ABSTRACT

Title of dissertation:	ESSAYS ON PRODUCT DYNAMICS OF MULTIPRODUCT FIRMS
	Diyue Guo Doctor of Philosophy, 2018
Dissertation directed by:	Professor John Haltiwanger Department of Economics

Multiproduct firms account for a large fraction of economic activity and actively change their product mix. This dissertation consists of two chapters studying the product dynamics of multiproduct firms.

In Chapter 1, I investigate changes in product scope, the number of products that a firm offers, over the business cycle and decompose the impact of such changes on aggregate output. I use the Nielsen Retail Scanner data of U.S. consumer goods purchases for 2007-2014. I find that firm product scope is an important margin of adjustment. In the recession, firm product scope decreases on average and the decreases are heterogeneous across firms. Such product scope changes affect aggregate consumption and output by changing the total number of products and by affecting firms' markups. These impacts are shown in a model featuring heterogeneous multiproduct firms, oligopolistic competition and free firm entry. Firm and aggregate outcomes vary in different states of economic activity. In a recession state, lower average product scope implies a lower number of product varieties, which disincentivizes consumption. Additionally, since the most productive firms have higher

market shares, as the data suggests, they charge higher markups as oligopolistic competitors. The average markup goes up and further decreases consumption.

In Chapter 2, I explore the within-firm product dynamics beyond the product scope changes. The measures of interest include within-firm product entry, exit, net entry and reallocation. The net entry is related to the product scope changes (and is expected to be procyclical), and the reallocation is an important channel for endogenous growth. To investigate the cyclicality of these measures and locate the firm-level factors that affect the within-firm product dynamics, I combine the Nielsen Retail Scanner data with the Compustat fundamental data for the listed firms, by matching the firm names. The listed Nielsen firms have lower net entry and reallocation rates in the recession years. The regressions of the net entry and reallocation rates on the unemployment rate reveal that the net entry is significantly procyclical on average and the reallocation is not. Moreover, firms' financial constraint condition and R&D significantly affect the reallocation, but not the net entry.

ESSAYS ON PRODUCT DYNAMICS OF MULTIPRODUCT FIRMS

by

Diyue Guo

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2018

Advisory Committee:
Professor John Haltiwanger, Chair
Professor Luminita Stevens
Professor John Shea
Professor Nuno Limão
Professor Phillip Swagel

Dedication

To my parents

Acknowledgments

I owe my gratitude to all the people who have made this thesis possible and because of whom my graduate experience will benefit me throughout the year.

First and foremost, I'd like to thank my advisors, John Haltiwanger, Luminita Stevens, John Shea, and Nuno Limão for the great guidance and comments they have provided. I am deeply indebted to John Haltiwanger for mentoring me as a research assistant. He introduced me to firm dynamics and demonstrated the rigorous empirical research. His expertise, inspiration and continuous encouragement have been invaluable. I am grateful to Luminita Stevens. She provides numerous insightful comments and the generous support in obtaining the Nielsen and GS1 data. I would also like to thank my John Shea for carefully reading every draft of my primary research and providing extensive feedback to improve the paper. I'd like to thank Nuno Limão for introducing me to international trade models, on which the paper heavily draws. I also thank Phillip Swagel for agreeing to serve on my dissertation committee.

I thank to Felipe Saffie, Borağan Aruoba, Şebnem Kalemli-Özcan, Eunhee Lee, Ginger Zhe Jin, Andrew Sweeting, Guido Kuersteiner and participants of my presentations at the Economics department and other conferences for useful comments.

My colleagues at the Economics department deserve a special mention for all the valuable discussions, encouragement and support throughout my doctoral studies, as well as for enriching my graduate life in many ways.

I also grateful to Paul Wachtel from the Stern Business School at New York

University for giving me my first research job as a research assistant.

I would like to acknowledge the University of Maryland Department of Economics for the financial support in obtaining the GS1 data. I am grateful to John Shea for making the funding possible. I would like to acknowledge the Graduate School at the University of Maryland for financial support in digital supplies for conducting the data work.

Finally, I owe my deepest thanks to my family and friends, who support me in any possible ways. I am grateful for having Shen, my husband and colleague at the Economics department, working by my side. I thank him for his supports.

Table of Contents

Dedication ii

Acknowledgements iii

List of Tables vii

List of Figures ix

1 Firm Product Scope, Oligopoly Competition and the Business Cycle: Evidence and Theory 1
- 1.1 Introduction . . . 1
- 1.2 Literature Review . . . 7
- 1.3 Data and Empirical Approaches . . . 10
- 1.4 Empirical Findings . . . 14
  - 1.4.1 Highly Skewed Distribution . . . 14
  - 1.4.2 Firm Dynamics and Product Scope Adjustment . . . 15
  - 1.4.3 Cyclicality of Firms' Product Scope . . . 17
  - 1.4.4 Firms' Product Scope Changes: Supply or Demand Driven? . 21
  - 1.4.5 Robustness checks . . . 22
    - 1.4.5.1 Continuing Firms Only . . . 23
    - 1.4.5.2 Alternative Firm Size Measure . . . 23
- 1.5 The Model . . . 24
  - 1.5.1 Household . . . 25
  - 1.5.2 Firms . . . 28
    - 1.5.2.1 Input Choice, Pricing, and Product Scope . . . 28
    - 1.5.2.2 Entry Decision . . . 31
  - 1.5.3 Equilibrium . . . 31
  - 1.5.4 The Aggregate Price Index . . . 32
  - 1.5.5 Calibration . . . 33
  - 1.5.6 Aggregate Impact of Product Scope Changes . . . 34
- 1.6 Conclusion . . . 36
- 1.7 Appendix . . . 51

2 Product Switching within Multiproduct Firms 61
2.1 Introduction 61
2.2 Literature Review 63
2.3 Data 66
2.3.1 The Nielsen Retail Scanner 66
2.3.2 Compustat 67
2.3.3 Product Switching Measures 70
2.4 Empirical Results: All the Nielsen firms 72
2.4.1 Product Switching Rates 72
2.5 Empirical Results: the listed Nielsen firms 75
2.5.1 Who Are the Listed Nielsen Firms? 75
2.5.2 Product and Sales Shares by Firm Types 75
2.5.3 Net Entry and Reallocation Rates 76
2.5.4 Robustness Checks 78
2.5.4.1 Alternative Firm Control 78
2.5.4.2 Sales-based Addition and Subtraction Rates 78
2.6 Discussion 79
2.6.1 Reconsider the Role of Multiproduct Firms in the Business Cycle Setting 79
2.6.2 Reallocation and Growth 80
2.6.3 Reallocation Types: Business Stealing or Own-product Improvement 82
2.7 Conclusion 83
2.8 Appendix 101

Bibliography 112

List of Tables

1.1 Summary Statistics 39
1.2 Distribution of Firm Types 40
1.3 Decomposition of Total Sales Growth 41
1.4 Cyclicality of Average Product Scope: Cell-based Approach 41
1.5 Cyclicality of Firms' Product Scope: Firm-level Analysis 42
1.6 Cyclicality of Firm Sales: Firm-level Analysis 43
1.7 Cyclicality of Firms' Product Scope: National vs. Regional Firms . . 44
1.8 Cyclicality of Average Product Scope: Cell-based Approach, Continuing firms 45
1.9 Cyclicality of Firms' Product Scope: Firm-level Analysis, Continuing firms 46
1.10 Cyclicality of Firm Sales: Firm-level Analysis, Continuing firms . . . 47
1.11 Cyclicality of Firms' Product Scope: Alternative Firm Size Measure . 48
1.12 Cyclicality of Firm Sales: Alternative Firm Size Measure 49
1.13 Parameter Values 49
1.14 Differences in Key Outcomes: Recession versus Normal State 50
1.15 Cyclicality of Firm Sales Share: Firm-level Analysis 53
1.16 Cyclicality of Firms' Average Product Scope: Alternative Business Cycle Indicator 54
1.17 Cyclicality of Firms' Product Scope: Additional Firm Control 55
1.18 Changes in Firms' Product Scope Distribution 56
1.19 List of the Nielsen product groups 59

2.1 Summary Statistics, All the Nielsen Firms 86
2.2 Summary Statistics, the Listed Nielsen Firms 86
2.3 Firms' Product Switching Rates 87
2.4 Probability of Adding/Dropping a Product 88
2.5 Products and Sales by Firm Types 90
2.6 Net Product Entry, the Listed Nielsen Firms 91
2.7 Product Reallocation, the Listed Nielsen Firms 92
2.8 Net Product Entry, the Listed Nielsen Firms 93
2.9 Product Reallocation, the Listed Nielsen Firms 94

2.10 Net Product Addition, the Listed Nielsen Firms 95
2.11 Product Sales-based Reallocation, the Listed Nielsen Firms 96
2.12 Firm Markup Growth, the Listed Nielsen Firms 96
2.13 Reallocation and Growth, All the Nielsen Firms 97
2.14 Reallocation and Growth, the listed Nielsen Firms 98
2.15 Own-product Improvement vs Business Stealing, All the Nielsen Firms 99
2.16 Own-product Improvement vs Business Stealing, the listed Nielsen Firms 100
2.17 Probability of Adding/Dropping a Product 101
2.18 Product Entry, the Listed Nielsen Firms 103
2.19 Product Exit, the Listed Nielsen Firms 104
2.20 Cyclicality of Firms' Product Scope, the Listed Nielsen Firms 106
2.21 Cyclicality of Firm Sales, the Listed Nielsen Firms 107
2.22 Standardization of Firm Names 108
2.23 Compustat Terms for Data Construction 109
2.24 Summary Statistics, the Listed Nielsen Firms 111

List of Figures

1.1 Total Sales in the Nielsen Data vs. Nondurable Goods Consumption . 38
1.2 Histogram of Firms' Product Scope 40
1.3 Model Fit: Distribution of Firm Product Scope 50

2.1 Average Product Scope, the Listed Nielsen firms vs All the Nielsen Firms 89

Chapter 1: Firm Product Scope, Oligopoly Competition and the Business Cycle: Evidence and Theory

1.1 Introduction

Multiproduct firms account for a large fraction of economic activity (Bernard et al. (2010) and Broda and Weinstein (2010)). Moreover, product additions and subtractions are common at the firm level. Bernard et al. (2010) find that one-half of firms alter their mix of products every five years and that such product additions and subtractions are influential in determining both firm and aggregate outcomes. Building on their results, my study examines within-firm product switching over a short horizon and investigates its impact on aggregate output over the business cycle.

In this paper, I document changes in product scope, the number of products that a firm offers, over the recent business cycle and decompose the impact of such changes on aggregate output with a quantitative general equilibrium model of multiproduct firms. I find that firm product scope is an important margin of adjustment and it is procyclical on average. Such changes affect not only product varieties available in the market but also firm markups, and through both channels affect aggregate consumption and output.

I first investigate the empirical patterns of product scope adjustment, using Nielsen's Retail Scanner data on U.S. consumer goods transactions for 2007–2014.[1] Large-scale micro-level data with product information, such as the Nielsen data, became available only recently, and enabled new insights for understanding product dynamics. The Nielsen data is a good proxy of nondurable goods consumption. The transactions are at the level of Universal Product Code (UPC or barcode), which is my definition of a product.[2] I assign UPCs to their manufacturers using a data tool provided by GS1, the registrar of UPCs.[3] To explore product group differences and regional variations, I divide the transactions into different product groups and regions (i.e., Scantrack markets). The final data contain observations for 1.3 million UPCs of 36,605 firms and cover 115 product groups of 49 regions in 8 years.

I establish four empirical facts on firm product scope in general as well as its business cycle properties. The first observation is that the cross-sectional distribution of firms' product scope is highly skewed, with the median firm offering 3 products and the largest firm offering 256 products.[4]

[1]All empirical results are calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Data copyright © 2018 The Nielsen Company (US), LLC. All Rights Reserved. The conclusions drawn from the Nielsen data are those of the researchers 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.

[2]A product can be defined in different ways. The choice of product definition usually depends on the data. For example, Bernard et al. (2010) use manufacturing Census data and define a product as a five-digit SIC category; on the contrary, Broda and Weinstein (2010) use similar Nielsen data to mine and define a product as a Universal Product Code, which is a more disaggregated product definition.

[3]Hottman et al. (2016) also use UPC-level data and map UPCs into manufacturer identifiers using the GS1 data tool.

[4]The product scope numbers are averaged across product groups, Scantrack markets and years.

Second, the product scope adjustment margin is important. In the Nielsen data, 39% of firms change their product scope annually, whereas only 24% of firms are new or exiting. About twice as many firms expand or shrink their product scope as firms that enter or exit the market. This finding is consistent with the empirical pattern in Broda and Weinstein (2010) that aggregate product additions and subtractions are much larger than firm entry and exit. Additionally, the product scope adjustment margin is 4.5 times more important than the firm entry and exit margin in terms of the contribution to total sales growth.

The third observation is about the variation in product scope over the business cycle.[5] I show that firm product scope is on average negatively correlated with the regional unemployment rate, suggesting product scope is procyclical on average. Broda and Weinstein (2010) has documented the procyclicality of product additions at the aggregate level.[6] However, the aggregate number of products depends on both the number of firms and the number of products per firm. The procyclicality of product scope at the firm level is a novel finding that isolates firm-level product switching from firm entry and exit. Furthermore, product scope adjustment redefines the boundary of firms and changes the size distribution of firms. In particular, product scope is the most procyclical for medium-sized firms relative to small or

[5] Axarloglou (2003) is the first study to show the business cycle properties of product introductions at the firm level, but their findings are based on anecdotal evidence from newspapers. Decker et al. (2014) also find that U.S. listed firms have more products (or more precisely speaking, industries, as defined by the four-digit SIC codes) in booms and fewer in recessions than in normal times. My analysis differs from the previous studies by using UPC-level data and investigating average firms.

[6] Both aggregate product additions and product additions net of product subtractions are procyclical. Very recently, Argente et al. (2018) study product reallocation, defined as additions plus subtractions, at the aggregate and firm level. The authors find that aggregate product reallocation is strongly procyclical and the cyclical pattern is almost entirely explained by within-firm reallocation.

large firms.[7] Consistent with the nonlinear response of product scope across firms, sales changes also vary by firm size. Medium-sized firms shrink more in a recession and large firms take more market share.

The measured procyclicality in firm product scope can arise because of local supply shocks that cause firms to adjust their product offerings, or because of local demand shocks that cause consumers to alter the varieties in their consumption baskets. The Nielsen data support the idea that some of the observed product scope changes are due to local supply shocks. To assess the relative strength of the supply and demand channels, I compare the cyclicality in product scope of local firms that sell in one region to that of national firms that sell in all regions. Local firms are affected by both local demand and supply channels. On the contrary, assuming that national firms can produce anywhere in the nation, their local product scope is only affected by the demand channel. The Nielsen data confirms that product scope is more procyclical for local firms than national firms, so product scope changes are partly driven by local supply shocks and firm-side adjustment. Furthermore, the result holds true for both medium and large firms.

