r + \hat{A}_r + (\sigma-1)\hat{a}_f \qquad \text{(A.4.4)}$$

A.5 Counterfactual: Market-specific Quality Choice

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

A.5.1 Price and Quality Choice

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

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

$$f^m(\phi_{rf}) \equiv b_m \beta_m (\phi_{rf})^{\frac{1}{\beta_m}} \tag{A.5.1}$$

where we allow fixed cost parameters b_m and β_m under market-specific quality to have different values from corresponding parameters b and β under uniform quality.[1]

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

$$\max_{\{\phi_{rf}, p^m_{rf}\}_{r\in k_f}} \pi^m_f = \sum_{r\in k_f} \left[\left(p^m_{rf} - mc(\phi_{rf}; a_f)\right) Q^m_{rf} - f^m(\phi_{rf}) - f^m_{0r} \right] \tag{A.5.2}$$

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

subject to demand condition

$$Q_{rf}^m = \phi_{rf}^{(\sigma-1)\gamma_r} (p_{rf}^m)^{-\sigma} (P_r^m)^{\sigma-1} S_r^m \tag{A.5.3}$$

We can show that the optimal price is

$$p_{rf}^m = mc(\phi_{rf}; a_f) \times \mu \tag{A.5.4}$$

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

$$\phi_{rf} = \left[S_{rf}^m \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m} \tag{A.5.5}$$

where

$$S_{rf}^m = (\phi_{rf})^{(\sigma-1)\gamma_r} \left(\frac{p_{rf}^m}{P_r^m} \right)^{1-\sigma} S_r^m \tag{A.5.6}$$

The profit under market-specific quality can be rearranged as

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

By plugging (A.5.5) into (A.5.1), we obtain the expression of equilibrium fixed cost for quality adjustments as $f^m(\phi_{rf}) = \beta_m(\mu^{-1}) S_{rf}^m (\gamma_r - \xi)$. By combining these two equations, we obtain

$$\pi_f^m = \sum_{r \in k_f} \left[\frac{1}{\sigma} \left[1 - \beta_m(\sigma - 1)(\gamma_r - \xi)\right] S_{rf}^m - f_{0r}^m \right] \tag{A.5.7}$$

The expression of sales of firm f in market r, S_{rf}^m, is derived using (A.5.4), (A.5.5), and (A.5.6) as

$$S_{rf}^m = \left[S_{rf}^m \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m(\sigma-1)(\gamma_r-\xi)} \left[\frac{\mu}{a_f} \right]^{1-\sigma} (P_r^m)^{\sigma-1} S_r^m \tag{A.5.8}$$

This implies

$$S_{rf}^m = \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right)^{\frac{\beta_m(\sigma-1)(\gamma_r-\xi)}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \left[\frac{\mu}{a_f} \right]^{\frac{1-\sigma}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \left[(P_r^m)^{\sigma-1} S_r^m\right]^{\frac{1}{1-\beta_m(\sigma-1)(\gamma_r-\xi)}} \tag{A.5.9}$$

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

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

$$p_{rf}^m = \left[S_{rf}^m \left(\frac{1}{b_m} \frac{\gamma_r - \xi}{\mu} \right) \right]^{\beta_m \xi} \left[\frac{\mu}{a_f} \right] \tag{A.5.10}$$

Note that from (A.5.9), $S_{rf}^m = S_{rf'}^m$ if $a_f = a_{f'}$. Also, it is clear from (A.5.9) that $\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0$ as long as $\beta_m(\sigma - 1)(\gamma_r - \xi) < 1$. Also, from (A.5.5) and (A.5.10), we have that if $a_f = a_{f'}$, then $\phi_{rf} = \phi_{rf'}$ and $p_{rf}^m = p_{rf'}^m$. These results imply that regardless of market network a firm has, each firm's optimal quality and price in market r only depends on local market condition and the productivity a_f under market-specific quality strategy. We summarize these results below.

Proposition 5. *(Productivity and Quality, Sales under Market-specific Quality Choice)*

Under market-specific quality choice, we have $S_{rf}^m = S_{rf'}^m$, $\phi_{rf} = \phi_{rf'}$, and $p_{rf}^m = p_{rf'}^m$ if $a_f = a_{f'}$.

Also, if $\beta_m > 0$ is sufficiently small that $\beta_m(\sigma - 1)(\gamma_r - \xi) < 1$, we have

$$\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0 \tag{A.5.11}$$

$$\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0 \tag{A.5.12}$$

Proof. We only need to prove $\frac{\partial \log \phi_{rf}}{\partial \log a_f} > 0$. We know $\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0$ under $\beta_m(\sigma-1)(\gamma_r-\xi) < 1$. Note that (A.5.5) implies $\frac{\partial \log \phi_{rf}}{\partial \log S_{rf}^m} > 0$. Thus, we have $\frac{\partial \log \phi_{rf}}{\partial \log a_f} = \frac{\partial \log \phi_{rf}}{\partial \log S_{rf}^m} \frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0$. □

Corollary 6. *Under the conditions in Proposition 5, the equilibrium profit π_f^m under market-specific quality strictly monotonically increases with firm productivity a_f.*

Proof. It is immediate from equation $(A.5.7)$ and $\frac{\partial \log S_{rf}^m}{\partial \log a_f} > 0$. □

A.5.2 Market Independence under Market-specific Quality

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

Proposition 7. *(Independence across Markets under Market-specific Quality Choice)*

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

Proof. $\frac{\partial \log S_{rf}^m}{\partial \log y_{r'}} = 0$ is immediate from (A.5.9) and the fact that $\frac{\partial \log P_r^m}{\partial \log y_{r'}} = \frac{\partial \log S_r^m}{\partial \log y_{r'}} = 0$ since we shutting down the general equilibrium effect through P_r^m. $\frac{\partial \log \phi_{rf}}{\partial \log y_{r'}} = \frac{\partial \log p_{rf}}{\partial \log y_{r'}} = 0$ follows from (A.5.4) and (A.5.5) and $\frac{\partial \log S_{rf}^m}{\partial \log y_{r'}} = 0$. □

Appendix B

Appendix to Chapter 2

B.1 Additional Tables

Table B.1: Autocorrelation of County-Company level Sales by Firms : Consider firms selling products in (≥ 2) counties

variable	**N**	**median**	**mean**	**sd**	**p10**	**p90**
$Corr_i(S_{i,l,06}, S_{i,l,07})$	14,327	.971	.847	.315	.539	.999
$Corr_i(S_{i,l,06}, S_{i,l,08})$	14,327	.944	.772	.388	.287	.998
$Corr_i(S_{i,l,06}, S_{i,l,09})$	14,327	.91	.716	.416	.114	.997

Note. For each company, we calculate correlations of county-company level sales between years 2006-2007, 2006-2008, and 2006-2009, respectively. This table provides summary statistics of such correlations.

Table B.2: Autocorrelation of County-Company level Sales by Firms : Consider firms selling products in (≥ 800) counties

variable	**N**	**median**	**mean**	**sd**	**p10**	**p90**
$Corr_i(S_{i,l,06}, S_{i,l,07})$	1,210	.989	.969	.0691	.929	.997
$Corr_i(S_{i,l,06}, S_{i,l,08})$	1,210	.981	.949	.0971	.88	.995
$Corr_i(S_{i,l,06}, S_{i,l,09})$	1,210	.975	.933	.115	.844	.993

Note. For each company, we calculate correlations of county-company level sales between years 2006-2007, 2006-2008, and 2006-2009, respectively. This table provides summary statistics of such correlations.