These findings are obtained using data defined at both the cell and firm level. A cell is a product group by Scantrack market by year observation. I measure cell-level data as averages across firms within the cell. For firm-level analysis, I identify firms within each product group by Scantrack market by year cell. Firm controls such as size are measured using the Nielsen data and included in the firm-level

[7] I use a firm's lagged product scope as the main firm size proxy. Similar results are obtained using sales instead of product scope. See this robustness check in section 4.5.

analysis.

To demonstrate the aggregate impacts of the cyclical changes in product scope, I build a quantitative general equilibrium model of multiproduct firms. The model features heterogeneous multiproduct firms, oligopolistic competition and free firm entry. I abstract from any interaction across product groups or regions. Within a given product group and region, firms that have heterogeneous productivity can produce multiple differentiated products. A firm's product scope is determined by a demand constraint: the benefit to adding a product is the extra profit earned, while the cost is the cannibalization of profits on existing products. The cannibalization effect framework was first proposed in Feenstra and Ma (2007) and has empirical support, e.g., Srinivasan et al. (2005).[8] The model features a finite number of firms who engage in oligopolistic competition, to match the empirical market shares of different firms in my data. I also model endogenous firm entry and exit, which enables me to compare the product scope adjustment margin and the firm churning margin. The firms consider all products on the market and endogenously choose their input demand, product prices, and product scope to maximize profits. In equilibrium, firms' choices (i.e., input demand, product prices, product scope) depend on their productivity. All else being equal, the higher is a firm's productivity, the higher are its market share and markup.

I calibrate the model so that the model moments in steady state match the data. The distribution of firm product scope generated by the model matches well with the distribution in the data. To decompose the aggregate impact of product

[8] See Section 2 for a broader discussion of the cannibalization effect model and its alternatives.

scope changes, I compare two steady states - one capturing normal times and the other capturing a recession in which average productivity is lower and productivity dispersion is higher.[9]

The comparative statics show that changes in product scope affect aggregate output in two ways. First, firms' procyclical product scope generates a product variety effect. In a recession state, firms' product scope is lower than in normal times, which means fewer product choices for consumers. Since consumers love variety, fewer products means a higher aggregate price of consumption relative to leisure, which disincentivizes consumption and output. This is the direct impact of procyclical product scope.

In addition to the direct impact, firms' product scope choices affect their markups. In a recession state, product scope reoptimization enables the most productive firms, which have more advantages relative to other firms as the productivity dispersion rises, to acquire more market share. Since firms are oligopolistic competitors, higher market share leads to a higher markup. Consequently, the average markup rises. The countercyclical markup intensifies the increase in the aggregate price of consumption relative to leisure and further decreases consumption and output. The Nielsen data support the model's prediction that large firms achieve higher market shares in recessions.

The remainder of this paper is structured as follows. In section 1.2, I review the literature on multiproduct firms and firm dynamics over the business cycle. In

[9] Lower mean productivity and higher productivity dispersion in recessions are supported by literature, e.g., Kehrig (2015).

section 1.3, I describe the data and my empirical approach. Section 1.4 reports the main empirical results and robustness checks. In section 1.5, I build and solve a general equilibrium model with a finite number of heterogeneous firms that can enter or exit the market and choose their product scope. In this section, I also calibrate the model and use it to demonstrate the aggregate impact of changes in product scope by comparing two steady states. Section 1.6 summarizes.

1.2 Literature Review

My study contributes to the empirical studies on multiproduct firms, of which examples include Axarloglou (2003), Bernard et al. (2010), Broda and Weinstein (2010), and Decker et al. (2014). In particular, Broda and Weinstein (2010) investigate ACNielsen Homescan data that record consumer goods purchases in the U.S. for 1994 and 1999–2003. They find that gross and net product additions are procyclical, while product subtractions are countercyclical. However, aggregate product additions and subtractions confound firm entry and exit with product switching within firms. As opposed to Broda and Weinstein (2010), my paper investigates the latter explicitly and also explores regional variations and identifies firm using the GS1 data. Broda and Weinstein (2010) also find that there are four times as many product additions and subtractions as firm entries and exits in terms of sales. This finding suggests that product switching at the firm level plays at least an equally important role as firm entry and exit, the latter of which is a well-documented important factor affecting aggregate dynamics, as discussed later.

My study is also related to two groups of theoretical studies: models of multiproduct firms and models of firm dynamics in business cycle analysis. The first relevant strand of the literature concerns modeling multiproduct firms. One field that emphasizes multiproduct firms is international trade.[10] There are two ways to constrain a firm's product scope: demand-side and supply-side factors. The demand-side constraint arises from the interactions of firms' products. Feenstra and Ma (2007) proposes that firms face a clear tradeoff when choosing their number of products. The positive side of expanding the product range is that firms' elasticity of demand falls and their market power increases. The downside is the cannibalization effect in demand, that is, producing more products cannibalizes the sales of existing products, because products within and across firms are imperfect substitutes. On supply-side constraints, for example, Bernard et al. (2010) claim that firms' choice of products is contingent on two attributes, one specific to firms and the other specific to firm–product pairs. In this setting, firms expand their product scope until the firm product-specific attribute for the marginal product falls below the cutoff level.[11] Alternatively, Yeaple (2013) assumes that fixed organizational capital is needed to produce any product. Firms thus face a tradeoff between more products and higher productivity. These different ways of modeling multiproduct firms are not mutually exclusive. For example, Eckel and Neary (2010) allows for the cannibalization effect

[10]Firms' product choice is also an important topic in industrial organization and finance. Such microeconomic studies have focused on firm-level implications rather than aggregate behavior. For example, Lang and Stulz (1994), Berger and Ofek (1995), and Maksimovic and Phillips (2002)) discuss firms' performance in financial markets and product scope.

[11]The model of Bernard et al. (2010) is a natural extension of the widely adopted market and firm setting studied in Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995), and Melitz (2003)

and additionally proposes that firms have a "core competency" in the production of a particular good.

My model follows Feenstra and Ma (2007), whose model of the cannibalization effect is consistent with the empirical findings in the marketing literature, such as Srinivasan et al. (2005). Hottman et al. (2016) also offers empirical evidence supporting the existence of a cannibalization effect. In this paper, I adopt the cannibalization effect framework and calibrate the model to match the empirical distribution of firm size.

The second strand of the literature is related to studies of the endogenous entry and exit of firms and their implications for business cycles. Firms are often assumed to produce only one product and firm entry and exit are shown to amplify and propagate business cycles. For example, Chatterjee and Cooper (2014) argue that firm entry determines product additions and that procyclical firm entry amplifies aggregate price changes through the product variety effect. Jaimovich and Floetotto (2008) argue that procyclical firm entry is important because it leads to countercyclical variations in markups that give rise to endogenous procyclical movements in productivity. Bilbiie et al. (2012) take firms as a special investment instrument and consider the return on investment. Since this return rises in booms, firm entry is procyclical. The study further shows that the sluggish response of the number of firms generates an endogenous propagation mechanism.

In contrast to the above studies, which assume single-product firms, Minniti and Turino (2013) investigate the role of homogeneous firms that produce multiple products. The authors show that lower product scope in a recession decreases aggregate output by reducing the number of products available in the market. In a dynamic setting, procyclical product scope changes amplify business cycle shocks. Different from that paper, I present empirical patterns first and highlight firm heterogeneity in both data and model.

Firm heterogeneity has been found to play an important role in linking firm dynamics and aggregate fluctuations. Ottaviano (2011) discusses the endogenous procyclical movement in productivity similar to Jaimovich and Floetotto (2008), but emphasizes the reallocation of market share among firms with different efficiency levels. Lee and Mukoyama (2012) and Clementi and Palazzo (2013) further highlight the different impacts of aggregate shocks on entrants and existing firms. The emphasis on firm heterogeneity in discussing the impact of firm entry and exit is supported by the empirical findings of Foster et al. (2001). My study complements this research by investigating the heterogeneous responses in product scope of different firms.

1.3 Data and Empirical Approaches

Nielsen's Retail Scanner data on consumer goods purchases are reported by participating retail stores in all U.S. markets at weekly frequency. Between 2007 and 2014, approximately 35,000 grocery, drug, mass merchandiser, and other stores reported their transactions. Another data set similar similar to Nielsen Retail Scanner but collected at the consumers' end is the Nielsen Consumer Panel. I choose Nielsen's Retail Scanner data over the Consumer Panel because the latter lacks retailer information, which prevents researchers from distinguishing the impact of retailer entry and exit and manufacturer adjustment.[12] By using Retail Scanner data, I can thus keep a balanced panel of stores. The balanced panel used in this study contains 28,953 stores and accounts for about 90% of all transactions. I do not distinguish variations across retailers and focus on manufacturer (firm) adjustment in my analysis.

The transaction data are available at the UPC level. A UPC is defined as a product. A rule of thumb in firms' assigning UPCs is that each variation in color, size or any other main characteristic is labeled by a different UPC. Therefore, each UPC represents a unique cost and revenue structure. I argue that a UPC is the real-life counterpart closest to the economic concept of a distinct product.

I retain products that use standard UPCs and drop so-called magnet products that use nonstandard UPCs such as weighted meat, fruit, and vegetables. In addition, I drop private labels, namely products directly owned by retail stores, the UPCs of which are masked. The products or UPCs remaining in the sample are assigned to product groups (e.g., baby food) to address product group composition changes in the data. This also enables me to control for product group fixed effects in the regression later. In total, there are 115 product groups.[13]

The Nielsen data also contain transaction locations. I define geographic units as Scantrack markets, such as Washington D.C.[14] In this way, I can explore regional

[12] The unbalanced panel also confounds consumers switching stores and manufacturer (firm) adjustment. As consumers switch to stores (Coibion et al. (2015)) and end up in stores carrying products of a certain type of manufacturers, the observed product scope might be affected.

[13] See Appendix B2 for a complete list of the product groups.

[14] Scantrack market is the most disaggregated level of geographic unit with a counterpart in the representative Consumer Panel. More specifically, to check the representativeness of Nielsen's

variations. There are 49 Scantrack markets with transactions of all product groups available.

The Nielsen UPC data alone do not produce clear information on manufacturing identity. Although the first several digits of a UPC are company prefix numbers and uniquely identify its manufacturer, it is not possible to accurately infer manufacturer from a UPC directly because the length of the company prefix is variable.[15] To link UPCs to their manufacturers, I use the official matches data of UPCs and their corresponding company prefix numbers from GS1, the standards institution for UPCs. The list of all the UPCs in the 49 Scantrack markets from 115 product groups in 2007–2014 are matched with their manufacturer information (identifier numbers, name, and location), using GS1's List Match data tool. The ratio of successful matching is 96%. 36,605 unique firms are identified.

I consider three complications when matching products with their manufacturers First, the matches data show the current manufacturer of a given UPC. A company prefix may be recycled after its owner exits the market or stops paying the annual renewal registration fee, although this is rare according to GS1. To confirm that the data capture aggregate firm dynamics well, I check the annual firm entry and exit rates, which are comparable to Census data. The second complication is that a firm can have more than one company prefix. I use company name to combine company prefixes belonging to the same firm. The third complication is that firms

Retail Scanner, I use the consumer panel as a benchmark, because the latter has a projection system transforming the data to be representative of the corresponding region. The most disaggregated geographic definition with a projection system in the Consumer Panel is a Scantrack market.

[15]There was a belief that the first six digits of a twelve-digit UPC represented the manufacturer. This practice had been abandoned to accommodate a growing number of firms adopting UPCs to label their products.

can assign a UPC to a different product over time. To rule out such cases, I drop UPCs that are grouped into different product modules in different years.[16]

The main measure of interest is firms' product scope (PS), the number of UPCs that a firm offers within a given product group in a given Scantrack market. To document the empirical patterns of the firm product scope distribution and its changes over the business cycle, I use two complementary analytical approaches: cell-based and firm-level analyses. In the cell based approach, a cell is a product group by Scantrack market by year observation. I use an across-firm average measurement as the cell-level measurement. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The firms in the final data on average are active in 2 product groups and sell to 17 Scantrack markets within a given product group.[17] Firm controls such as size are measured using the Nielsen data and included in the firm-level analysis. Other potential firm controls such as productivity and age are not available.[18]

Total sales of the 115 product groups and 49 Scantrack markets serves as a good proxy of aggregate nondurable goods consumption from the National Income and Product Accounts (NIPA) over the sample period. Figure 1.1 plots the two time series in billions of dollars. The solid line represents Nielsen sales and the dashed

[16]Product module is a lower level of aggregation than product group. For example, baby food is a product group, while baby food, junior is a product module. The regrouping of UPCs into different product modules can also result from product module definition changes. However, distinguishing between UPCs labeling different underlying products and UPCs being regrouped into a different product module because of a definition change is challenging. Therefore, the rare cases of regrouped UPCs are dropped.

[17]The median firm is active in only 1 product group. Within a given product group, the median number of Scantrack markets that a firm covers is 7.

[18]In the appendix, I include results with firm age inferred from the Nielsen data.

line plots NIPA nondurable goods spending against the secondary axis. Nielsen sales align well with nondurable goods consumption for most years except 2010, when the former had recovered from the global financial crisis, whereas the latter had not. The discrepancy is partly because the Nielsen data also include some durable goods, e.g., small electronics.

1.4 Empirical Findings

I present four facts in this section. First, the cross-sectional distribution of firm product scope is highly skewed. Second, within-firm product scope changes are an important margin of adjustment. Third, product scope is procyclical on average, and the changes are heterogeneous across firms of different size, defined by their last-period product scope. Fourth, part of the product scope changes are directly due to firm-side adjustment. I also conduct two robustness checks at the end of the section.

1.4.1 Highly Skewed Distribution

Table 1.1 shows the summary statistics of firms grouped by cells. There are 45,080 Scantrack markets by product group by year cells. The table documents firms' product scope as the number of UPCs a firm sells within a cell, and firm sales as a share of total sales within a cell. I also report the total number of firms and total sales in a cell to keep track of aggregate activity. The values in the third (fourth) column are averages (standard deviations) of cell-level moments across the

45,080 cells. Since the mean product scope is much larger than the median, the distribution of firms' product scope is highly skewed. The distribution features a large number of firms with a few products and some exceptional firms with large product scope. In terms of firms' sales' share, most firms are small while some have non-trivial market shares. This is consistent with the product scope observation. It is reasonable to assume that firms that have high market share behave strategically.

The skewness of the distribution of firms' product scope is confirmed in the histogram shown in Figure 1.2. About 67% of firms have more than one product. The largest firms have more than 100 products.

1.4.2 Firm Dynamics and Product Scope Adjustment

How important is the product scope adjustment margin relative to the firm entry and exit margin? Table 1.2 presents the shares of all firms that are new firms, exiting firms, and continuing firms with expanding, shrinking, and unchanged product scope. For each pair of years in the sample period, a firm is an entrant (exiter) if it only has sales in the next (base) year. Since reentry is rare, I argue that this serves as a reasonably good proxy of actual firm entry and exit. The firm ratios reported are the averages across product group by Scantrack market by year observations.

While about 24% of firms are new or exiting firms, about 39% change their product scope. Specifically, 1.5 (1.8) times as many firms expand (shrink) their product scope compared with firms that enter (exit) the market: 17.7% versus 12%

(21.7% versus 12.3%). Note that the annual firm entry and exit rates are comparable to but slightly higher than Census data: Dunne et al. (1988) report the average industry-level five-year entry (exit) rate of manufacturing firms is 30.7%–42.7% (30.8%–39%) between Census years for 1963–1982, which puts the annual entry (exit) rate in the range of 10%. If the entry and exit firm ratios are overestimated in my data, the product scope adjustment margin is even more important relative to the firm entry and exit margin than indicated by my data. Moreover, since new and exiting firms have lower sales than continuing firms in general, the shares of sales accounted for by entrants and exiters are even smaller.

Table 1.3 further shows sales growth and weighted sales growth by different firm types, to decompose the growth of total sales into contributions from firm entry and exit and product scope adjustment.[19] The first row shows the average contributions of firm types across the sample years. On average, total sales growth is -0.11%, which equals the sum of 0.72% (entrants), -0.20% (exiters), 2.41% (firms expanding product scope), -2.67% (firms shrinking product scope), and -0.38% (firms with unchanged product scope). In terms of sales growth contribution, the product scope adjustment margin is 4.5 times more important than the firm entry and exit margin. Table 1.3 also reports the decomposition by pairs of years, which are represented by the second year in a pair. The contributions of different firm types vary year by year, but the product scope adjustment margin is always more important than the

[19]The growth rates in this study are all constructed in the Davis-Haltiwanger-Schuh fashion if not otherwise specified, i.e., growth= $\frac{sales_t - sales_{t-1}}{0.5\times(sales_t + sales_{t-1})}$. This growth rate can account for entering and exiting firms. The weighted sales growth of firm type k is defined as $\frac{sales_{kt} - sales_{kt-1}}{0.5\times\sum_k(sales_{kt} + sales_{kt-1})}$. The summation of weighted sales growth across all five types equals total sales growth.

firm entry and exit margin.[20]

1.4.3 Cyclicality of Firms' Product Scope

I use both cell-based and firm-level analyses to investigate the cyclicality of firms' product scope. For the cell-based approach, I use the across-firm average measurement as the cell-level measurement. The business cycle indicator is the regional unemployment rate for the Scantrack market. Procyclicality (countercyclicality) means a negative (positive) correlation of the firms' product scope measure with the unemployment rate. The correlation is computed by using the following regression equation:

$$y_{grt} = \alpha_g + \psi_r + \omega_t + \beta UR_{rt} + \epsilon_{grt}, \tag{1.1}$$

where y_{grt} is the growth rate of firms' average product scope in a given cell of product group g, Scantrack market r, and year t. I choose the growth rate as the main dependent variable because the aggregate product scope levels of many product groups have a time trend. The main control on the right-hand side is the unemployment rate at the Scantrack market by year level.[21] The right-hand side also has fixed effects for product group, Scantrack market, and year. Since different product groups might have different time characteristics, I also consider the interaction fixed effects of product group and year. Notably, the regression reveals

[20] In Appendix A1, I present the correlations of total sales growth with firm number growth and average product scope growth, respectively.

[21] A Scantrack market contains several counties. The local unemployment rate is the average across all the counties in a given market.

the correlation between growth in average product scope and the business cycle indicator, but does not necessarily establish a causal relationship. The standard errors for the regression estimates are clustered at the level of Scantrack market.

Column (1) of Table 1.4 shows the baseline regression result for the growth rate of average product scope. The regional unemployment rate has a significant and negative effect on the growth rate of average product scope, meaning that firms' product scope is procyclical on average. When the unemployment rate increases by 1%, average product scope growth decreases by 0.23%. Although not shown explicitly, this remains true when controlling for the interaction fixed effect. Additionally, if I add an interaction of recession years with the unemployment rate, average product scope growth is still negatively correlated with the unemployment rate in non-recession years, and slightly more so in the two recession years. Column (2) uses the change in the unemployment rate as the business cycle indicator to account for the fact that unemployment is often a lagged indicator of the business cycle (i.e., it peaked after the trough of the Great Recession). The strong negative correlation between average product scope growth and the change in the unemployment rate confirms the procyclicality of the former.[22]

In addition to the cell-based analysis, I can further run the following firm-level regression to explore firm variations:

$$y_{m,grt} = \alpha_g + \psi_r + \omega_t + \beta UR_{rt} + \text{controls}_{m,grt-1} + \epsilon_{mgrt}, \tag{1.2}$$

[22]Here, all firms, including entrants and exiters, are included to construct the cell-level measurement. In the robustness checks in Section 4.5, I show the results using only continuing firms.

where m denotes the firm, g the product group, r the Scantrack market, and t the year. The primary firm-level control is a firm size indicator.[23] A firm is "Small" if it is an entrant or its lagged product scope in logs is in the first tercile. A "Medium" ("Large") firm's lagged product scope in logs is in the second (largest) tercile. Specifically, the first tercile means less than the 34th percentile and the second tercile means less than the 67th percentile. Typically, a 34th percentile firm has one product, while a 67th percentile firm has five. As a robustness check, results using a sales-based firm size indicator are discussed section 1.4.5.

I run the regression using both the log level and the growth rate of firms' product scope as the dependent variable for 2008–2014.[24] The standard errors for the regression estimates are clustered at the level of Scantrack market. Columns (1) and (2) of Table 1.5 summarize the results. Both the log of firms' product scope and the product scope growth rates are negatively correlated with the unemployment rate, though the estimated coefficients are not statistically significant.

As documented in the firm dynamics literature, firms of different size respond to the same business cycle in different magnitude (Fort et al. (2013)). In my study, this suggests that the correlation with the regional unemployment rate may differ by firm size. I test this hypothesis including interaction terms of the above firm size indicators and the regional unemployment rate in the regression equation. Column (3) of Table 1.5 reports the differentiated coefficients. Small firms' product scope is on average negatively and significantly correlated with the regional unemployment

[23] Other firm-level controls that I experiment with include an indicator of the number of markets that the firm accesses (section 4.4) and inferred firm age (appendix).

[24] The year 2007 is available for the log(PS) regression. Including it only slightly changes the coefficient.

rate. Below, however, I show that small firms' product scope is no longer significantly procyclical if we look only at continuing firms. The difference is driven by the new entering firms. In other words, firms entering the market in bad times are typically smaller in product scope than in normal times, while the continuing small firms' product scope doesn't change much because they have few products. In contrast, the responses of medium-sized and large firms are largely driven by continuing firms' product scope changes. On average, medium-sized (large) firms' product scope is procyclical (acyclical).

Regression (1.2) can also be estimated on firm-level sales. Table 1.6 reports the firm-level regression results for firm sales, similar to those reported in Table 1.5 for firms' product scope. Columns (1) and (2) show that firm sales are procyclical on average, although the response is statistically significant only for the log level of sales. Since firms of different size adjust their product scope in different ways over the business cycle, their sales are also likely to be affected by the regional unemployment rate differently. Column (3) confirms this conjecture. Small firms' sales are most procyclical, medium firms' sales are moderately procyclical, and large firms' sales respond the least. Combining the product scope and sales regression results, although the product scope levels of small and medium-sized firms decrease by the same amount when a recession hits, small firms lose more sales than medium-sized firms. This suggests that the sales per product of small firms are also procyclical and more so than the sales per product of medium-sized firms. Large firms are most recession-proof and acquire more market share in recessions than in normal times. Since large firms are most likely to have high productivity, the data suggests that the most productive firms acquire more market share in a recession. Table 1.15 in Appendix A2 directly confirms this conjecture.

1.4.4 Firms' Product Scope Changes: Supply or Demand Driven?

Changes in firms' product scope over the business cycle could be due to consumers changing products in their shopping basket or firms switching their products. Local firms are affected by both local consumer demand changes and local supply shocks, whereas national firms' local product scope is only affected by the demand channel assuming they can produce anywhere in the country. Therefore, local firms' product scope should be more procyclical than that of national firms, and their difference is the contribution of local supply shocks. While national firms could also be subject to local supply shocks such as distribution cost increases, they are likely to be less sensitive to local supply conditions because they do not set up production facilities in every market they access. Some of national firms' cost shocks should be orthogonal to the idiosyncratic conditions of the local market.

To distinguish local from national firms most clearly, I look at a subsample including only local firms selling in only one region and national firms operating in all 49 regions. This leaves me with 1,585 firms. On average, 62% (38%) of these firms are local (national). I extend the above firm-level regression by adding a local firm indicator and its interaction with the regional unemployment rate.[25]

Table 1.7 reports the firm-level regression results when interacting the business

[25] I also run the cell-based regression in equation (2.4) for national and local firms respectively, finding that the local business cycle indicator has a larger impact on local firms than on national firms.

cycle indicator with not only the firm size indicator but also the dummy variable for local firms. Column (1) is the baseline firm-level regression with firm size fixed effects and the interaction term of the firm size indicator and the regional unemployment rate. Small firms' product scope is now on average positively although insignificantly correlated with the regional unemployment rate. This is partly because of a cleansing effect taking place at the firm entry and exit margin: small firms entering or remaining in bad times on average have higher product scope than normal times and are likely to be more productive than exiters. In contrast, the responses of medium-sized and large firms are more driven by firms' product scope changes. On average, medium-sized (large) firms' product scope is procyclical (acyclical). Column (2) of Table 1.7 shows the local and national difference, while allowing for firms of different sizes to respond to the same business cycle differently. The cleansing effect is shown in the responses of small firms. This effect is stronger for local firms than national ones. For medium-sized and large firms, their negative coefficients for the interaction terms of firm size, local firm, and the unemployment rate (-0.01 and -0.12 for medium-sized and large firms, respectively) suggest that local firms are affected more by local unemployment than national firms, which suggests an important role for local supply shocks.

1.4.5 Robustness checks

In this subsection, I discuss two robustness checks. I examine average product scope changes of continuing firms only, and I adopt an alternative firm size measure for the firm-level regressions. More robustness checks are provided in the Appendix.

1.4.5.1 Continuing Firms Only

To isolate the impact of firm entry and exit on firms' average product scope, I build an alternative dataset that contains only continuing firms in pair-wise years. I re-run the cell-based and firm-level regressions for these continuing firms. The results in Table 1.8 are similar to those in Table 1.4 in that average product scope is procyclical among continuing firms.

The firm-level estimates for firm product scope and sales are shown in Tables 1.9 and 1.10 respectively. Without the entering firms, small firms' product scope is no longer significantly procyclical. This is because small firms are more likely to completely exit the market, i.e. responding at the firm entry and exit margin, when the recession hits. Although small continuing firms' product scope doesn't change much over the business cycle, their sales are still the most procyclical. Small firms' sales per product must have decreased dramatically in bad times and by more than for other firms.

1.4.5.2 Alternative Firm Size Measure

Firm size can be alternatively measured by a firm's lagged log sales, instead of lagged log product scope. Similar to the construction of the firm size indicator in Section 4.3, a firm is considered "Small" if it is an entrant or if its lagged log sales are in the first tercile. A "Medium" firm's lagged log sales are in the second tercile and a "Large" firm's lagged log sales are in the largest tercile. Table 1.11 reports similar regression results to those in columns (1) and (2) of Table 1.5. The procyclicality of firms' product scope on average is robust to the use of this alternative firm size indicator. Additionally, column (3) demonstrates that firms respond to the local unemployment rate differentially by firm size: small firms have the most procyclical product scope. Table 1.15 reports the regression results for firm sales. Similar to the results using product scope as the size indicator, the small firms' sales are most procyclical. The medium-sized firms' responses to the business cycle are moderate and the large firms' reactions in sales are insignificant.

1.5 The Model

To study how firms decide their product scope and how product scope changes affect aggregate output, I build a general equilibrium model in which heterogeneous firms are free to enter and exit the market and to choose their number of products. The model abstracts from product group or region interactions. Since firms in a given product group and region can have nonnegligible sales shares and can use the market power to their advantage, I adopt a market structure in which firms behave as oligopolists by assuming a finite number of firms. There are two groups of players in the model: one representative household and a finite number of manufacturing firms. The household supplies labor and purchases the products supplied by firms. Firms use labor in production. Each of them produces a unique and mutually exclusive set of goods.

I solve the model and calibrate it to match some data moments. Then, to demonstrate how product scope changes in a recession and decompose the aggregate impact of such product scope changes, I conduct comparative statics by comparing a normal times steady state versus a steady state with recession features.

1.5.1 Household

The representative household supplies L units of labor at wage rate w and maximizes her expected intertemporal utility $\mathrm{E}_t \sum_{s=t}^{\infty} \beta^{s-t} U_s$, where $\beta \in (0,1)$ is the subjective discount factor. The period utility function takes the form

$$U_t \equiv \ln C_t - \chi \frac{{L_t}^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}, \tag{1.3}$$

where C_t is aggregate consumption in period t, $\chi > 0$ is a preference parameter, and $\xi > 0$ is the Frisch elasticity of labor supply.

The household finances her consumption using labor income, risk-free bonds B with interest rate r, and the profits of all the firms she owns Π. Her budget constraint in period t is $P_t C_t + B_{t+1} = (1+r_t) B_t + w_t L_t + \Pi_t$.

Utility maximization implies the following equations describing intratemporal and intertemporal substitution:

$$\chi {L_t}^{\frac{1}{\xi}} = \frac{1}{P_t C_t} \tag{1.4}$$

$$\frac{1}{P_t C_t} = \beta \mathrm{E}\left[\frac{1+r_{t+1}}{P_{t+1}C_{t+1}}\right]. \tag{1.5}$$

Since I am interested in consumption, which equals output in equilibrium, and its price, I let the wage rate be the numeraire, i.e. $w_t = 1$ in (1.5) and what follows.

Aggregate consumption C_t is an aggregator of differentiated products in different markets. Suppose there are G groups of products and R markets. I adopt a Cobb–Douglas function for the total production of the final good in period t: $Q_t = \prod_{g\in G, r\in R}(Q_{grt})^{\nu_{gr}}$, where Q_{grt} is the production of product group g in market r in time t and ν_{gr} is the expenditure share on product group g and market r. This functional form is chosen because Hottman et al. (2016) find that product group expenditure shares are relatively constant over time. The production decisions across product groups are hence independent of each other.[26] In what follows, I focus on a given product group in a given market, and the g and r subscripts are suppressed for notational simplicity.

Within a product group in a given market, the number of firms is finite and denoted as M. A firm denoted by m produces N_m products. A product is denoted by two indices, firm m and product i. Suppose that the elasticities of substitution across and within firms are the same and denote both by $\eta > 1$.[27] The total final

[26]In contrast to the Cobb–Douglas function, a CES aggregator would allow potential interactions across product groups. This could be an extension in future research.

[27]An extension is to consider different elasticities of substitution across and within firms. For example, Hottman et al. (2016) estimate a higher elasticity within than across firms.

goods production of a given product group in a given market in period t is

$$Q_t \equiv \left(\sum_{m=1}^{M_t} \lambda_{mt} q_{mt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{1.6}$$

with

$$q_{mt} = \left(\sum_{i=1}^{N_{mt}} (q_{mit})^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{1.7}$$

where M_t is the number of firms, q_{mt} is the production of all the products of firm m, λ_{mt} is the quality or taste attribute associated with firm m, and q_{mit} is the production of product i of firm m.