Table B.3: Summary Statistics: Downstream Firms (Full Sample)

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Δ House Price (06-09)	18128	-.159	.134	-.352	-.154	-.002
Δ Sale (07-09)	18128	-.247	.706	-1.388	-.093	.547
Sale (07)	18128	8.16	83.031	0	.072	5.647
Total Sales in Sample (07)	18128	147919.1	0	147919.1	147919.1	147919.1
Med. HH Income	18128	48596.29	6663.89	40280.42	48512.33	56100.77
Educ (Less than HS)	18128	.169	.039	.123	.169	.216
Num. County	18128	173.545	275.124	2	29	688

Table B.4: Summary Statistics: Downstream Firms (Matched Sample)

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Δ House Price (06-09)	1758	-.166	.1	-.27	-.168	-.062
Δ Sale (07-09)	1758	-.181	.643	-1.217	-.044	.504
Sale (07)	1758	32.565	195.743	.003	1.355	51.385
Total Sales in Sample (07)	1758	57249.57	0	57249.57	57249.57	57249.57
Med. HH Income	1758	48776.44	5127.367	42904.48	48896.47	54088.66
Educ (Less than HS)	1758	.17	.029	.135	.171	.2
Num. County	1758	381.784	354.044	6	269.5	905

Table B.5: Summary Statistics: Downstream Firms (Restricted Sample)

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Δ House Price (06-09)	469	-.167	.097	-.27	-.172	-.061
Δ Sale (07-09)	469	-.181	.557	-.953	-.073	.413
Sale (07)	469	69.147	358.18	.008	3.422	101.283
Total Sales in Sample (07)	469	32429.79	0	32429.79	32429.79	32429.79
Med. HH Income	469	48782.79	4683.352	43149.17	49087.73	53875.84
Educ (Less than HS)	469	.172	.027	.145	.171	.2
Num. County	469	429.736	366.785	7	387	928
Num. Supplier	469	11.512	22.625	1	4	37

Table B.6: Summary Statistics: Suppliers

Variable	Obs	Mean	Std. Dev.	P10	P50	P90
Δ House Price (06-09)	659	-.161	.067	-.211	-.171	-.068
Δ Sale (07-09)	659	-.012	.25	-.32	-.004	.319
Sale (07)	659	6849.301	23664.95	31.378	493.725	14771
Short Liquidity (07)	659	-.185	.251	-.593	-.088	.036
Avg. Δ DS Sale (07-09)	659	-.09	.409	-.619	-.078	.447
Avg. DS Sale (07)	659	449.799	1423.843	.045	18.862	807.478
Med. HH Income	659	48280.33	3810.055	44289.56	48855.94	50783.25
Educ (Less than HS)	659	.169	.017	.152	.169	.184
Num. Customer	659	2.37	1.565	1	1	5

Table B.7: The Number of Local Markets of Downstream Firms

variable	N	mean	sd	p25	p50	p75
Num. County (Full)	18,128	174	275	5	29	202
Num. County (Matched)	1,758	382	354	36	270	751
Num. County (Restrict)	469	430	367	46	387	808

Note. For each company, we calculate the number of counties (i.e. local markets) in which the firm generated positive sales in 2007. This table shows the summary statistics of such measure for the full sample, matched sample, and the restricted sample.

Table B.8: Upstream Propagation - Other Linkage Weights and Sector Definition

	(1)	(2)	(3)	(4)	(5)
	ΔSale (%)	ΔSale (%)	ΔSale (%)	ΔSale (%)	ΔSale (%)
ΔHP (%)	0.619***	0.624***	0.531***	0.503***	0.663**
	(0.199)	(0.203)	(0.191)	(0.187)	(0.267)
Firm Controls	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓
Network FE	✓	✓	✓	✓	✓
Version	Equal Weight	Linkage-Revenue Weight	Sales Weight	Equal Weight (Customer)	NAICS 6 digit
R^2	0.219	0.219	0.216	0.216	0.238
Observations	659	659	659	659	555

Note. For Columns (1)-(4), sectors are defined based on NAICS 4-digit code. Column (1) shows the result based on the benchmark equal linkage weight. Column (2) shows the result using percentage of supplier's revenue arising from linkage with a particular downstream company as weight whenever possible, and applying uniform weight for the remaining missing cases. Column (3) shows the result using downstream firms' initial sales as linkage weight. Column (4) shows the result using linkage weight constructed based on the assumption that each downstream firm puts equal weights across suppliers. For Column (5), we define sectors based on NAICS 6-digit code while using equal weights when constructing supplier-specific variables. Firm controls include log of initial sales, initial short-term liquidity, and supplier-specific demographic controls. Supplier-specific demographic controls are weighted average of firm-specific demographic controls weighted based on linkage weights, and capture average demographic properties faced by a given supplier's downstream companies (see Section 2.3.3 for details). All standard errors are clustered at the sector level.

B.2 Additional Figures

Figure B.1: The Number of Local Markets each Firm Participates (2007) (Full Sample)

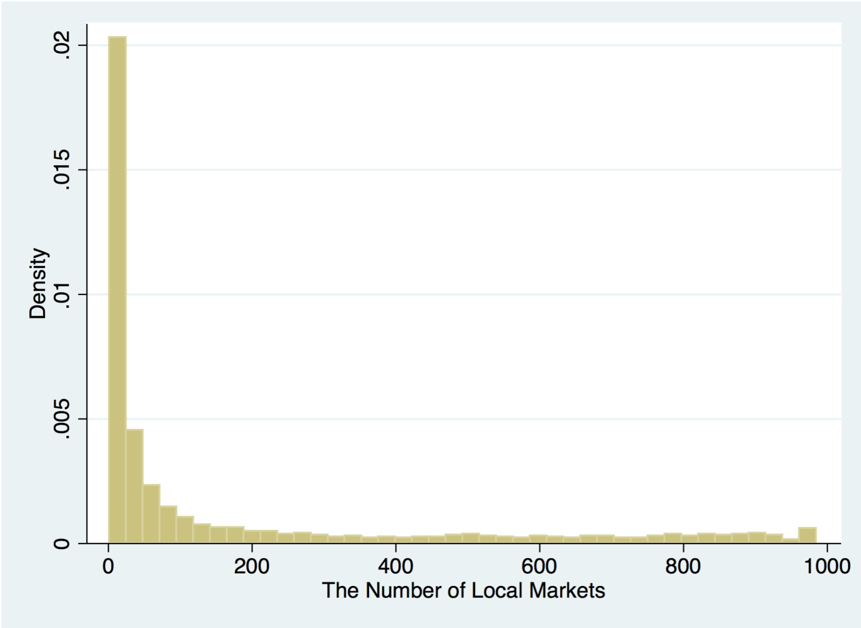
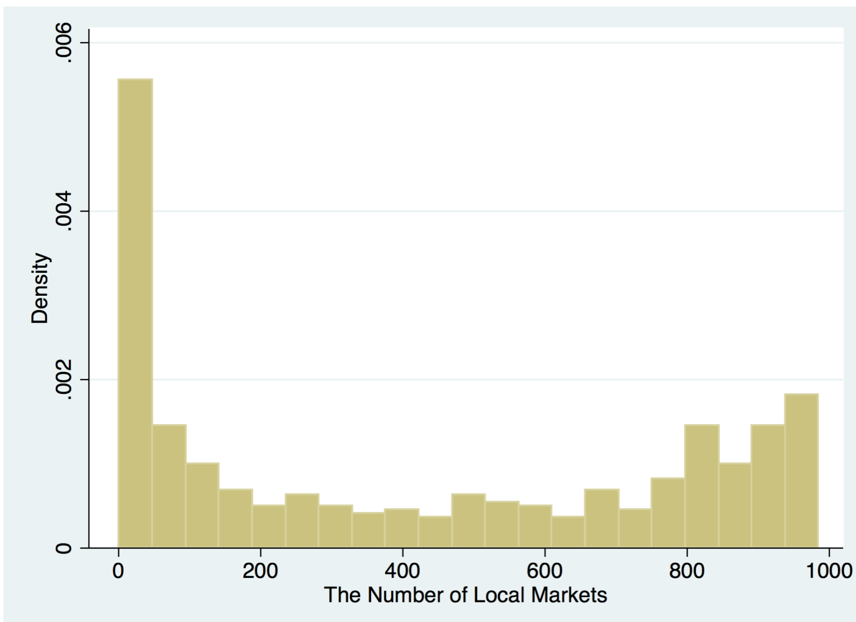


Figure B.2: The Number of Local Markets each Firm Participates (2007) (Restricted Sample)



B.3 Derivation of Equilibrium

We shut down the productivity shock: $z = 0$. More detail explanation of derivation, and the solution in the presence of productivity shock can be found in **?**. The unit cost function of firm i is given by

$$C_i(p, w) = B_i w^{\alpha_i^l} \Pi_{j=1}^N p_j^{a_{ij}} \tag{B.3.1}$$

where $p \equiv (p_1, ..., p_N)'$ and

$$B_i = \left[\frac{1}{\alpha_i^l}\right]^{\alpha_i^l} \Pi_{j=1}^N \left[\frac{1}{a_{ij}}\right]^{a_{ij}} \tag{B.3.2}$$

Zero profit condition for firm i implies

$$\ln p_i = \ln B_i + \alpha_i^l \ln w + \sum_{j=1}^N a_{ij} \ln p_j \tag{B.3.3}$$

for all $i \in S$. We will use wage as numeraire ($w = 1$), and thus we get

$$\ln p_i = \ln B_i + \sum_{j=1}^N a_{ij} \ln p_j \tag{B.3.4}$$

or

$$\ln p = (I - A)^{-1} \ln B \tag{B.3.5}$$

where $\ln p \equiv (\ln p_1, ..., \ln p_N)^T$ and $\ln B \equiv (\ln B_1, ..., \ln B_N)^T$,[1] and

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix}$$

Thus, for a given vector of productivities, the equilibrium price vector is uniquely determined regardless of the vector of household expenditure shocks H.

Now note that profit maximization yields

$$a_{ij} = \frac{p_j x_{ij}}{p_i y_i}, \quad \text{and} \quad \alpha_i^l = \frac{w l_i}{p_i y_i} \tag{B.3.6}$$

[1] Note that we are assuming $z = 0$. If we allow variation in z, this will appear in (B.3.1) and thus (B.3.5).

and utility maximization implies

$$\frac{p_i c_i}{\beta_i} = \frac{p_j c_j}{\beta_j},\ i, j \in S_D \tag{B.3.7}$$

and

$$-\frac{\gamma'(l)l}{\gamma(l)} = \frac{wl}{wl - T} \tag{B.3.8}$$

As in **?**, we assume $\gamma(l) = (1-l)^\lambda$, which gives us

$$l = \frac{1+\lambda T}{1+\lambda} \tag{B.3.9}$$

By combining (2.6.5), (2.6.6), (B.3.7), and (B.3.9), we get

$$\begin{aligned} p_i c_i &= \beta_i (l - T) \\ &= \frac{\beta_i}{1+\lambda}\left[1 - \sum_{j=1}^{N} p_j H_j\right] \end{aligned} \tag{B.3.10}$$

where $\beta_i = 0$ (and thus $p_i c_i = 0$) if $i \in S_U$. From this equation, we can completely pin down c_i.

Finally, by combining (2.6.3) and (B.3.6),

$$p_i y_i = (p_i c_i + p_i H_i) + \sum_{j=1}^{N} a_{ji} p_j y_j \tag{B.3.11}$$

Define $\tilde{y}_i \equiv p_i y_i$, $\tilde{c}_i \equiv p_i c_i$, and $\tilde{H}_i \equiv p_i H_i$. We also define $\tilde{V}_i \equiv \tilde{c}_i + \tilde{H}_i$. Then

$$\begin{aligned} \tilde{y} &= (I - A^T)^{-1}(\tilde{c} + \tilde{H}) \\ &= (I - A^T)^{-1}(\tilde{V}) \end{aligned} \tag{B.3.12}$$

where for $x \in \{y, c, H, V\}$, we define $\tilde{x} \equiv (\tilde{x}_1, ..., \tilde{x}_N)^T$. Note that $\sum_{i=1}^N \tilde{y}_i$ indicates gross output, and $\sum_{i=1}^N \tilde{V}_i$ indicates value added.

We completely characterized the equilibrium.

Appendix C

Appendix to Chapter 3

C.1 Equilibrium Conditions : Benchmark Model

The equilibrium is defined by sequence of 10 endogenous variables

$$\{Y_t, C_t, L_t, I_t, K_t, E_t, W_t, R_t^k, R_t, \Xi_t\}$$

and that of 3 exogenous variables $\{\varepsilon_t^a, g_t, P_t^e\}$ satisfying

$$Y_t = F(K_{t-1}, L_t, E_t; \varepsilon_t^a) \tag{C.1.1}$$

$$\lambda \frac{Y_t}{L_t} \left[\alpha_l + \beta_{el} \log \left(\frac{E_t}{E_{ss}} \right) \right] = W_t \tag{C.1.2}$$

$$\lambda \frac{Y_t}{K_{t-1}} \alpha_k = R_t^k \tag{C.1.3}$$

$$\lambda \frac{Y_t}{E_t} \left[\alpha_e + \beta_{el} \log \left(\frac{L_t}{L_{ss}} \right) \right] = P_t^e \tag{C.1.4}$$

$$I_t = K_t - \big(1 - \delta\big) K_{t-1} \tag{C.1.5}$$

$$\Xi_t = U_C(C_t, L_t) \tag{C.1.6}$$

$$-\frac{U_L(C_t, L_t)}{U_C(C_t, L_t)} = W_t \tag{C.1.7}$$

$$\Xi_t = \beta R_t E_t \left[\Xi_{t+1} \right] \tag{C.1.8}$$

$$\Xi_t = \beta E_t \left[\Xi_{t+1} (1 - \delta + R_{t+1}^k) \right] \tag{C.1.9}$$

$$Y_t = C_t + K_t - (1 - \delta) K_{t-1} + Y \cdot g_t \tag{C.1.10}$$

$$\log(\varepsilon_t^a) = \rho_a \log(\varepsilon_{t-1}^a) + \eta_t^a, \ \eta_t^a \sim i.i.d. \ N(0, \sigma_a^2) \tag{C.1.11}$$

$$\log(g_t) = (1 - \rho_g) \log(g_{ss}) + \rho_g \log(g_{t-1}) + \eta_t^g, \ \eta_t^g \sim i.i.d. \ N(0, \sigma_g^2) \tag{C.1.12}$$

$$\log(P_t^e) = (1 - \rho_e) \log(P_{ss}^e) + \rho_e \log(P_{t-1}^e) + \eta_t^e, \ \eta_t^e \sim i.i.d. \ N(0, \sigma_e^2) \tag{C.1.13}$$

C.2 A Model with Endogenous Energy Price

In this section, we provide a simple model that features the endogenous energy producing sector. Importantly, the energy price is no longer exogenous but endogenously determined (see Kilian (2008) for discussion). We focus on industrial energy usage by abstracting energy consumption by household as in Finn (2000) and Kormilitsina (2011). The model provided in this appendix differs from that in Finn (2000) and Kormilitsina (2011), however, in two dimensions. First, to be consistent with the empirical specification in section 2, we assume that firms directly choose energy as a factor input (instead of assuming that households provide energy to firms by choosing amounts of capital utilization). Letting firms choose the energy input (instead of households providing it) is necessary in this paper, because the empirical specification assumes energy as a factor input is directly chosen by firms. Second, we accommodate the important discussion by Kilian (2008) and make the energy price endogenous, whereas Finn (2000) and Kormilitsina (2011) assume in exogenous energy price (oil price).

C.2.1 The Model

C.2.1.1 Households

The economy is populated by a large number of identical infinitely lived households. The representative household chooses sequence of consumption C_t, labor supplied L_t^h, investment I_t, capital stock K_t, and borrowing B_t to solve

$$\max_{C_t, L_t, I_t, K_t, B_t} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_t^h)$$

subject to the budget constraint

$$C_t + I_t + \frac{B_t}{R_t} + T_t = R_t^k K_{t-1} + B_{t-1} + W_t L_t^h + \Pi_t + \Pi_t^e$$

and the law of motion of capital

$$K_t = I_t + (1-\delta) K_{t-1} \tag{C.2.1}$$

where R is the (gross) risk-free rate, R^k is the real rental rate of capital, W is the real wage, T is the tax paid by the household in terms of consumption unit, Π is the dividend paid to the households by the intermediate goods firms, and Π^e is the dividend paid by the energy firms. We assume $U_{C,t} > 0$, $U_{CC,t} \leq 0$, $U_{L,t} \leq 0$, $U_{LL,t} \leq 0$.

The FOCs are given by

$$U_C(C_t, L_t^h) = \beta E_t \left[U_C(C_{t+1}, L_{t+1}^h) \left\{ R_{t+1}^k + 1 - \delta \right\} \right] \tag{C.2.2}$$

$$W_t = -\frac{U_L(C_t, L_t^h)}{U_C(C_t, L_t^h)} \tag{C.2.3}$$

$$U_C(C_t, L_t^h) = \beta R_t E_t \left[U_C(C_{t+1}, L_{t+1}^h) \right] \tag{C.2.4}$$

C.2.1.2 The Final Goods Firm

The final goods producers purchase differentiated intermediate goods and aggregate them using the Dixit-Stiglitz CES technology. We assume that the final goods sector is perfectly competitive. Each final goods producer solves

$$\max_{Y_t, Y_{it}} Y_t - \int_0^1 P_{it} Y_{it} di$$

subject to

$$Y_t = \left[\int_0^1 Y_{it}^{\lambda} di \right]^{1/\lambda}$$

where Y_t, $Y_t(i)$ are the final and intermediate goods, respectively, and $P_t(i)$ is the price of intermediate goods. λ is the inverse of markup.