The aggregate price index dual to (1.6) is

$$P_t = \left(\sum_{m=1}^{M_t} \left(\frac{p_{mt}}{\lambda_{mt}} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}, \tag{1.8}$$

with the price received by firms m being $p_{mt} = \left(\sum_{i=1}^{N_{mt}} p_{mit}^{1-\eta} \right)^{\frac{1}{1-\eta}}$, where p_{mit} is the price of product i of firm m.

Cost minimization implies that the quantity of product i produced by firm m demanded by the household is

$$q_{mit} = \left(\frac{p_{mit}}{p_{mt}} \right)^{-\eta} q_{mt}, \tag{1.9}$$

with $q_{mt} = \frac{1}{\lambda_{mt}} \left(\frac{p_{mt}}{\lambda_{mt} P_t} \right)^{-\eta} Q_t$. Thus, the sales share of firm m's products in total sales is

$$s_{mt} \equiv \frac{p_{mt} q_{mt}}{P_t Q_t} = \left(\frac{p_{mt}}{\lambda_{mt} P_t} \right)^{1-\eta} > 0. \tag{1.10}$$

1.5.2 Firms

There is a large number of potential firms compared with the number of firms that actually enter the market each period that live only one period. Before entry, all potential firms are identical and face a sunk cost of f^E units of labor. A proportion of this sunk cost can be thought of as the periodic renewal fee of the company prefix number and its UPCs, which are registered with the barcode regulation institution GS1. Upon paying the sunk cost, each firm gets a draw of firm-specific productivity ϕ_{mt}. Firm m then chooses its input demand, product prices and product scope to maximize profit. It takes the input cost as given and faces a fixed cost of f^V units of labor for every product it produces. By backward induction, I first solve the profit maximization problem and then examine which firms enter the market.

1.5.2.1 Input Choice, Pricing, and Product Scope

Assume that firm m's production function of product i is $q_{mit} = \phi_{mt} l_{mit}$, where l_{mit} is the labor employed. By taking residual demand q_{mit} and the cost of labor as given, firm m's profit maximization problem is

$$\max_{l_{mit}, p_{mit}, N_{mt}} \pi_{mt} = \sum_{i=1}^{N_{mt}} (p_{mit} q_{mit} - l_{mit}) - N_{mt} f^V, \tag{1.11}$$

subject to the demand function given in equation (1.9) and $\phi_{mt} l_{mit} \geq q_{mit}$.

Denote μ_{mit} as the shadow price or marginal cost of producing product i in period t. I find $\mu_{mit} = \mu_{mt} = 1/\phi_{mt}$. The optimal demand for labor is $l_{mit} = \mu_{mt} q_{mit}$.

Although the firm can choose a separate pricing rule for each product, the optimal price turns out to be the same across products:

$$p_{mit} = \frac{\eta - (\eta - 1)s_{mt}}{(\eta - 1)(1 - s_{mt})}\mu_{mt} = \frac{\varepsilon_{mt}}{\varepsilon_{mt} - 1}\mu_{mt}, \tag{1.12}$$

where $\varepsilon_{mt} \equiv \eta - (\eta - 1)s_{mt}$, the elasticity of substitution perceived by firm m. Apparently, for $s_{mt} > 0$, the perceived demand elasticity ε_{mt} is lower than the demand elasticity in the eyes of the household η as a result of the oligopolistic market structure.[28] Moreover, the higher the sales share s_{mt}, the lower is the perceived elasticity and the higher is the markup.

Since the prices of and thus demand for all the products produced by firm m are the same, I denote them by p^I_{mt} and q^I_{mt}. The firm's profit maximization problem can be rewritten as $\max_{N_{mt}} \pi_{mt} = N_{mt}q^I_{mt}(p^I_{mt} - \mu_{mt}) - N_{mt}f^V$. The first-order condition with respect to N_{mt} yields

$$q^I_{mt}(p^I_{mt} - \mu_{mt}) - s_{mt}q^I_{mt}(p^I_{mt} - \mu_{mt}) = f^V. \tag{1.13}$$

The first term is the gain in profits from the marginal product and the second term is the loss in the profits of existing products (i.e., the cannibalization effect). It is clear that the larger the sales share, the larger is the cannibalization effect.

The implied optimal product scope depends on aggregate revenue $R(\equiv PC)$

[28] An oligopolistic structure is not the only scenario under which the price depends on the market share. Another scenario considers a polynomial utility function. For a general discussion, see Mayer et al. (2016).

and the firm's sales share:

$$N_{mt} = \frac{s_{mt}(1 - s_{mt})}{\eta - (\eta - 1)s_{mt}} \frac{R_t}{f^V}. \tag{1.14}$$

The firm's sales share in turn depends on the firm's productivity and the productivity and sales share of the marginal producing firm denoted by subscript 1 (implied by equations (1.9), (1.12), and (1.14)):

$$s_{mt} = s\left(\phi_{mt}, \phi_{1t}, s_{1t}\right) = 1 - \frac{1}{(\eta - 1 + \frac{1}{1-s_{1t}})(\frac{\tilde{\phi}_{mt}}{\tilde{\phi}_{1t}})^{\frac{\eta-1}{\eta}} - \eta + 1}, \tag{1.15}$$

where $\tilde{\phi}_{mt} \equiv \lambda_{mt}\phi_{mt}$ is the quality-adjusted productivity of firm m.

Equation (1.15) indicates that a firm's sales share always increases in its productivity relative to the marginal firm, all else being equal. However, from equation (1.14), the optimal product scope does not necessarily increase in relative productivity. Product scope increases in relative productivity only when the corresponding sales share is not too large, which is the region of interest. When a firm becomes more productive relative to the marginal firm and its sales share is not too large, equation (1.13) shows that the gain from the profits of the marginal product dominates the cannibalization effect. Hence, expanding product scope is preferable. If the sales share is too large, the cannibalization effect dominates. The model is thus calibrated so that product scope increases in relative productivity.

1.5.2.2 Entry Decision

Once the firm has determined the optimal product scope and price of each product, its maximized profit is

$$\pi_{mt} = \frac{s_{mt}^2 R_t}{\eta - (\eta - 1)s_{mt}}. \tag{1.16}$$

The profit increases in sales share s_{mt}.

Denote the number of entering firms as M^e. The expected profit for an entrant is $E[\frac{1}{M_t^e}\sum_{m=1}^{M_t^e} \pi_{mt}]$ with $\pi_{mt} = 0$ if $\phi_{mt} < \phi_{1t}$. Firms will keep entering the market as long as the expected profit is greater than or equal to the fixed cost of entry $\left(E[\frac{1}{M^e}\sum_{m=1}^{M_e} \pi_{mt}] \geq f^E\right)$, until the expected profit from having one more entrant becomes strictly less than the fixed cost of entry $\left(E[\frac{1}{M^e+1}\sum_{m=1}^{M_e+1} \pi_{mt}] < f^E\right)$.

1.5.3 Equilibrium

Following Feenstra and Ma (2007), I define the unique equilibrium as follows:

Definition The equilibrium is achieved if

(1) M_t^e is the smallest number of entering firms such that $E[\frac{1}{M_t^e}\sum_{m=1}^{M_t^e} \pi_{mt}] \geq f^E$ and $E[\frac{1}{M_t^e+1}\sum_{m=1}^{M_t^e+1} \pi_{mt}] < f^E$, where π_{mt} is given by equation (1.16);

(2) Given M_t^e, there are M_t active firms and the marginal firm is determined by $\sum_{m=1}^{M_t} s_{mt} = 1$, where s_{mt} is given in equation (1.15);

(3) Firms maximize profits according to equations (1.12) and (1.14);

(4) Consumers maximize utility according to equations (1.4) and (1.5), and the

budget constraint, given the aggregate price index in equation (1.8);

(5) The goods, labor, and bonds markets clear:

$$C_t = Q_t, \quad L_t = (\alpha(\eta - 1) + 1) R_t \sum_{m=1}^{M_t} \frac{s_{mt}(1 - s_{mt})}{\eta - (\eta - 1) s_{mt}} + M_t^E f^E, \quad B_t = 0. \quad (1.17)$$

1.5.4 The Aggregate Price Index

It is convenient to refer to the aggregate price index when thinking of how product scope affects aggregate consumption (output):

$$\begin{aligned} P_t &= \left(\sum_{m=1}^{M_t} \sum_{i=1}^{N_{mt}} (p_{mit})^{1-\eta} \right)^{\frac{1}{1-\eta}} \\ &= \left(\sum_{m=1}^{M_t} N_{mt} \left[\frac{\varepsilon_{mt}}{\varepsilon_{mt} - 1} \frac{1}{\phi_{mt}} \right]^{1-\eta} \right)^{\frac{1}{1-\eta}}. \end{aligned} \quad (1.18)$$

The price index is the price of consumption relative to leisure. If the price index is high, consumers will be incentivized to substitute consumption with leisure. As a result, output decreases. A procyclical number of firms (M_t), procyclical product scope (N_{mt}), and countercyclical markups ($\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}$) all imply a higher price index in recessions, which disincentivizes consumption. The latter two interact because the most productive firms acquire more market share and charge higher markups in a recession, partly because they reoptimize their product scope.

1.5.5 Calibration

The model is calibrated to show the impact of product scope changes quantitatively. I assume that quality-adjusted productivity $\tilde{\phi}_{mt} \in [\underline{\phi}, \bar{\phi}]$ is drawn from a Pareto distribution with shape parameter γ. There are nine parameters to calibrate, as summarized in Table 1.13.

The values of the first two parameters are taken from the literature. The Frisch elasticity of labor supply ξ is 2, which is a common macro-level estimate (e.g., Smets and Wouters (2007)). The elasticity of substitution across firms is set to 3.9, the median estimate in Hottman et al. (2016). The lower bound of quality-adjusted productivity is normalized to 1.

I interpret periods as years and set the discount factor $\beta = 0.96$ so that the annual interest rate is 4% as in King and Rebelo (1999). The preference parameter for labor χ is set to be 8 so that steady-state labor supply is about one-quarter of the available time, as in King and Rebelo (1999). The remaining four parameters (productivity shape parameter and upper bound, fixed cost per product, and entry cost) are chosen such that the following targets are matched: average product scope (13), average product scope weighted by sales (130), median product scope (3), and overhead labor ratio (0.5). Table 1.13 shows that the model matches the targets reasonably well.

Figure 1.3 plots the distribution of firms' product scope in the data (left) and in the model (right). The product scopes are adjusted by dividing by average product scope. For the data, the average is cell-based. The model generated distribution matches the data well.

1.5.6 Aggregate Impact of Product Scope Changes

The model in this paper is in essence static, and I use comparative statics to demonstrate different states of economic activity.[29] To demonstrate how product scope changes in a recession and to decompose the aggregate impact of such product scope changes, I compare a normal times steady state computed using the benchmark calibrated parameter values to a "recession" steady state implied by changes in benchmark parameter values. In recessions, average productivity is lower but productivity dispersion is higher than in normal times (Kehrig (2015)).[30] A simultaneous decrease in the upper and lower bounds of the quality-adjusted productivity distribution can produce such patterns.

I set the recession productivity range to $[1-d, 1.6-d]$ where $d = 0.0378$, such that output decreases by 3.5%, an output drop similar in magnitude to that during the Great Recession. The second column of table 1.14 reports changes in key aggregate and firm-level variables when moving from normal times to a recession. While the number of firms doesn't change, product scope affects aggregate output in two ways. First, firms have lower product scope in the recession steady state, which means fewer product choices for consumers and a higher aggregate price of consumption relative to leisure (i.e., the aggregate price index in (1.18) is higher).

[29] A dynamic model is not a trivial task in my setting because there is a finite number of firms. Modeling the dynamic game played among the firms requires solving an "oblivious equilibrium" introduced in Weintraub et al. (2008). To my knowledge, such a dynamic game has not been considered in macroeconomic literature.

[30] The Kehrig (2015) findings may be driven by endogenous changes in dispersion in productivity. The current way of modeling a shock is not exclusive.

This is the direct impact of procyclical product scope. Second, firms' product scope choices interact with their markups. In the recession steady state, the most productive firms acquire more market share by reoptimizing input demand, prices, and product scope. Higher market share implies a higher markup. Consequently, the average markup rises, and this further decreases consumption. The changes in the market shares of top firms are consistent with the empirical results on the differential effects of regional unemployment on firm sales by firm size.

The next column in Table 1.14 documents the changes in the steady-state values generated by an alternative multiproduct firms model with fixed product scope. A recession steady state is obtained by decreasing the productivity range by the same magnitude as in the baseline case. Comparing the results of the full model and the one with fixed product scope, the two generate similar aggregate impacts. When only the firm entry and exit margin is present, the number of firms declines considerably in the recession state. In contrast, when the firm entry and exit margin and the product scope adjustment margin are both present, the latter dominates. From the view of the model, this is because a firm can have infinitely small product scope and still survive. Indeed, only when shocks are sufficiently large will the marginal firm exit. The dominance of the product scope margin, nevertheless, is consistent with data observations. This implies that one cannot measure aggregate product dynamics over the business cycle simply by firm dynamics. Neglecting product scope adjustment underestimates aggregate product dynamics and its aggregate impact.

The last column in Table 1.14 reports the comparative statics using the model of fixed product scope and targeting the same change in total product number instead of the same shock as in full model. The full model generates about one third more consumption decrease than the model of fixed product scope.

1.6 Conclusion

By using Nielsen's Retail Scanner data on U.S. consumer goods purchases for 2007–2014, the paper describes multiproduct firms' product scope and makes four main observations. First, the distribution of firms' product scope is highly skewed. Second, product scope adjustment is important. Third, firms' product scope is procyclical on average. Moreover, large firms among firms of all sizes are the most resilient in a recession, in terms of both product scope and sales adjustments. Fourth, the procyclical changes in product scope are partly driven by local supply shocks.

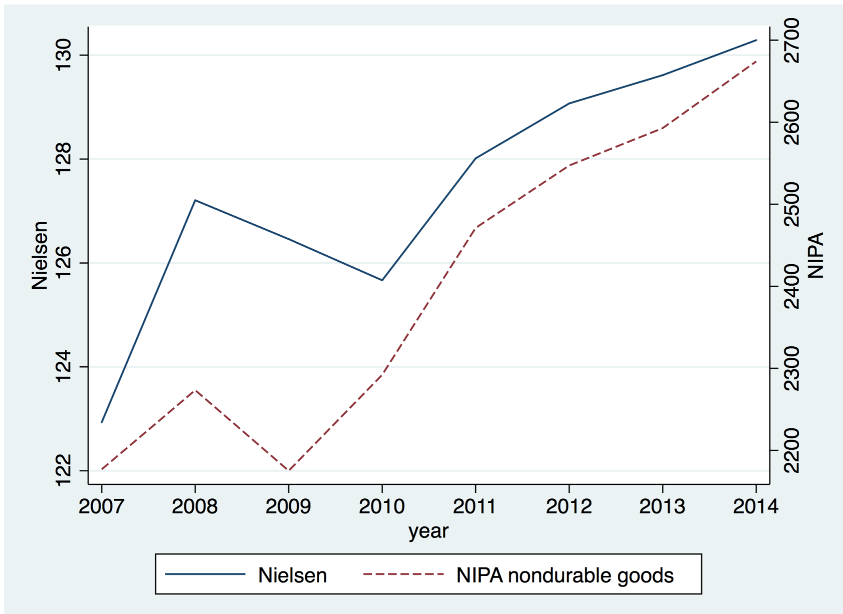
In addition, I build a general equilibrium model of multiproduct firms that can produce similar patterns to the data and compare a normal times steady state with a recession steady state. I find that firms optimally choose lower product scope in the second steady state. Holding fewer product varieties decreases consumption directly because consumers love variety. In the mean time, the reoptimized product scope helps large firms acquire more market share and charge higher markups to make use of their higher market power. The resulting average markup rises, which further decreases consumption.