The optimality implies

$$Y_{it} = Y_t \cdot P_{it}^{1/(\lambda-1)} \tag{C.2.5}$$

C.2.1.3 Intermediate Goods Producers

We assume a monopolistic competitive intermediate goods sector. Following (3.3.1), I assume intermediate goods producer i's technology is characterized by the following normalized Translog production function.

$$Y_{it} = \varepsilon_t^a \left[(K_{it}^s)^{\alpha_k} L_{it}^{\alpha_l} E_{it}^{\alpha_e} \right] \cdot \left[\left(\frac{L_{it}}{L_{ss}} \right)^{\beta_{el} \log\left(\frac{\tilde{E}_t}{E_{ss}} \right)} \left(\frac{E_{it}}{E_{ss}} \right)^{\beta_{el} \log\left(\frac{\tilde{L}_t}{L_{ss}} \right)} \right] \tag{C.2.6}$$

Here, Y_{it} is intermediate goods producer i's output, K^s_{it} is the capital services used in production, L_{it} is labor input, and E_{it} is energy input. $\tilde{L}_t$ and $\tilde{E}_t$ are cross-section average labor and energy, which individual firms take as given. Total factor productivity ε^a_t follows

$$\log \varepsilon^a_t = \rho_a \log \varepsilon^a_{t-1} + \eta^a_t,\ \eta^a_t \sim N(0, \sigma^2_a) \tag{C.2.7}$$

Each intermediate goods producer's periodic profit is given by

$$\Pi_{it} = P_{it} Y_{it} - W_t L_{it} - R^k_t K^s_{it} - P^e_t E_{it} \tag{C.2.8}$$

where W_t, R^k_t, and P^e_t are the aggregate real wage, the real rental rate of capital, and the real energy price, respectively. Note that because there is no price rigidity, the final good is used as a numeraire.

Each intermediate goods producer maximizes $(C.2.8)$ subject to the demand for its output $(C.2.5)$ and the technology $(C.2.6)$. The FOCs, after dropping subscript i's, are given by

$$\lambda \frac{Y_t}{L_t} \left[\alpha_l + \left\{ \beta_{el} \log \left(\frac{E_t}{E_{ss}} \right) \right\} \right] = W_t \tag{C.2.9}$$

$$\lambda \frac{Y_t}{K^s_t} \alpha_k = R^k_t \tag{C.2.10}$$

$$\lambda \frac{Y_t}{E_t} \left[\alpha_e + \left\{ \beta_{el} \log \left(\frac{L_t}{L_{ss}} \right) \right\} \right] = P^e_t \tag{C.2.11}$$

C.2.1.4 Energy Producer

We introduce an energy producer that combines labor, capital and raw material to produce energy that is used by intermediate goods producers. We assume that the energy sector operates in a perfectly competitive market. The energy production function is given by

$$\begin{aligned} E_t &= G\left(K^{es}_t, L^e_t, M^e_t; a_{et}\right) \\ &\equiv \varepsilon^e_t \left[(K^{es}_t)^{\theta_k} (L^e_t)^{\theta_l} (M^e_t)^{\theta_m} \right] \end{aligned} \tag{C.2.12}$$

where K_t^{es}, L_t^e, M_t^e are capital service, labor, and a raw material (e.g. fossil fuel) used in energy production. ε_t^e is the energy production technology shock following

$$\log \varepsilon_t^e = \rho_e \log \varepsilon_{t-1}^e + \eta_t^e,\ \eta_t^e \sim N(0, \sigma_e^2) \tag{C.2.13}$$

We assume constant returns to scale in energy production : $\theta_k + \theta_l + \theta_m = 1$.

Each energy producer solves the following problem :

$$\max_{K_t^{se}, L_t^e, M_t^e} P_t^e \cdot \varepsilon_t^e \left[(K_t^{es})^{\theta_k} (L_t^e)^{\theta_l} (M_t^e)^{\theta_m} \right] - W_t L_t^e - R_t^k K_t^{se} - P_t^m M_t^e$$

where P_t^m follows the exogenous process

$$\log P_t^m = \rho_m \log P_{t-1}^m + (1 - \rho_m) \log P^m + \eta_t^m,\ \eta_t^m \sim N(0, \sigma_m^2) \tag{C.2.14}$$

The FOCs are given by

$$R_t^k = \theta_k P_t^e \frac{E_t}{K_t^{es}} \tag{C.2.15}$$

$$W_t = \theta_l P_t^e \frac{E_t}{L_t^e} \tag{C.2.16}$$

$$P_t^m = \theta_m P_t^e \frac{E_t}{M_t^e} \tag{C.2.17}$$

C.2.1.5 Government

The government budget constraint is given by

$$G_t + B_{t-1} = T_t + \frac{B_t}{R_t} \tag{C.2.18}$$

where G_t is government spending, and T_t is lump-sum taxes (or subsidies). Following \cite{smetsandwouters2007}, we denote $g_t = \frac{G_t}{Y_{ss}}$, where Y_{ss} is the steady state value of output, and assume g_t follows exogenous process

$$\log g_t = (1 - \rho_g) \log g_{ss} + \rho_g \log g_{t-1} + \eta_t^g,\ \eta_t^g \sim N(0, \sigma_g^2) \tag{C.2.19}$$

C.2.1.6 Resource Constraint

Market clearing implies

$$K_{t-1} = K_t^s + K_t^{es}$$

$$L_t^h = L_t + L_t^e$$

The social resource constraint can be written as

$$Y_t = C_t + K_t - (1-\delta)K_{t-1} + G_t$$

C.2.2 Functional Form

To simulate the model we impose the following functional form of utility function, which is widely used in the literature.

$$U(C,L) = \frac{1}{1-\sigma_c}C^{1-\sigma_c} - \psi\frac{L^{1+\sigma_l}}{1+\sigma_l} \tag{C.2.20}$$

C.2.3 Equilibrium Conditions

The equilibrium is defined by sequence of 15 endogenous variables

$$\left\{Y_t, C_t, L_t^h, L_t, L_t^e, K_t, K_t^s, K_t^{es}, E_t, M_t^e, W_t, R_t^k, R_t, P_t^e, \Xi_t\right\}$$

and that of 4 exogenous variables $\{\varepsilon_t^a, g_t, \varepsilon_t^e, P_t^m\}$ satisfying

$$Y_t = F(K_t^s, L_t, E_t; \varepsilon_t^a) \tag{C.2.21}$$

$$\lambda\frac{Y_t}{L_t}\left[\alpha_l + \left\{\beta_{el}\log\left(\frac{E_t}{E_{ss}}\right)\right\}\right] = W_t \tag{C.2.22}$$

$$\lambda\frac{Y_t}{K_t^s}\alpha_k = R_t^k \tag{C.2.23}$$

$$\lambda\frac{Y_t}{E_t}\left[\alpha_e + \left\{\beta_{el}\log\left(\frac{L_t}{L_{ss}}\right)\right\}\right] = P_t^e \tag{C.2.24}$$

$$\Xi_t = U_C(C_t, L_t^h) \tag{C.2.25}$$

$$\Xi_t = \beta E_t\left[\Xi_{t+1}\left\{R_{t+1}^k + 1 - \delta\right\}\right] \tag{C.2.26}$$

$$W_t = -\frac{U_L(C_t, L_t^h)}{U_C(C_t, L_t^h)} \tag{C.2.27}$$

$$\Xi_t = \beta R_t E_t\left[\Xi_{t+1}\right] \tag{C.2.28}$$

$$Y_t = C_t + K_t - (1-\delta)K_{t-1} + G_t \tag{C.2.29}$$

$$K_{t-1} = K_t^s + K_t^{es} \tag{C.2.30}$$

$$L_t^h = L_t + L_t^e \tag{C.2.31}$$

$$R_t^k = \theta_k P_t^e \frac{E_t}{K_t^{es}} \tag{C.2.32}$$

$$W_t = \theta_l P_t^e \frac{E_t}{L_t^e} \tag{C.2.33}$$

$$P_t^m = \theta_m P_t^e \frac{E_t}{M_t^e} \tag{C.2.34}$$

$$E_t = \varepsilon_t^e \left[(K_t^{es})^{\theta_k} (L_t^e)^{\theta_l} (M_t^e)^{\theta_m} \right] \tag{C.2.35}$$

$$\log \varepsilon_t^a = \rho_a \log \varepsilon_{t-1}^a + \eta_t^a,\ \eta_t^a \sim N(0, \sigma_a^2) \tag{C.2.36}$$

$$\log g_t = (1-\rho_g) \log g_{ss} + \rho_g \log g_{t-1} + \eta_t^g,\ \eta_t^g \sim N(0, \sigma_g^2) \tag{C.2.37}$$

$$\log \varepsilon_t^e = \rho_e \log \varepsilon_{t-1}^e + \eta_t^e,\ \eta_t^e \sim N(0, \sigma_e^2) \tag{C.2.38}$$

$$\log P_t^m = \rho_m \log P_{t-1}^m + (1-\rho_m) \log P^m + \eta_t^m,\ \eta_t^m \sim N(0, \sigma_m^2) \tag{C.2.39}$$

C.2.4 Dynamics of the Economy

In this section, we replicate our results in Section 4 using the model provided in this appendix. All the main results remain robust, even if we endogenize the energy market. In other words, using the Normalized Translog production technology with procyclical RTS (i) generates procyclical real wage, capital, and investment with respect to demand shock, (ii) amplifies shocks regardless of the sources, and (iii) has the potential to reconcile the micro- vs. macro-Frisch elasticity debate. In addition, we show that explicitly considering the energy production sector and endogenizing the energy price render the economy less sensitive to raw material price shocks.

C.2.4.1 Procyclical Wage, Capital, Investment with respect to the Government Spending Shock

- Procyclicality : Increase in government spending by 1 % : Figure C.7

C.2.4.2 Strong Amplification

- Amplification : Increase in productivity by 1 % : Figure C.8

- Amplification : Increase in government spending by 1 % : Figure C.9

C.2.4.3 Using Micro-consistent Frisch Elasticity

- Frisch elasticity : Increase in productivity by 1 % : Figure C.10

C.2.4.4 Impulse Response w.r.t. Raw material Price shock

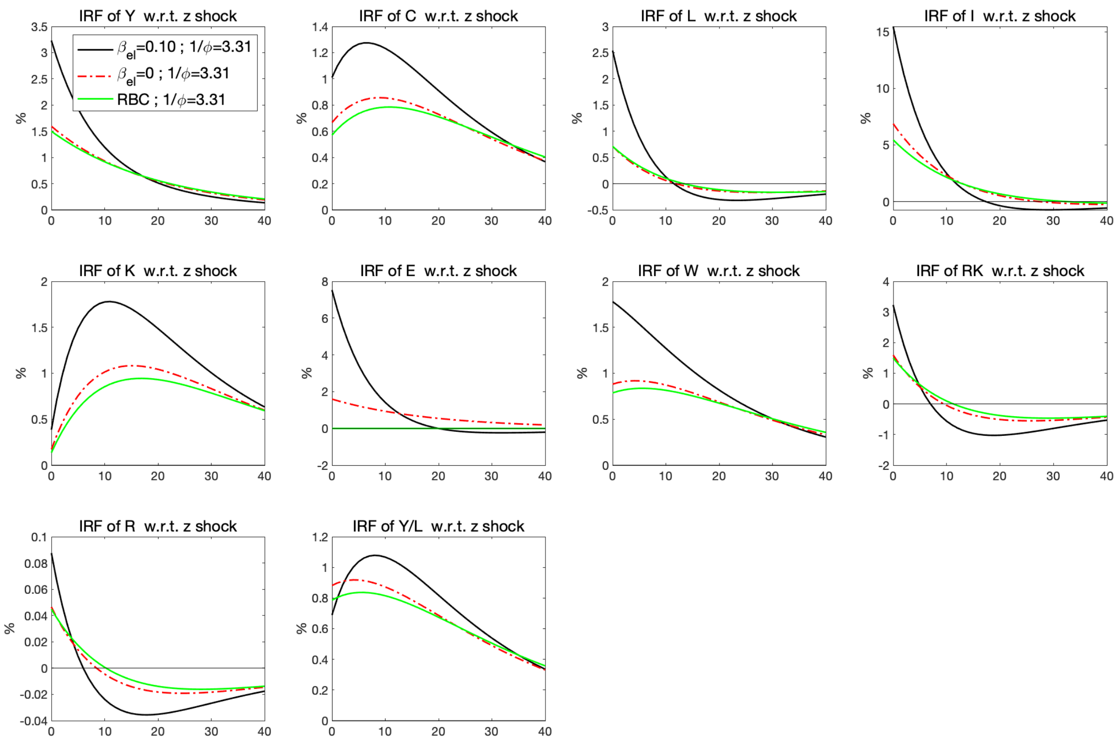
- Impulse Response : Increase in raw material price (P_m) by 1 % : Figure C.11

C.3 Additional Figures

C.3.1 All Variables

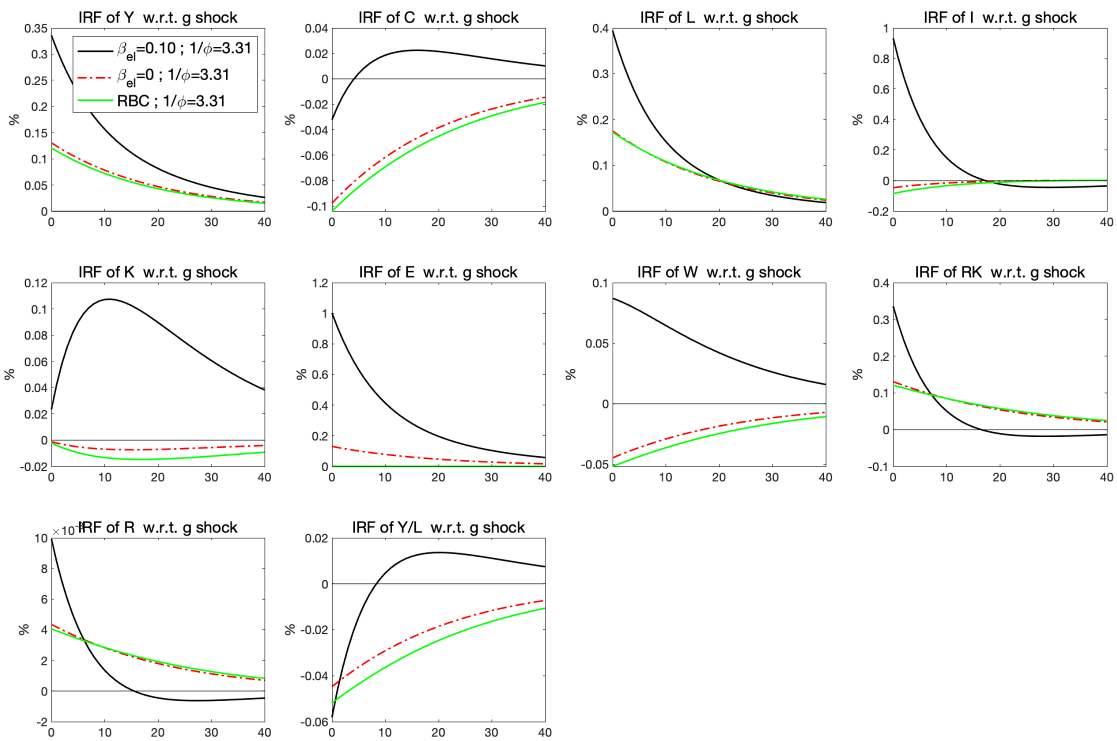
Figure C.1: Impulse response w.r.t. 1% productivity shock:

Cobb-Douglas vs. Translog



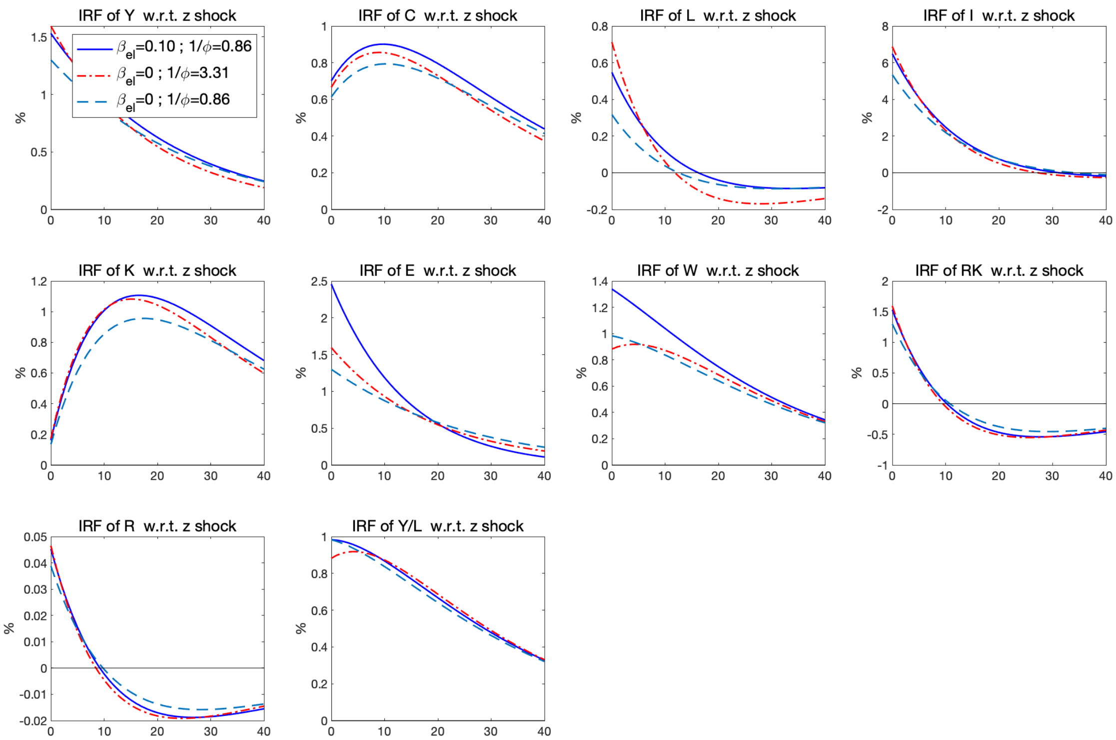
Note. Y-axis represents a percent deviation from steady state. The solid black line represents the model with a normalized Translog production function. The red dashed line represents the model with a Cobb-Douglas production function. The solid green line represents the model with a Cobb-Douglas production function and no energy input (i.e., standard RBC without energy).