Both the data and the model suggest that the product scope adjustment margin dominates the firm entry margin. Therefore, neglecting the former and only focusing on the firm entry margin would result in underestimated product dynamics in a recession.

Further exploration will involve identifying empirical patterns by using a broader definition of product (i.e., grouping UPCs of the same brand, size, color, shape, and packaging into one product). This broader definition requires an in-depth discussion of the key characteristics of a product and will allow us to separate out major changes in products from minor adjustments that are more volatile but less influential. Moreover, the rich information on price in the Nielsen data is called for more investigation. For example, firm and product dynamics might affect the frequency and magnitude of price adjustment. In addition to these future empirical studies, I will extend the model by using different elasticities of substitution across and within firms to match heterogeneity across and within firms. To account for the small firms with only one product in data, I will also include a "residual firm", which will address the large impact of firm entry and exit on firm-level averages.

Tables and Figures

Figure 1.1: Total Sales in the Nielsen Data vs. Nondurable Goods Consumption



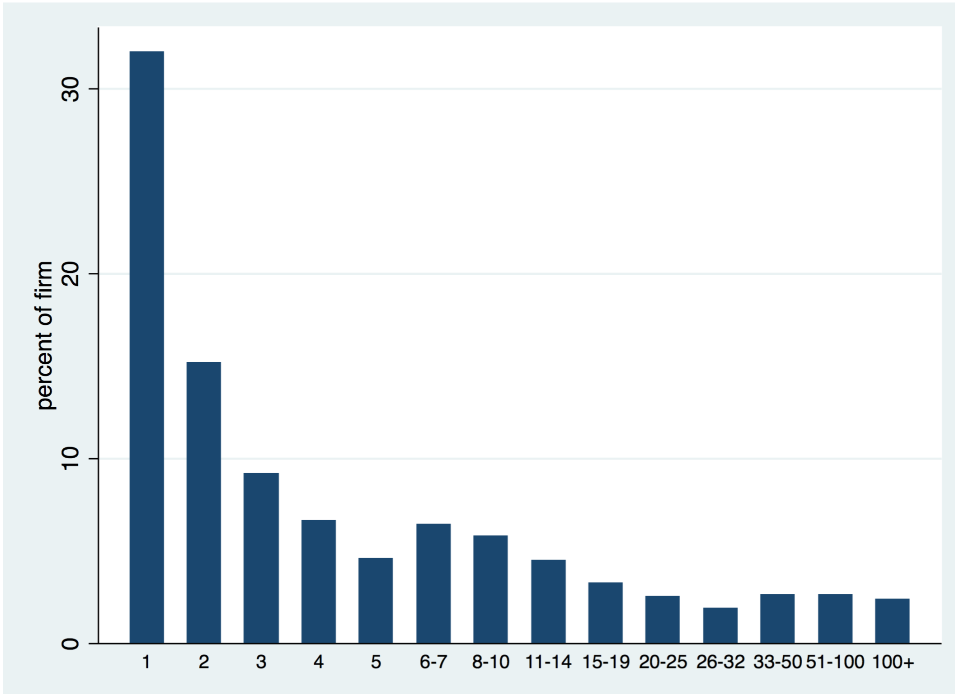
Source: Nielsen Retail Scanner data (left-axis) and the NIPA (right-axis).

Table 1.1: Summary Statistics

	Obs.	Mean	St. Dev.
Product scope			
mean	45,080	13.472	13.624
10%ile	45,080	1.030	0.292
median	45,080	3.290	3.634
90%ile	45,080	31.925	39.184
Firm sales (ratio over total sales)			
mean	45,080	0.027	0.078
10%ile	45,080	0.005	0.070
median	45,080	0.008	0.075
90%ile	45,080	0.064	0.140
Firm number	45,080	119	109
Total sales	45,080	22M	34M

Notes: Observations are at the product group by Scantrack market by year level. Product scope is defined as the number of products that a firm offers. Total sales are in millions. The values in the third (fourth) column are averages (standard deviations) across the 45,080 cells.

Figure 1.2: Histogram of Firms' Product Scope



Notes: The histogram pools over all firms across different product groups, Scantrack markets and years. Product scope on the x-axis is defined as the number of products that a firm offers in a single cell. The y-axis shows the percentage of firms in each range of product scope.

Table 1.2: Distribution of Firm Types

	Firm ratio
Entrants	0.123
Exiters	0.120
Continuing firms of	
Expanding PS	0.177
Shrinking PS	0.217
PS unchanged	0.379

Notes: For each pair of years in 2007–2014, a firm is an entrant (exiter) if it only has sales in the next (base) year. The firm shares reported are the averages across product group by Scantrack market by year observations.

Table 1.3: Decomposition of Total Sales Growth

	Total	Entrants	Exiters	Continuing firms		
				Expanding	Shrinking	Others
Across-year average	-0.11	0.72	-0.20	2.41	-2.67	-0.38
Year-pair						
2008	3.08	0.64	-0.16	3.48	-1.10	0.21
2009	-2.24	0.70	-0.19	1.56	-3.71	-0.61
2010	-1.32	0.60	-0.19	2.17	-3.51	-0.39
2011	2.14	0.63	-0.21	3.60	-1.71	-0.18
2012	-1.18	0.82	-0.16	1.89	-3.05	-0.67
2013	-0.52	0.70	-0.20	2.56	-3.09	-0.48
2014	-0.74	0.94	-0.27	1.65	-2.53	-0.53

Notes: Growth rates are in percentages. For each pair of years in 2007–2014 (represented by the second year), a firm is an "Entrant" ("Exiter") if it only has sales in the next (base) year. Continuing firms have three types: expanding product scope ("Expanding"), shrinking product scope ("Shrinking") and product scope unchanged ("Others"). The growth rates by firm type are weighted by their sales shares. The growth rates reported are averaged across product groups and Scantrack markets.

Table 1.4: Cyclicality of Average Product Scope: Cell-based Approach

	(1)	(2)
	$\bar{PS}$ growth$_{grt}$	$\bar{PS}$ growth$_{grt}$
UR_{rt}	-0.2328***	
	(0.0660)	
ΔUR_{rt}		-0.2545***
		(0.0632)
Product group fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R^2	0.0928	0.0929
Observations	39,445	39,445

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. In the cell-based approach, a cell is a product group by Scantrack market by year observation. I use an across-firm average measurement as the cell-level measurement. The dependent variable is the growth of average product scope. The main independent variable in column (1) is the regional unemployment rate, and the alternative in column (2) is its change.

Table 1.5: Cyclicality of Firms' Product Scope: Firm-level Analysis

	(1) $\log(\text{PS})_{m,grt}$	(2) PS growth$_{m,grt}$	(3) $\log(\text{PS})_{m,grt}$
UR_{rt}	-0.0024	-0.1651	
	(0.0015)	(0.1397)	
Small × UR_{rt}			-0.0031**
			(0.0013)
Medium × UR_{rt}			-0.0032**
			(0.0015)
Large × UR_{rt}			-0.0006
			(0.0021)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.8224	0.4098	0.8224
Observations	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile or the firm is a new entrants, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.6: Cyclicality of Firm Sales: Firm-level Analysis

	(1) $\log(\text{sales})_{m,grt}$	(2) sales growth$_{m,grt}$	(3) $\log(\text{sales})_{m,grt}$
UR_{rt}	-0.0199***	-0.3125	
	(0.0058)	(0.2207)	
Small $\times$ UR_{rt}			-0.0274***
			(0.0073)
Medium $\times$ UR_{rt}			-0.0197***
			(0.0062)
Large $\times$ UR_{rt}			-0.0121
			(0.0073)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.9044	0.1882	0.9044
Observations	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile or the firm is a new entrants, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are firm sales in logs (columns (1) and (3)) and firm sales growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.7: Cyclicality of Firms' Product Scope: National vs. Regional Firms

	(1) $\log(\text{PS})_{m,grt}$	(2) $\log(\text{PS})_{m,grt}$
Small × UR_{rt}	0.0019	0.0003
	(0.0021)	(0.0024)
Medium × UR_{rt}	-0.0041*	-0.0038*
	(0.0022)	(0.0022)
Large × UR_{rt}	0.0003	0.0006
	(0.0025)	(0.0026)
Small × Local × UR_{rt}		0.0195***
		(0.0053)
Medium × Local × UR_{rt}		-0.0113**
		(0.0051)
Large × Local × UR_{rt}		-0.1201***
		(0.0241)
Product group fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm size fixed effects	Yes	Yes
Local-firm fixed effects	Yes	Yes
R^2	0.9160	0.9162
Observations	1543563	1543563

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile or the firm is a new entrants, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. A firm is local if it sells in only one market and national if it sells in all 49 markets. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variable is product scope in logs. The main regressor is the regional unemployment rate.

Table 1.8: Cyclicality of Average Product Scope: Cell-based Approach, Continuing firms

	(1) $\bar{PS}$ growth$_{grt}$	(2) $\bar{PS}$ growth$_{grt}$
UR_{rt}	-0.2066***	
	(0.0999)	
UR change		-0.2280***
		(0.1085)
Product group fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R^2	0.4495	0.4496
Observations	39,445	39,445

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. In the cell-based approach, a cell is a product group by Scantrack market by year observation. I use the average measurement across continuing firms as the cell-level measurement. The dependent variable is the growth of average product scope. The main independent variable in column (1) is the regional unemployment rate, and the alternative in column (2) is its change.

Table 1.9: Cyclicality of Firms' Product Scope: Firm-level Analysis, Continuing firms

	(1) $\log(\text{PS})_{m,grt}$	(2) PS growth$_{m,grt}$	(3) $\log(\text{PS})_{m,grt}$
UR_{rt}	-0.0026	-0.0966	
	(0.0016)	(0.0840)	
Small × UR_{rt}			-0.0022
			(0.0014)
Medium × UR_{rt}			-0.0039**
			(0.0015)
Large × UR_{rt}			-0.0013
			(0.0021)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.8428	0.0500	0.8428
Observations	4035742	4035742	4035742

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.10: Cyclicality of Firm Sales: Firm-level Analysis, Continuing firms

	(1) $\log(\text{sales})_{m,grt}$	(2) sales growth$_{m,grt}$	(3) $\log(\text{sales})_{m,grt}$
UR_{rt}	-0.0192***	-0.2690	
	(0.0057)	(0.1658)	
Small $\times$ UR_{rt}			-0.0253***
			(0.0077)
Medium $\times$ UR_{rt}			-0.0209***
			(0.0063)
Large $\times$ UR_{rt}			-0.0132*
			(0.0070)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.9114	0.0560	0.9114
Observations	4035742	4035742	4035742

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are firm sales in logs (columns (1) and (3)) and firm sales growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.11: Cyclicality of Firms' Product Scope: Alternative Firm Size Measure

	(1) $\log(\text{PS})_{m,grt}$	(2) PS $\text{growth}_{m,grt}$	(3) $\log(\text{PS})_{m,grt}$
UR_{rt}	-0.0022*	-0.2202	
	(0.0011)	(0.1473)	
Small × UR_{rt}			-0.0023**
			(0.0012)
Medium × UR_{rt}			-0.0021
			(0.0013)
Large × UR_{rt}			-0.0019
			(0.0019)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm-size fixed effects	Yes	Yes	Yes
R^2	0.7304	0.2634	0.7304
Observations	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(sales) are in the first tercile or the firm is a new entrants, "Medium" if lagged log(sales) are in the second tercile, and "Large" if lagged log(sales) are in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.12: Cyclicality of Firm Sales: Alternative Firm Size Measure

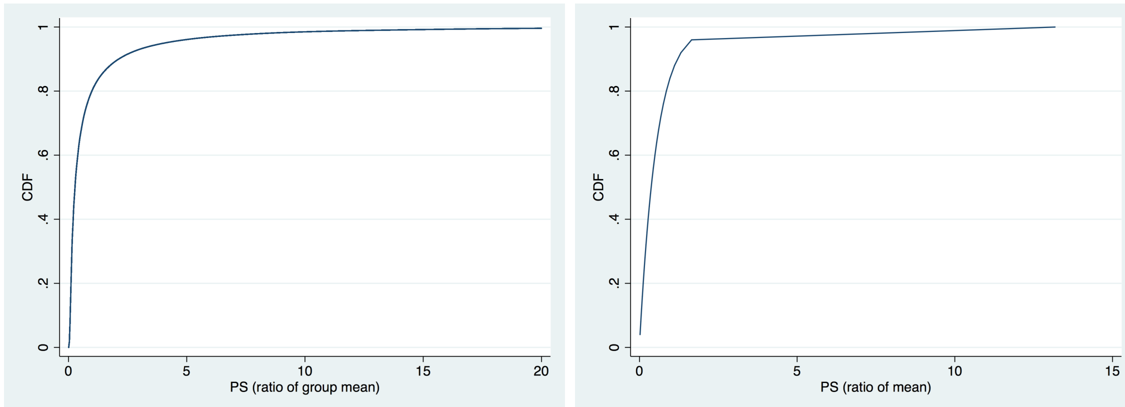
	(1) log(sales)$_{m,grt}$	(2) sales growth$_{m,grt}$	(3) log(sales)$_{m,grt}$
UR$_{rt}$	-0.0204***	-0.3607*	
	(0.0058)	(0.2114)	
Small × UR$_{rt}$			-0.0308***
			(0.0092)
Medium × UR$_{rt}$			-0.0172**
			(0.0066)
Large × UR$_{rt}$			-0.0084
			(0.0094)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.9405	0.1531	0.9405
Observations	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(sales) are in the first tercile or the firm is a new entrants, "Medium" if lagged log(sales) are in the second tercile, and "Large" if lagged log(sales) are in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are firm sales in logs (columns (1) and (3)) and firm sales growth (column (2)). The main regressor is the regional unemployment rate.

Table 1.13: Parameter Values

Parameter		Value	Source	
Frisch elasticity of labor supply	ξ	2	From King and Rebelo (1999)	
Elasticity of substitution	η	3.9	From Hottman et al. (2015)	
Lower bound of $\tilde{\phi}_m$	$\underline{\lambda}$	1	Normalization	
Parameter		**Value**	**Data**	**Model**
Annual discount factor	β	0.96	4%	4%
Preference parameter for labor	χ	8	0.25	0.25
Shape parameter of $\tilde{\phi}_m$ dist.	γ	160	13	14
Upper bound of $\tilde{\phi}_m$	$\bar{\lambda}$	1.6	130	117
Fixed cost per product	f^V	0.00015	3	3
Entry cost	f^E	0.000057	0.5	0.39

Figure 1.3: Model Fit: Distribution of Firm Product Scope



Notes: The data plot (left) pools over firms of different product groups, Scantrack markets and years. The product scope levels on x-axes are adjusted by dividing by average product scope. In the data, the average is calculated at the level of product group by region by year.