Figure C.2: Impulse response w.r.t. 1% government spending shock: Cobb-Douglas vs. Translog



Note. Y-axis represents a percent deviation from steady state. The solid black line represents model with normalized Translog production function. The red dashed line represents model with a Cobb-Douglas production function. The solid green line represents model with a Cobb-Douglas production function and no energy input (i.e., standard RBC without energy).

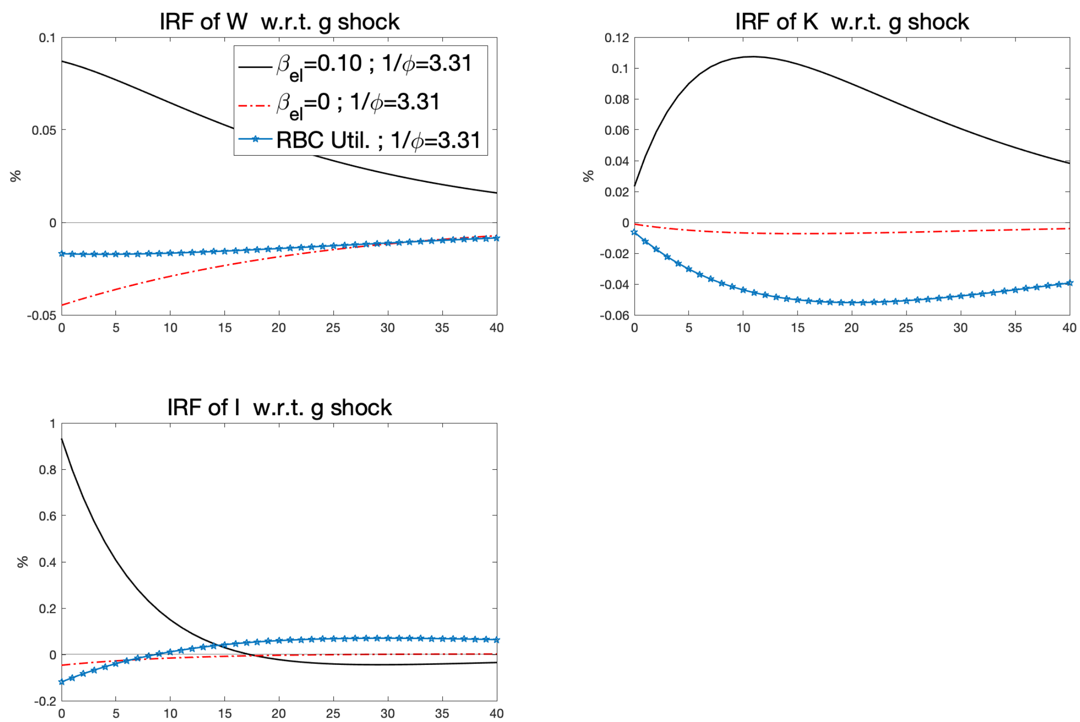
Figure C.3: Frisch elasticity: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. The blue solid line represents the model with a normalized Translog with micro-consistent Frisch elasticity of 0.86. The green dashed line represents model with Cobb-Douglas with micro-consistent Frisch elasticity of 0.86. The red dotted-dashed line represents the model with a Cobb-Douglas with macro-consistent Frisch elasticity of 3.31.

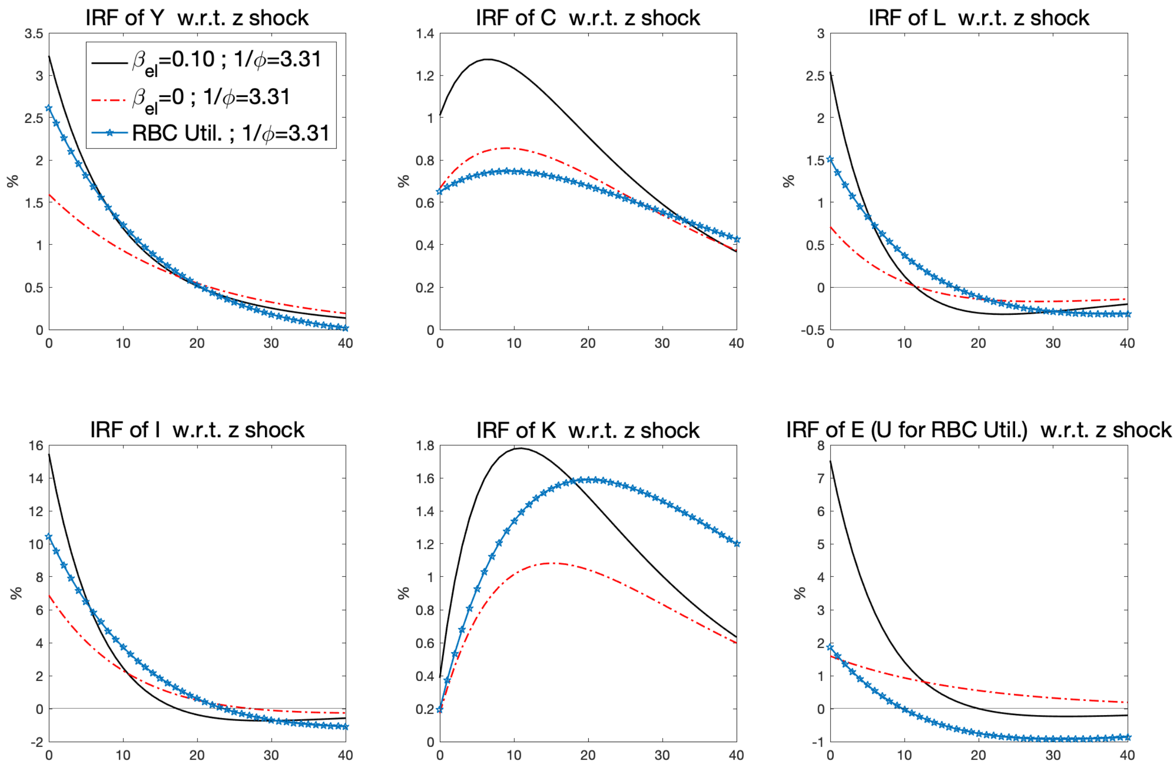
C.3.2 Comparison with RBC model with Capital Utilization