Table 1.14: Differences in Key Outcomes: Recession versus Normal State

	Full model	Fixed PS	
	(1)	(2)	(3)
Consumption (output) growth	-3.50	-3.53	-2.55
Price index growth	3.75	3.77	2.73
Labor growth	-0.51	-0.50	-0.36
Continuing firms: Average PS growth	-0.62	-	-
Net firm entry rate	0	-17.39	-12.57
Average markup change	0.014	0.012	0.009

Notes: Two models are considered: the full model with endogenous product scope (PS) and an otherwise identical model with fixed product scope. For each model, I compare two steady states. The normal steady state is obtained with the parameter values provided in Table 1.13. The recession steady state has lower average productivity level and higher productivity dispersion and is obtained by decreasing the range of firm level productivity such that productivity$\in [1-d, 1.6-d]$. The cases (1) and (2), the same shock is considered: $d = 0.0378$. Case (3) targets the same change in the total product number as in (1). Consumption equals output.

1.7 Appendix

Appendix A. More empirical findings

A1. Firm dynamics and product scope adjustment: correlations with aggregates

To compare the within-firm product scope adjustment margin with the firm entry and exit margin, I also run the following regression using total sales R:

$$\Delta ln(\bar{N_m})_{grt} = \alpha_g + \phi_r + \mu_t + \beta \Delta ln(R)_{grt} + \epsilon_{grt}, \tag{1.19}$$

where $\bar{N_m}$ is the average product scope of each firm, g represents product group, r denotes Scantrack market, and t is year.

The estimated coefficient is 0.11, the correlation between the log growth rates of total sales and firms' product scope. By replacing the left-hand side with the log growth in number of firms in the regression equation, the estimated coefficient, 0.13, is the correlation between the log growth rates of total sales and firm number. By employing a simple accounting identity $R = M\bar{N_m}\bar{R_{mi}}$, where $\bar{R_{mi}}$ is the average sales per product, I know that the correlation between the log growth rates of total sales and the average firm sales per product is 0.77(=1-0.11-0.13).

A2. Cyclicality of firm sales share

Table 1.5 shows that small firms' sales are moderately procyclical, medium firms' sales are mostly procyclical, and large firms' sales respond the least. The nonlinear changes in firm sales implies that the ratio of firm sales over the total sales respond to the local unemployment rate differentially by firm size. Table 1.15 column (3) demonstrates that the large firms are most recession-proof and acquire more market share in recessions than in normal times, while columns (1) and (2) confirm that the firms surviving the recession on average have higher market shares than in normal times.

Table 1.15: Cyclicality of Firm Sales Share: Firm-level Analysis

	(1) sales share$_{m,grt}$	(2) Δ(sales share)$_{m,grt}$	(3) sales share$_{m,grt}$
UR$_{rt}$	0.0003	0.0002*	
	(0.0017)	(0.0001)	
Small $\times$ UR$_{rt}$			-0.0124***
			(0.0040)
Medium $\times$ UR$_{rt}$			-0.0089***
			(0.0031)
Large $\times$ UR$_{rt}$			0.0246***
			(0.0069)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes
R^2	0.1815	0.0009	0.1816
Observations	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rates are in percentages. A firm is "Small" if its lagged log(PS) is in the first tercile or the firm is a new entrants, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are firm sales share in percentage (columns (1) and (3)) and changes in firm sales share (column (2)). The firm sales share is the ratio of firm sales over the total sales. The main regressor is the regional unemployment rate.

A3. More robustness checks

A3.i Firm-specific business cycle indicators

The firm-level data can be used to construct a Bartik-type firm-specific business cycle indicator, the sales growth of rival firms. This firm-specific business cycle indicator can replace regional unemployment rate in firm-level regression:

$$y_{m,grt} = \alpha_g + \psi_r + \omega_t + \beta SalesGrowth^{\sim m}_{grt} + \epsilon_{mgrt}, \tag{1.20}$$

where m denotes the firm, g the product group, r the Scantrack market, and t the year. $SalesGrowth^{\sim m}_{grt}$ is the business cycle indicator specific to firm m: the growth rate of product group g's sales in Scantrack market r and year t excluding firm m. In other words, $SalesGrowth^{\sim m}_{grt}$ represents how well the firm's rivals do in the economy.

Table 1.16 summarizes the regression results. Both the log of firms' product scope and the product scope growth rates are positively correlated with the firm-specific business cycle indicator. This again suggests that firms product group is procyclical on average.

Table 1.16: Cyclicality of Firms' Average Product Scope: Alternative Business Cycle Indicator

	(1) $\log(\text{PS})_{m,grt}$	(2) PS $\text{growth}_{m,grt}$
$\text{SalesGrowth}^{\sim m}_{grt}$	0.0003***	0.2726***
	(0.0001)	(0.0168)
Product group fixed effect	Yes	Yes
Scantrack market fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	0.0447	0.0123
Observations	4700009	4700009

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. The dependent variables are product scope in logs (column (1)) and product scope growth (column (2)). $SalesGrowth^{\sim m}_{grt}$ is the business cycle indicator specific to the firm: the growth rate of the firm's rivals within the product group by Scantrack market by year cell. Growth rates are in percentages.

A3.ii Additional firm control: Firm age

Firm age can be inferred in the Nielsen data. I keep the later periods in the sample (2011–2014) and define a firm as "Old" if it is more than five years old and "Young" if not. Table 1.17 reports the regression results with the additional firm control, showing that the empirical pattern that firms' product scope is procyclical on average remains true.

Table 1.17: Cyclicality of Firms' Product Scope: Additional Firm Control

	(1) $\log(\text{PS})_{m,grt}$	(2) $\log(\text{PS})_{m,grt}$	(3) PS $\text{growth}_{m,grt}$	(4) PS $\text{growth}_{m,grt}$
UR_{rt}	-0.0071***	-0.0073***	-0.8140***	-0.7392***
	(0.0020)	(0.0020)	(0.2215)	(0.2299)
Product group fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes	Yes
Firm age fixed effects	-	Yes	-	Yes
R^2	0.8218	0.8220	0.4334	0.4498
Observations	2712215	2712215	2712215	2712215

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Only firms in 2011–2014 are considered. The dependent variables are product scope in logs (columns (1) and (2)) and product scope growth (columns (3) and (4)). Firm age is the last year minus the first year that the firm operates and plus one. Growth rates are in percentages.

A3.iii Changes in firm distribution

I next compute the skewness of firms' product scope distribution, using robust measures of skewness, which equal $(90\%tile + 10\%tile + 2 * median)/(90\%tile - 10\%tile)$. I also consider a weighted concentration measure, the Theil index, defined as follows:

$$T_{grt} = \frac{1}{M_{grt}} \sum_{m \in M_{grt}} \frac{N_{m,grt}}{\bar{N}_{grt}} log(\frac{N_{m,grt}}{\bar{N}_{grt}}), \tag{1.21}$$

where $N_{m,grt}$ is the product scope of firm m (total firm number M) in product group g, Scantrack market r, and year t, and $\bar{N}_{grt}$ is the across-firm average.

I run the regression in equation (2.4) for these measures and their changes. Table 1.18 summarizes the results.[31] A positive coefficient implies that the advantage of large firms relative to small firms becomes more pronounced in times of recession. The estimated coefficient in front of regional unemployment are always positive and sometimes also significant.

Table 1.18: Changes in Firms' Product Scope Distribution

	(1) Skewness$_{grt}$	(2) Δ(Skewness)$_{grt}$	(3) Theil$_{grt}$	(4) Δ(Theil)$_{grt}$
UR_{rt}	0.0009	0.0014**	0.0011*	0.0003
	(0.0009)	(0.0006)	(0.0005)	(0.0004)
Product group fixed effect	Yes	Yes	Yes	Yes
Scantrack market fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	44,746	39,130	45,080	39,445
R-squared	0.4056	0.0154	0.9293	0.0941

Note: Note: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Skewness equals $(90\%tile + 10\%tile + 2 * median)/(90\%tile - 10\%tile)$. Theil index formula is given in (1.21).

[31]Similar weak results are obtained by using other skewness measures (e.g., $90\%tile/50\%tile$, $50\%tile/10\%tile$) and concentration measures (e.g., the Herfindahl index).

Appendix B. Data details

B1. Data cleaning

1. Data in 2006: The Nielsen Scanner data is available from 2006. However, the sales related to the state of Winsconsin experience 175% increase from 2006 to 2007. I only keep the data starting from 2007.

2. Private labels: The UPCs of private labels goods are altered by Nielsen by mapping several different UPCs to a single "masked" UPC. There is no way to accurately link these UPCs to their manufacturers. Therefore, I drop the private label UPCs.

3. UPC version: In addition to UPC codes, Nielsen assigns a version number to each unique UPC. The idea is that the key attributes of a given UPC can change over time. For example, the size attibute of a UPC changes temporarily to reflect special promotion and then reverts to its original value. More generally speaking, there are three cases associates with UPC version changes: (a) a few characteristics of a product may have changed, such as the size changes; (b) the same UPC code can refer to completely different products; or (c) the product has been assigned to a different product module by Nielsen, and none of the main characteristics of the product have changed.

   For case (a), treating the same UPC codes of the different versions as different products will over-identify products. Case (b) is the result of recycling UPC codes within and across firms. The former will interupt a firm's inventory system and the latter is said to be rare according to GS1. Therefore, I neglect this possibility. Case (c) is due to arbitrary changes of product module definition. I detect and drop the UPCs of which their product module changes.

After the clearning, I treat the UPCs of different versions as the same product and link the UPCs to their manufacturers using GS1 data. This is consistent with the GS1 data system for that it also identifies a product by UPC codes only.

4. Prices: In the Nielsen weekly datasets, the reported prices are the volume weighted averages for the associated UPCs with certain packing size and measurement units specified. Although not perfectl reflecting all the discounts and taxes faced by the cousumers, the prices are good approxies of the final prices in the eyes of the consumers. When I use price information, I further convert the prices to unit prices: e.g. the price of 1-oz carbonated beverage.

B2. Data summary

Table 1.19: List of the Nielsen product groups

AUTOMOTIVE	BABY FOOD
BABY NEEDS	BAKED GOODS-FROZEN
BAKING MIXES	BAKING SUPPLIES
BATTERIES AND FLASHLIGHTS	BEER
BOOKS AND MAGAZINES	BREAD AND BAKED GOODS
BREAKFAST FOOD	BREAKFAST FOODS-FROZEN
BUTTER AND MARGARINE	CANDY
CANNING, FREEZING SUPPLIES	CARBONATED BEVERAGES
CEREAL	CHARCOAL, LOGS, ACCESSORIES
CHEESE	COFFEE
CONDIMENTS, GRAVIES, AND SAUCES	COOKIES
COOKWARE	COSMETICS
COT CHEESE, SOUR CREAM, TOPPINGS	COUGH AND COLD REMEDIES
CRACKERS	DEODORANT
DESSERTS, GELATINS, SYRUP	DESSERTS/FRUITS/TOPPINGS-FROZEN
DETERGENTS	DIET AIDS
DISPOSABLE DIAPERS	DOUGH PRODUCTS
DRESSINGS/SALADS/PREP FOODS-DELI	EGGS
ELECTRONICS, RECORDS, TAPES	ETHNIC HABA
FEMININE HYGIENE	FIRST AID
FLORAL, GARDENING	FLOUR
FRAGRANCES - WOMEN	FRESH MEAT
FRESH PRODUCE	FRESHENERS AND DEODORIZERS
FRUIT - CANNED	FRUIT - DRIED
GLASSWARE, TABLEWARE	GROOMING AIDS
GRT CARDS/PARTY NEEDS/NOVELTIES	GUM
HAIR CARE	HARDWARE, TOOLS
HOUSEHOLD CLEANERS	HOUSEHOLD SUPPLIES
HOUSEWARES, APPLIANCES	ICE
ICE CREAM, NOVELTIES	INSECTICDS/PESTICDS/RODENTICDS
JAMS, JELLIES, SPREADS	JUICE, DRINKS - CANNED, BOTTLED
JUICES, DRINKS-FROZEN	KITCHEN GADGETS
LAUNDRY SUPPLIES	LIGHT BULBS, ELECTRIC GOODS
LIQUOR	MEDICATIONS/REMEDIES/HEALTH AIDS
MEN'S TOILETRIES	MILK
NUTS	ORAL HYGIENE
PACKAGED MEATS-DELI	PACKAGED MILK AND MODIFIERS
PAPER PRODUCTS	PASTA
PERSONAL SOAP AND BATH ADDITIVES	PET CARE
PET FOOD	PHOTOGRAPHIC SUPPLIES
PICKLES, OLIVES, AND RELISH	PIZZA/SNACKS/HORS DOEURVES-FRZN

PREPARED FOOD-DRY MIXES	PREPARED FOOD-READY-TO-SERVE
PREPARED FOODS-FROZEN	PUDDING, DESSERTS-DAIRY
SALAD DRESSINGS, MAYO, TOPPINGS	SANITARY PROTECTION
SEAFOOD - CANNED	SEASONAL
SEWING NOTIONS	SHAVING NEEDS
SHOE CARE	SHORTENING, OIL
SKIN CARE PREPARATIONS	SNACKS
SNACKS, SPREADS, DIPS-DAIRY	SOFT DRINKS-NON-CARBONATED
SOUP	SPICES, SEASONING, EXTRACTS
STATIONERY, SCHOOL SUPPLIES	SUGAR, SWEETENERS
TABLE SYRUPS, MOLASSES	TEA
TOBACCO & ACCESSORIES	TOYS & SPORTING GOODS
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	VEGETABLES - CANNED
VEGETABLES AND GRAINS - DRIED	VEGETABLES-FROZEN
VITAMINS	WINE
WRAPPING MATERIALS AND BAGS	YEAST
YOGURT	

Chapter 2: Product Switching within Multiproduct Firms

2.1 Introduction

The existing literature on firm and product dynamics has been mainly focused on firm entry and exit and the associated reallocation across firms. But as recent empirical studies point out, within-firm product adjustments are more important than across-firm adjustments (Broda and Weinstein (2010), Bernard et al. (2010) and Garcia-Macia et al. (2016)). In this chapter, I investigate within-firm product dynamics in detail. The measures of such dynamics include entry, exit, net entry and reallocation across products. I focus the latter two measures using the Nielsen consumer product sales data for 2007–2014 along with manufacturer annual fundamental information from Compustat for listed firms.[1]

I first show, with the data for all the Nielsen firms, that firms' net product entry and product reallocation are low in recession years. Regressions of the net

[1]All empirical results are calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Data copyright © 2018 The Nielsen Company (US), LLC. All Rights Reserved. The conclusions drawn from the Nielsen data are those of the researchers 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. In addition to the Nielsen data, Wharton Research Data Services (WRDS) was used in preparing the empirical results. This service and the data available thereon constitute valuable intellectual property and trade secrets of WRDS and/or its third-party suppliers.

entry and reallocation rates on a business cycle indicator, the unemployment rate, reveals that net entry and reallocation are procyclical on average. Moreover, firms of different size have different sensitivities to aggregate conditions. Among small, medium-sized and large firms, net product entry and product reallocation are the most procyclical for small firms. The impacts of a recession on large firms' net product entry and reallocation tend to be small.