Figure C.4: Procyclicality: Increase in government spending by 1 %



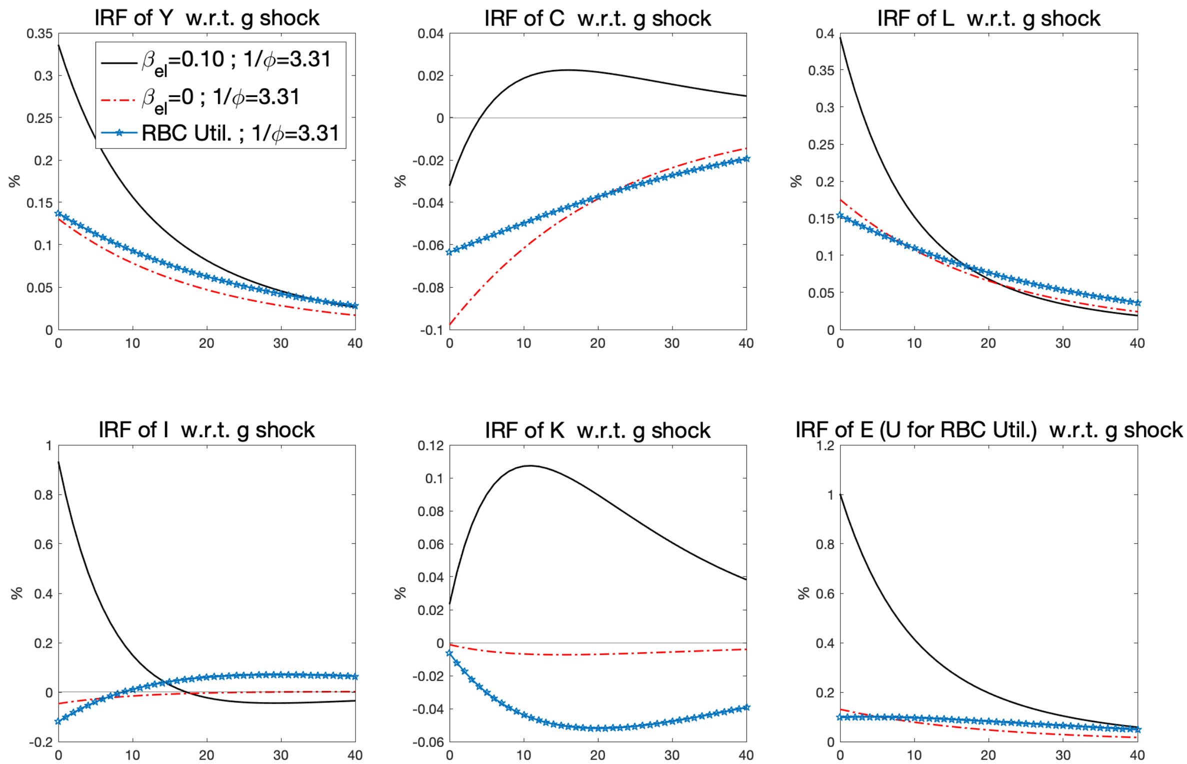
Note. Y-axis represents a percent deviation from steady state. Dashed lines represent the model with a Cobb-Douglas production function, and solid lines represent the model with a normalized Translog production function.

Figure C.5: Amplification: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. The solid black lines represent the model with a normalized Translog production function (with energy input). The red Dashed lines represent the model with a Cobb-Douglas production function with energy input. The blue starred line represent the RBC model with capital utilization but without energy input. In (2,3) panel, we plot energy for the normalized Translog and Cobb-Douglas model with energy input (E), and plot utilization (U) for the RBC model with capital utilization.

Figure C.6: Amplification: Increase in government spending by 1 %

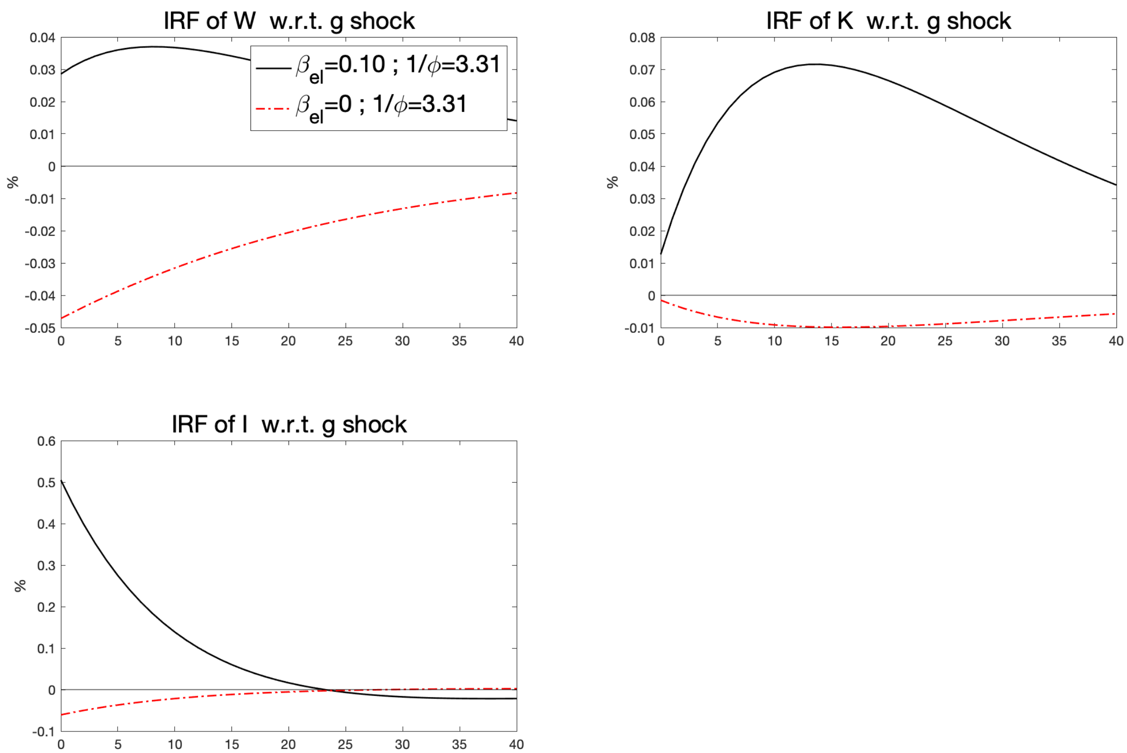


Note. Y-axis represents a percent deviation from steady state. The solid black lines represent the model with a normalized Translog production function (with energy input). The red Dashed lines represent the model with a Cobb-Douglas production function with energy input. The blue starred line represent the RBC model with capital utilization but without energy input. In (2,3) panel, we plot energy for the normalized Translog and Cobb-Douglas model with energy input (E), and plot utilization (U) for the RBC model with capital utilization.

C.3.3 Dynamics: A Model with Endogenous Energy Price

C.3.3.1 Procyclical Wage, Capital, Investment with respect to the Government Spending Shock

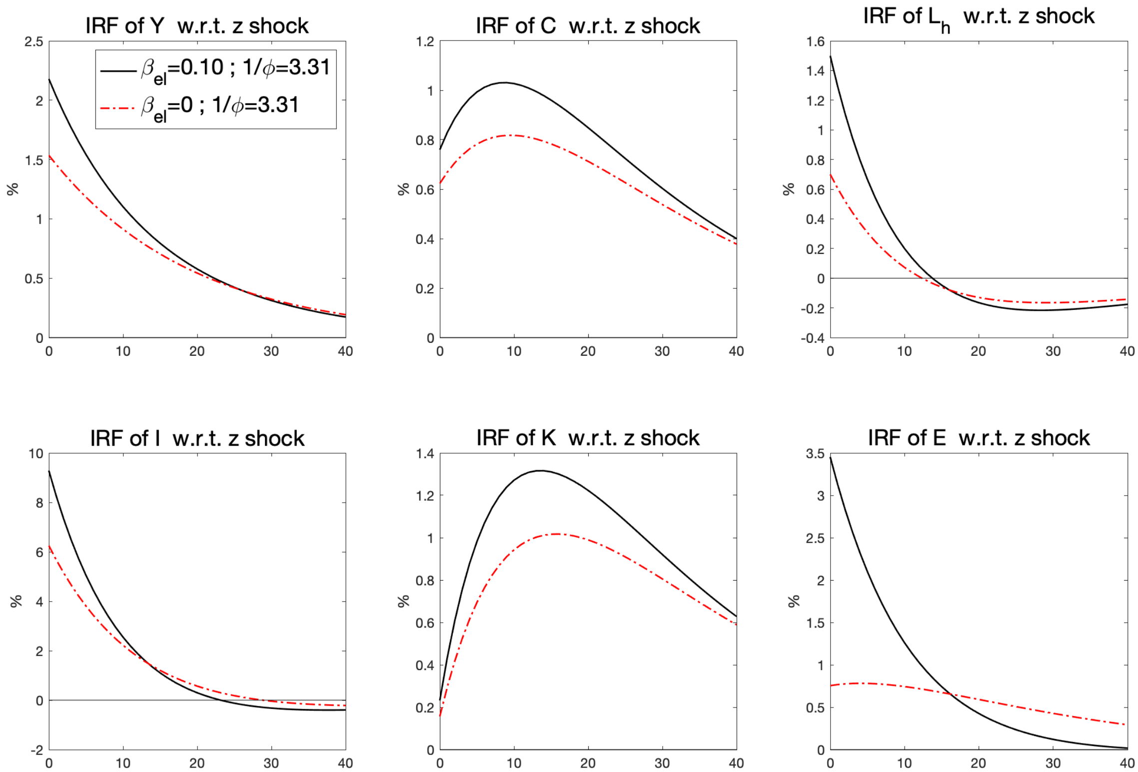
Figure C.7: Procyclicality: Increase in government spending by 1 %



Note. Y-axis represents a percent deviation from steady state. The dashed line represents the model with a Cobb-Douglas production function, and the solid line represents the model with a normalized Translog production function.