The listed Nielsen firms correspond to the largest firms in the Nielsen data.[2] Using the Nielsen-Compustat merged data, I establish empirical patterns of the net product entry and product reallocation within firms and their relationship with the aggregate economic conditions and firm fundamentals.

The listed Nielsen firms' product net entry rates decrease as aggregate economic conditions worsen. This is consistent with Axarloglou (2003), which is among the first studies showing the business cycle properties of product introductions at the firm level. The author collects anecdotal evidence of product introductions from newspapers and finds that product introductions are procyclical and rise when aggregate or market demands increase. Controlling for aggregate economic conditions, firm-level factors don't affect the net entry rates.

Product reallocation of the listed Nielsen firms is low in the Great Recession. But the correlation between reallocation and the unemployment rate, the business cycle indicator, is only weakly negative. When controlling for firm fundamentals, the impact of the business cycle indicator on reallocation further declines. Firm

[2] The sizes of the listed Nielsen firms and the large Nielsen firms in terms of product scope are comparable. Note that the boundaries of firms change from the Nielsen data to the Compustat data. See section 3 for details.

R&D expenses and financial constraints are the main factors that affect reallocation. The higher the R&D, or the the looser the financial constraints, the higher the reallocation. My observation of weak cyclicality of product reallocation within firms is not in conflict with Argente et al. (2018). The authors' claim of the procyclicality of the reallocation refers to the lower average reallocation rates in recession years. In the firm-level regression, the main contribution factor for reallocation is R&D expense.

The remainder of this paper is structured as follows. In section 2.2, I review the related literature. In section 2.3, I describe the data and main product switching measures. Section 2.4 reports the empirical results for all the continuing Nielsen firms. In section 2.5, I run the regressions for the listed Nielsen firms only, while controlling for firm fundamental factors. Section 2.6 summarizes.

2.2 Literature Review

The first relevant literature studies the importance of within-firm product adjustments. Broda and Weinstein (2010) investigate ACNielsen Homescan data that record consumer goods purchases in the U.S. for 1994 and 1999–2003. Most product switching occurs within firms, and product additions and subtractions are common within firms. Bernard et al. (2010) use longitudinal data covering 1987-1997 from the US Census Bureau and find that an average of 54 percent of the surviving firms in their sample alter their mix of products over a period of five years. Garcia-Macia et al. (2016) also contribute to the discussion and show that most firm employment growth occurs through firms' own-product improvements.

The discovery of the importance of within-firm adjustments and the recent availability of large-scale micro-level data has stirred researchers' interest in the investigation of the cyclicality of firm-level product switching. The growing literature mostly focuses on product reallocation. For example, Bernard and Okubo (2016) use annual firm-product data set covering all Japanese manufacturing firms in 1992–2006 and show that firms' reallocation rates are the highest during transitions from recessions to expansions. Argente et al. (2018) show that product reallocation within firms is low in recession years. Moreover, when considering firm fundamentals, R&D is the most important factor affecting product reallocation. Argente et al. (2018) is also an example of making use of the new micro-level data, being the first to combine the Nielsen data with the Compustat data.

Compared to Argente et al. (2018), my main improvements are (i) distinguishing firms belonging to product groups, (ii) using regressions with a business cycle indicator in the cyclicality investigation and (iii) discussing net entry and reallocation at the same time. Controlling for differences across product groups is particularly important because the product groups in the Nielsen data might differ greatly in nature. For instance, the three product groups of photographic supplies, housewares and appliances, and electronics have high reallocation rates across products within the product group, as found by Hottman et al. (2016). In addition to these improvements, I also refine the name matching method between the Nielsen and Compustat firms. On the one hand, some Nielsen firms are small local producers and their names could sometimes be confused with the names of large listed firms if only looking at the key words in the company names. On the other hand, some Nielsen firms can be subsidiaries or divisions of a listed firm and their matching with the parent firm can be easily neglected if we apply a strict rule. The solution is to combine the two ways of matching. When matching the whole names, I keep as much information as possible, not dropping generic terms. A second-round of key-word matching will then pick up overlooked subsidiaries and divisions.

Another strand of relevant literature considers the firm fundamentals that play a role in product switching. These firm factors affect product switching, especially product reallocation, through innovations, which increase product reallocation (Grossman and Helpman (1991) and Aghion and Howitt (1992)). R&D is one measure of firms' innovations, and financial conditions can also affect innovation. Empirical studies on the impact of financial conditions show that financial constraints hurt innovation. For example, Savignac (2008), using a direct measure of financial constraints from a survey addressed to French established firms, finds that financial constraints significantly reduce the likelihood that firms have innovative activities.

More broadly, the paper is also related to the literature on endogenous growth, in which innovations translate into growth through firm and product dynamics taking the forms of: (i) improving on existing products of other firms, i.e, creative destruction (Schumpeter et al. (1939), Stokey (1988), Grossman and Helpman (1991), Aghion and Howitt (1992), Klette and Kortum (2004), Lentz and Mortensen (2008), Acemoglu et al. (2013)), (ii) improving firms' own products (Lucas Jr and Moll (2014)), and (iii) introducing brand new products (Romer (1990), Acemoglu (2003) and Jones (2016)).[3] My paper emphasizes the latter two types of reallocation. The within-firm product improvement, measured by the within-firm product reallocation, is the most important among the three forms in my data. The introduction of brand new products is measured by the net entry of products and moves cyclically. This paper tests the implications of these endogenous growth theories, by testing for a the positive correlation between R&D and reallocation and between reallocation and growth. In addition, the paper also provides new stylized facts and moments for modeling and calibration.

2.3 Data

2.3.1 The Nielsen Retail Scanner

The Nielsen Scanner dataset contains consumer goods purchases reported by retail stores in all US markets. The data contains the geographic locations of the retail stores, the transaction dates, and the Universal Product Codes (UPCs) of the products that were bought. The UPC codes define products. My Retail Scanner sample covers years 2007–2014. The data have approximately 35,000 participating grocery, drug, mass merchandiser, and other stores. To isolate from the impacts of store entry and exit, I focus on a balanced panel of stores. The balanced panel contains 28,953 stores, which account for about 90% of the total transactions.

I keep products that use standard UPCs and drop the so-called magnet products which use non-standard UPCs, such as weighted meat, fruits and vegetables.

[3] Aghion et al. (2014) drive home an extensive survey of the literature.

In addition, I drop private labels, products directly owned by retail stores, of which the UPCs are masked. UPCs are assigned to a product group. Furthermore, sales are grouped into different regions, specifically Scantrack markets. In the baseline Nielsen analysis, controlling for product group fixed effects takes care of the industry composition changes in the data, and distinguishing regions allows me to use regional variation in the business cycle indicator. In the baseline Nielsen sample, which is balanced in terms of product group and regions, there are 115 product groups for 49 Scantrack markets, and 1.3 million unique UPCs.

The Nielsen data don't directly identify manufacturers of UPCs. I use data matching UPCs and their corresponding company prefix number from GS1 US, the standards institution for UPCs. 96% of the Scanner UPCs are matched with their manufacturers.

In the following empirical analysis, the Nielsen firm by product group by region by year data is used as the starting point and benchmark. Moreover, I supplement the Nielsen sales data with data on firm fundamentals from Compustat.

2.3.2 Compustat

The Compustat annual data provides an in-depth description of listed firms that participate in the consumer goods market. Variables relating to firm fundamentals include but are not limited to firm size, productivity, financial constraint conditions and Research and Development expenses. See Appendix B for the discussion of variable construction.

To match the Nielsen firms with the Compustat data, I adopt a matching protocol based on Schoenle (2017). In essence, the matches are made by firm names. Following Schoenle (2017), I remove the cases of the letters in the firm names and omit punctuation marks.[4] The cleaned firm names are further simplified by standardizing generic terms. Table 2.23 in the Appendix summarizes the steps. After standardization and dropping the spaces in the firm name texts, perfect matches are detected and saved.

A fuzzy matching algorithm is applied to the non-matched Nielsen firms and the Compustat firms.[5] Some of the non-matched Nielsen firms are small local producers. Some have almost the same names as large publicly listed firms except for standardized terms such as “Inc”. As a precaution when handling these small local firms, standardized terms, already minimized in the text length as shown in the Appendix table, are kept during the fuzzy matching. This is in contrast to Schoenle (2017). The firm pairs identified in the fuzzy matching with high scores are then manually checked based on their company information to insure that they are true matches- the same firm or a division/subsidiary-parent pair.[6]

Another improvement in matching is specifically linking listed firms and their divisions or subsidiaries. Some Nielsen firms are explicitly labeled as a firm’s business or geographic divisions. Some other Nielsen firms are subsidiaries of a listed firm and share the same key words, e.g. Unilever, with their parent firms. These

[4]The punctuation marks include “.”, “,”, “;”, “/”, “-”, “(”, “)”, “””, “[”, “]”, “{”, “}”, “&”, “+”, “’ ”, “””, “:”, “!”.

[5]I use the Stata command reclink.

[6]One useful resource for the checking is the listed firms’ Exhibit 21 filings to the U.S. Securities and Exchange Commission. The filings contain the list of their subsidiaries. In addition, Bloomberg.com provides private firm information and links a firm to its parent firm if applicable.

division/subsidiary-parent pairs usually have low matching scores, because of the differences in the length of the firm names, and are easily neglected. To deal with such cases, another round of fuzzy matching is run based on low-frequency words in firm names: Compustat firms whose names contain low-frequency words are kept and matched against non-matched Nielsen firms. The matched pairs are also manually checked.

In the Nielsen sample of the 115 product groups in 49 U.S. Scantrack markets, there are 36,605 firms or firm divisions and subsidiaries, 449 of which have Compustat counterparts, either the firms themselves or their parent firm. The number of the listed Nielsen firms is 309 and they account for 34% of the total sales in the Nielsen data. For the analysis of the listed Nielsen firms, divisions and subsidiaries of the same firm are combined.

Notably, 40% of the publicly listed Nielsen firms operate in all 49 U.S. Scantrack markets, while the fraction of these firms selling products in 1-3 product groups is more than 50%.[7] In other words, a typical listed Nielsen firm has a national sales network and concentrates its business in few product groups. At the same time, the firm controls from Compustat are not specific to regions and the only regional control is the unemployment rate. Therefore, variation in a firm's performance across regions within product groups can only be accounted for by the business cycle indicator. However, across-region variations are small for these listed Nielsen firms.[8] Therefore, in the baseline listed Nielsen firm data, I define firms only by product

[7]For all the Nielsen firms, only 10% of the firms sell in all 49 regions, and about 70% of them sell products in 1 product group.

[8]The standard deviations of the entry and exit rates are about 1/10 of the means, across regions within firms and product groups.

groups instead of by product group and region cells, while defining firms by product group and region cells in the analysis of all the Nielsen firms to be consistent with Chapter 1.

2.3.3 Product Switching Measures

To study the intensity of product switching in the data, I use the definition of entry and exit rates in equation (2.1). For year t, an "entering" product (firm) is a product (firm) not observed in the year $t-1$ but observed in t, an "entering" product (firm) is a product (firm) not observed in the year t but observed in $t-1$. Continuing products are those observed in both periods. For a firm m in product group g and region r, its entry rate at year t is defined as the number of new products (N^{New}) entering in the current period divided by the average of the total number of products (N^{All}) in the current and base periods. Meanwhile, the exit rate is the number of exiting products (N^{Exit}) from the last period over the two-period average of the total number of products. The entry and exit rates are both bounded by [0,2] and can account for entering and exiting firms. When a firm is new, its entry rate is 2 (exit rate 0). When a firm exits from the market, its exit rate is 2 (entry rate 0). Continuing firms' entry and exit rates are bounded by (0,2).

$$
\begin{aligned}
Entry_{m,grt} &= \frac{N^{New}_{m,grt}}{0.5(N^{All}_{m,grt} + N^{All}_{m,grt-1})} \\
Exit_{m,grt} &= \frac{N^{Exit}_{m,grt}}{0.5(N^{All}_{m,grt} + N^{All}_{m,grt-1})}
\end{aligned}
\tag{2.1}
$$

In addition to the gross entry and exit rates, two other statistics describing entry and exit behaviors at firm level can be defined as in equation (2.2). The net entry rate equals the gross entry rate minus the gross exit rate, while the reallocation rate is the sum of the two.

$$\begin{aligned} NetEntry_{m,grt} &= Entry_{m,grt} - Exit_{m,grt} \\ Reallocation_{m,grt} &= Entry_{m,grt} + Exit_{m,grt} \end{aligned} \tag{2.2}$$

These four product switching measures are computed using the numbers of new, exiting or all the existing products. Another set of similar statistics can be built based on firms' product sales by types. The definitions are given in the equation below. Instead of counting the number of new or exiting products, the addition (subtraction) rates are the ratios of the sales of new (exiting) products over the average total sales over the two subsequent periods. The net addition rate equals the addition rate minus the subtraction rate, and the sales reallocation rate is the sum of the two. Notably, the net addition rates are also the firm-level sales growth rates.

$$\begin{aligned} Addition_{m,grt} &= \frac{Sales^{New}_{m,grt}}{0.5(Sales^{All}_{m,grt} + Sales^{All}_{m,grt-1})} \\ Subtraction_{m,grt} &= \frac{Sales^{Exit}_{m,grt}}{0.5(Sales^{All}_{m,grt} + Sales^{All}_{m,grt-1})} \\ NetAddition_{m,grt} &= Addition_{m,grt} - Subtraction_{m,grt} \\ SalesReallocation_{m,grt} &= Addition_{m,grt} + Subtraction_{m,grt} \end{aligned} \tag{2.3}$$

Summary statistics for all the Nielsen firms' product switching rates are given in Table 2.1. The rates are expressed in percentage points. For continuing firms, the average annual net product entry rate across all product groups and regions is -2.14% over the years of 2007–2014 and -3.72% in the recession years 2008–2009. The average annual reallocation rate also decreases slightly in the recession, being 34.98% annually for 2007–2014 and 34.64% for 2008–2009.

The same sets of product dynamics measures can be defined at the firm by product group by year level for the listed Nielsen firms. Summary statistics are shown in Table 2.2. The continuing listed firms' net entry and reallocation rates also decreases in the recession: -3.27% for all the years vs -4.26% for 2008-2009, and 33.06% for all the years vs 32.02 % respectively.

2.4 Empirical Results: All the Nielsen firms

2.4.1 Product Switching Rates

As in the firm-level regressions in Chapter 1, I regress firms' product switching measures on a business cycle indicator to reveal the cyclicality of the firms' choices. For the firm by product group by region by year Nielsen sample, the business cycle indicator is the regional unemployment rate. A positive (negative) correlation with the business cycle indicator means (countercyclicality) procyclicality. The regression also controls for product group, region and year fixed effects. The regression also includes a firm size indicator, as a simple dummy variable and interacted with regional unemployment. A firm is "Small" if it is a new firm (observed in the current period but not in the previous one) or its lagged product scope in logs is in the first tercile, "Medium" if its product scope in logs is in the second tercile, and "Large" if its product scope in logs is in the largest tercile. The interaction allows the correlation between the product switching statistics and the regional unemployment rate to vary among firms of different sizes.