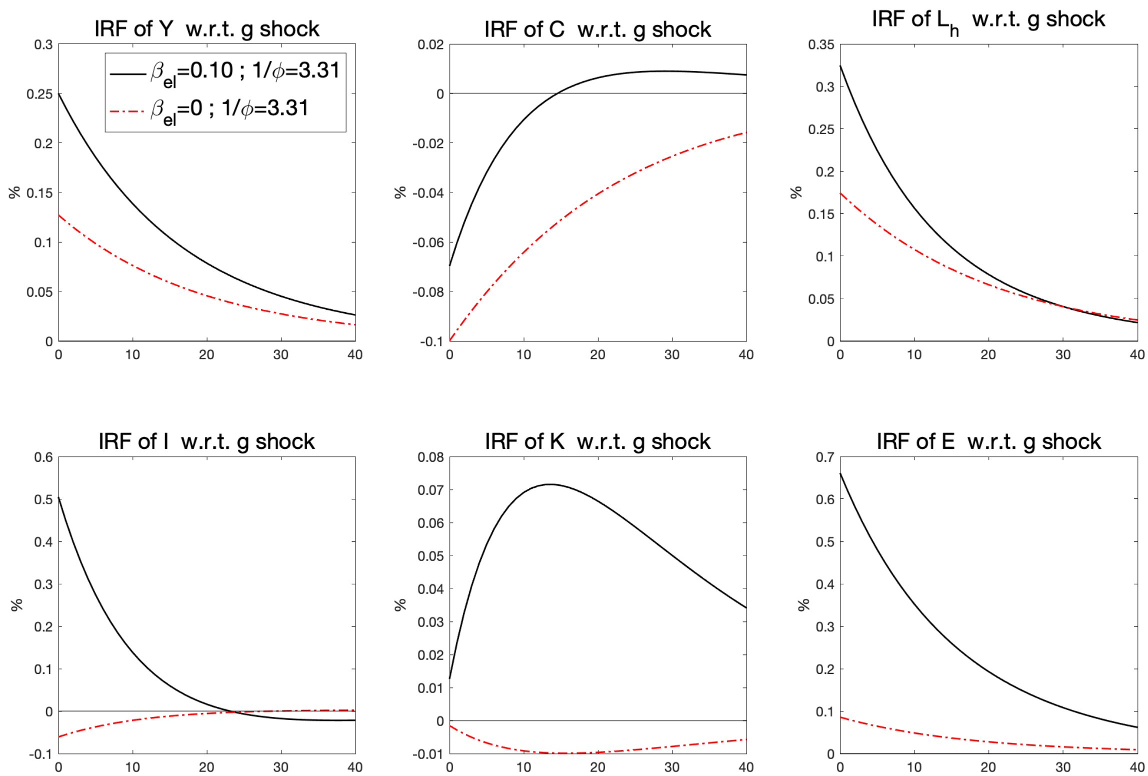
C.3.3.2 Strong Amplification

Figure C.8: Amplification: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. The dashed line represents the model with a Cobb-Douglas production function, and the solid line represents the model with a normalized Translog production function.

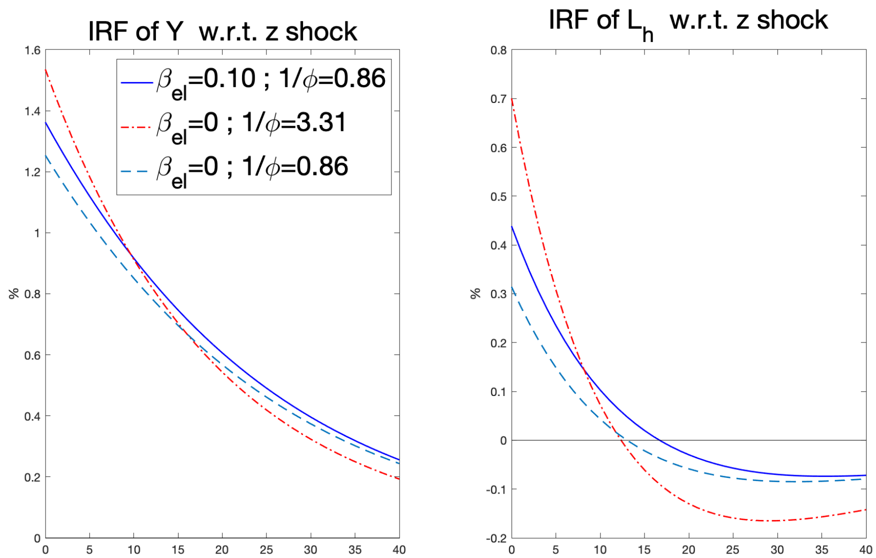
Figure C.9: Amplification: Increase in government spending by 1 %



Note. Y-axis represents a percent deviation from steady state. The dashed line represents the model with a Cobb-Douglas production function, and the solid line represents the model with a normalized Translog production function.

C.3.3.3 Using Micro-consistent Frisch Elasticity

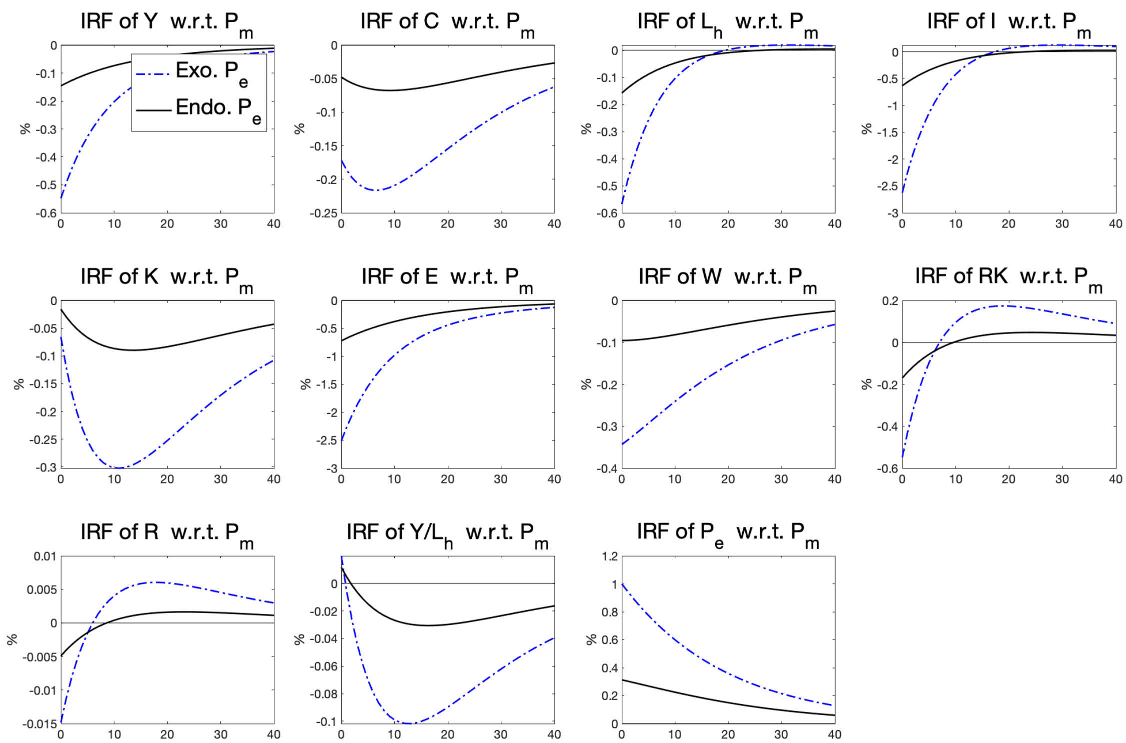
Figure C.10: Frisch elasticity: Increase in productivity by 1 %



Note. Y-axis represents a percent deviation from steady state. The blue solid line represents the model with a normalized Translog with micro-consistent Frisch elasticity of 0.86. The green dashed line represents the model with a Cobb-Douglas with micro-consistent Frisch elasticity of 0.86. The red dotted-dashed line represents the model with a Cobb-Douglas with macro-consistent Frisch elasticity of 3.31.

C.3.3.4 Impulse Response w.r.t. Raw material Price shock

Figure C.11: Impulse Response: Increase in raw material price (P_m) by 1 %



Note. Y-axis represents a percent deviation from steady state. The dashed blue line represents the model with a normalized Translog production function with exogenous energy price (Section 4 model), and the solid black line represents the model with a normalized Translog production function with endogenous energy price (Appendix D model). For the dashed blue line (Section 4 model), energy price is identical to the raw material price (i.e., $P_e = P_m$).