The regression results for the entry, exit, net entry and reallocation rates of all the Nielsen firms are reported in Table 2.3. When I do not distinguish the differentiated responses among firms of different sizes, the entry, net entry and reallocation rates are marginally procyclical, and the exit rates are acyclical (Columns (1), (3), (5) and (7)). The procyclicality of net entry is comparable to the procyclicality of the net product scope growth reported in Chapter 1.[9]

Columns (2), (4), (6) and (8) show that the cyclicality of firms' product switching varies by firm size. Small firms' net entry is close to being procyclical and has the largest coefficient among the small, medium-sized and large firms. If we further look at entry and exit rates separately, small firms' entry rates are the most sensitive to the business cycle. This strong procyclicality is due to the lower probability for small firms to enter the market during recessions, and to small firms' lower within-firm product entry rates. Small firms' exit rates also decrease with the unemployment rate. As a result, their net rates are weakly procyclical and their reallocation rates are strongly procyclical. As opposed to small firms, large firms' entry rates are acyclical and their exit rates are strongly procyclical. Their net entry rates are procyclical, and their reallocation rates are acyclical. For medium-sized

[9]See Table 1.5 of Chapter 1 for cross-check.

firms, the regional unemployment rate has only a weak impact on their product switching rates.

One concern with the entry and exit measures defined using UPCs is that a small change in characteristics might be considered as a different product. In other words, the rates of product switching might be overestimated. As a complementary exercise, let us look at the incidence of switching and define a dummy variable such that $Dummy(Add) = 1$ if a firm adds one or more products from the last to the current period and 0 otherwise. Similarly, $Dummy(Drop) = 1$ if a firm drops one or more products from the last to the current period and 0 otherwise. Running the firm-level regression for these dummy variables will shed some light on the cyclicality of the probability of adding or dropping products, on average or by different firms.

Table 2.4 reports the results. Not surprisingly, the larger the firm, the higher the probability to add a product. The pattern holds true for the probability of dropping a product. So the incidence of reallocation is higher for large firms. When distinguishing firms' heterogeneous responses to the business cycle, Columns (2) and (4) suggest that the probabilities of adding or dropping a product are significantly procyclical and decrease more in the recession for small firms than for medium-sized and large firms.[10] For medium-sized firms, the probability of adding a product is procyclical and the probability of dropping a product is acyclical. Large firms' probability of adding or dropping a product doesn't move with the business cycle.

[10]Table 2.17 in Appendix reports the results when restricting the sample to the continuing firms. Conditional on survival, the small firms' probability of adding a product becomes less procyclical than the medium-sized firms.

2.5 Empirical Results: the listed Nielsen firms

2.5.1 Who Are the Listed Nielsen Firms?

In this section, I consider only the listed Nielsen firms whose fundamental data are available from Compustat. Before moving to the firm by product group by year data, I first construct the firm by region by product group by year data of the listed Nielsen firms, to compare with the baseline Nielsen firms.

Figure 2.1 compares the average product scope (number of products) of the listed Nielsen firms to the average product scope of all the Nielsen firms whose product scope lies in the first (left panel) and second terciles (right panel). The listed firms' average product scope lines well with the largest Nielsen firms in terms of product scope, i.e. the first tercile firms, and is usually bigger than the medium-sized Nielsen firms in terms of product scope. This suggests that the listed Nielsen firms correspond to the large firms in the baseline Nielsen data.[11] The empirical patterns of product entry and exit of the listed Nielsen firms are likely to resemble the large firms in the previous section.

2.5.2 Product and Sales Shares by Firm Types

Using the firm by product group by year data of the listed Nielsen firms, I first show that product switching is pervasive at the firm level. Table 2.5 shows the shares of product and sales accounted for by different groups of firms. The

[11] Table 2.20 reports the regression results estimating the cyclicality of firms' product scope.

left side of the upper and lower panels uses the current period as the benchmark and looks backward. There are three types of firms: continuing firms with product switching, entering firms, and continuing firms without product switching. The right side of the upper and lower panels uses the current period as the benchmark and looks forward. I consider continuing firms with product switching, exiting firms, and continuing firms without product switching. We can see that continuing firms who add or drop products account for the majority of the products in the consumer goods market.[12] Their shares are higher in terms of sales, since continuing firms are usually larger than entrants and exiters.

The upper panel of the table is for all the sample years while the lower panel focuses on the recession years 2008-2009. In the recession years, if we look backward, the sales share of the continuing firms who switch products drops from 92.5% to 91.9% and the sales share of the continuing firm who don't adjust products goes up. The same pattern holds when we look forward or use product shares. This suggests that reallocation weakens in the recession.

2.5.3 Net Entry and Reallocation Rates

Two product switching measures of special interest are the net product entry and reallocation rates. The former affects how many products are available in the market, together with firm dynamics. The latter are important for growth, as discussed intensively in the endogenous growth literature.

[12]The continuing firms with product switching can further be divided into the firms with only product entry, with only product exit, and with both. The last type is the most common.

I run the following regression for the net entry and reallocation rates:

$$y_{m,gt} = c_m + \alpha_g + \beta UR_t + \text{controls}_{m,t-1} + \epsilon_{m,gt}, \tag{2.4}$$

where m stands for a listed Nielsen firm, g is product group and t is year. The economy-wide regressor is the national unemployment rate. The firm level controls include lagged total sales of the listed across all product types (Firm size), the lagged Kaplan-Zingales index (Financial constraint, a measure proposed in Kaplan and Zingales (1997)), and the lagged ratio of the research and development expense out of the total sales in percentage points (R&D). The construction of the firm controls are discussed in details in Appendix B. I also consider firm fixed effects and product group fixed effects in the firm-level regressions.

Table 2.6 shows results for net entry.[13] Firms' net entry rates are significantly procyclical. While controlling for the business cycle, the impacts of other firm-level factors such as firm size, financial constraints and R&D are not significant. Table 2.7 shows results for reallocation. In contrast to the case of the net entry, the impact of the business cycle is not significant. Two factors influencing reallocation are firms' R&D ratios and financial constraints. As R&D ratio increases or financial constraint loosens, reallocation increases. When the R&D ratio increases by 1%, product reallocation increases by 5%. When the financial constraint decreases by 1, product reallocation increases by 0.02%.

[13] See Appendix A for the regression results of the underlying entry and exit rates.

2.5.4 Robustness Checks

In this section, I conduct robustness checks of the firm level regressions for the net entry and reallocation rates. First, I consider an alternative firm control: firm's productivity (TFP). Second, I run the regressions for the sales based product addition and subtraction rates.

2.5.4.1 Alternative Firm Control

Instead of the lagged size of the listed firms, I use lagged productivity as the main firm-level control. To some extent, the productivity level stands for the potential size of the firm. The higher the productivity level, the higher the potential. Table 2.8 reports results for net entry. As the unemployment rate increases, the net entry rate decreases. The negative correlation is close to being significant. As above, the impacts of firm controls on the net entry rate are not significant.

In Table 2.9, we see similar results for reallocation to when firm size is the main control, except that the impact of firms' productivity on reallocation is negative and significant. This suggests that although technology might grow as the reallocation rates rise, the converse is not true.

2.5.4.2 Sales-based Addition and Subtraction Rates

The baseline regressions can be repeated for measures of net entry and reallocation in terms of sales instead of product number counts. Table 2.10 shows the result for the net product addition rate. Although the unemployment still has the negative coefficient, the coefficient is not significant. Recall that the net addition rate equals the sales growth rate at the firm level. The regression results confirm that large firms' sales growth are insensitive to the business cycle changes, even when controlling for these firm fundamentals. This is consistent with the model and empirical results from Chapter 1. Table 2.11 shows results for the reallocation rates. Firms' financial condition and R&D significantly affect reallocation. The tighter the financial conditions, or the lower the R&D expenses, the lower the sales-based reallocation rate. The results are consistent with those of the net entry and reallocation rates measured in terms of product counts.

2.6 Discussion

2.6.1 Reconsider the Role of Multiproduct Firms in the Business Cycle Setting

In Chapter 1, I investigate firms' product scope, a specific aspect of multiproduct firms' product choices in a business cycle setting. I look at how firms' product scope levels change over the recent business cycle and see the aggregate implications of such changes through the lens of a multiproduct firms model. One stylized fact is that firms' product scope is procyclical on average. Therefore, in the context of the product entry and exit rates, I expect that the within-firm product net entry rates are procyclical. This pattern is confirmed in the data for both all the Nielsen firms and for the listed Nielsen firms.

With the Compustat firm-level data, I can test the implication of the model of Chapter 1 that firm-level markups are countercyclical. I cannot test for countercyclical markups in the full Nielsen sample, due to the lack of manufacturers' cost information in the Nielsen datasets. Here I define the markup as the margin of price over total cost and look at the cyclicality of this margin. The data points are firm by year observations from Compustat for the listed Nielsen firms. The regression equation for cyclical markups simplifies as follows

$$y_{m,t} = c_m + \beta UR_t + controls_{m,t-1} + \epsilon_{m,t}, \tag{2.5}$$

Table 2.12 shows the regression results when y$_{m,t} ismarkupgrowth.The firm -$

$levelcontrolinColumn(2)isthelaggedmarkup.When the unemployment rate increases by 1 point, mar$

In addition to the cyclicality of firms' product entry, this chapter also discusses other factors that can potentially affect firms' product choices, such as R&D and financial constraints. These firm controls don't have significant impacts on net product entry within firms, which is in favor of the product scope model of chapter 1. But that is not the end of the story– reallocation also matters.

2.6.2 Reallocation and Growth

Another important measure of product dynamics is reallocation, which is an important channel through which innovations affect growth. This is extensively discussed in the literature studying innovation, reallocation and growth. In this chapter, I investigate within-firm product reallocation, and show its contribution to short-run growth through its correlation with the future growth of firms' sales per product. The growth of firms' sales per product, as opposed to the growth of firm-level total sales across products, is isolated from the direct impact of product scope changes, which are cyclical and important in their own right. By a simple accounting identity, the growth rate of sales per product equals the growth of firm sales minus the growth of firm product scope.

I first show the correlation between a firm's reallocation rate and its future growth of sales per product using the full Nielsen sample. Table 2.13 reports the result. The main regressors are lagged reallocation and the regional unemployment rate. No matter whether the differentiated response to the business cycle is considered or not, lagged reallocation has a positive and significant impact on future growth of sales. As reallocation rate increased by 1%, growth of sales per product increases by 0.02%.

Column (2) of Table 2.14 shows the results from regressing the growth of firm sales per product on the lagged reallocation rate for the listed Nielsen firms. Lagged reallocation has a significant positive impact on sales growth. As reallocation rate increased by 1%, growth of sales per product increases by 0.2%. The correlation between a firm's reallocation rate and its future growth of sales per product is higher for the listed firms than for all the firms.Lagged R&D also has a significant large positive impact on growth, when controlling for the last-period reallocation.

2.6.3 Reallocation Types: Business Stealing or Own-product Improvement

From Table 2.5, we can see that continuing firms that add and/or drop products account for the majority of the sales, while neither entering or exiting firms contribute much to sales. For continuing firms' product switching, is there shuffling across firms (business stealing) or does the reallocation happen mostly within the boundaries of firms (own-product improvement)? To answer this, I regress firms' product exit rates on their own last-period product entry rates and their rivals' last-period average product entry rates weighted by the size of their product scope sizes. The rivals of a firm are all the other firms in the same product group observed in the same period.

Table 2.15 reports the result for all the Nielsen firms. I consider the regional unemployment as the main other regressor. The lagged own entry rate has a positively significant impact on the own exit rate. The lagged entry rate of a firm's rivals, in contrast, has no significant impact on a its exit rate.

In Column (2) of Table 2.16, lagged own entry has a significant positive impact on the own exit rate, while the lagged entry of rival firms does not. This suggests that reallocation happens mostly within firms in the form of renewing and improving the firms' own products.[14] In addition, increases in lagged R&D incentivize the firms' to give up products, through the implied potential innovations not picked up by

[14] Distinguishing the types is important because their policy implications are distinct. Burstein et al. (2015) discuss the policy implications of these competing reallocation types.

lagged entry.

2.7 Conclusion

Firms in the Nielsen sample are heterogeneous in characteristics such as size, and respond to the business cycle in different ways. Using the Nielsen-Compustat merged data, I investigate extensively the within-firm product switching behavior of the listed Nielsen firms. Although the listed firms do business in the same sets of product groups as the unlisted firms, most of them have a sales network covering the whole nation and have a large number of products in a given product group and region. I interpret them as equivalent to the large firms in the Nielsen baseline sample.

The main measures of interest are the within-firm net entry and reallocation rates, both of which are low in the recession years. I make use of the rich firm-level fundamental information in the Compustat data to reveal the factors governing the changes in firms' product dynamics. The potential influential factors include the business cycle indicator, firm size, financial constraints, and R&D.

I use firm-level regressions to pin down the factors that influence these product switching rates. Net product entry has a negative correlation with the unemployment rate, the business cycle indicator, while its correlation with firm-level fundamentals is not significant. Reallocation correlates with firm R&D expense and financial constraints, while its correlation with the business cycle indicator is not significant.

The analysis of within-firm product switching is among the first investigating the new margins made observable by the recent availability of large-scale micro data. Although the results are informative, I interpret them as confined to the sample of the listed firms that is not representative of small or medium-sized firms. Additionally, the results are for the Great Recession and might not apply to other business cycles.

This chapter is a further investigation of the product dynamics of multiproduct firms and is therefore related to Chapter 1. The procyclicality of net product entry is consistent with the procyclical product scope observed in the previous chapter. Furthermore, with the Compustat data, I investigate the cyclicality of firm markups for the listed Nielsen firms and find that their markups are countercyclical. I can improve the current markup measure by using the production-function approach to markup estimation, as in De Loecker and Warzynski (2012). The authors estimate the markup using the wedge between a variable input's expenditure share in revenue and that input's output elasticity, which is obtained by estimating the associated production function.

Beside the business cycle, this chapter also relates product adding and dropping to growth. The data suggests that across- and within- firm reallocations are both important. Schumpeterian growth models show that firms grow through successful innovations– either through creative destruction, own-product improvement or introducing new products. The theoretical emphasis had largely been on the creative destruction margin. The large magnitude of the within-firm adjustments, observed in the new large-scale micro data, calls for further exploration, both in terms of its contribution to growth but also its role in the business cycle.

Tables and Figures

Table 2.1: Summary Statistics, All the Nielsen Firms

	All years		Recession years	
	Mean	Std. Dev.	Mean	Std. Dev.
Entry	16.28	29.07	15.46	28.36
Exit	18.69	30.52	19.18	30.89
Net Entry	-2.41	39.16	-3.72	38.93
Reallocation	34.98	44.94	34.64	44.74

Notes: Notes: Observations are at firm by product group by Scantrack market by year level. All the rates or ratios are in percentage points.

Table 2.2: Summary Statistics, the Listed Nielsen Firms

	All years		Recession years	
	Mean	Std. Dev.	Mean	Std. Dev.
Entry	14.90	24.17	13.88	22.89
Exit	18.17	24.92	18.14	25.14
Net Entry	-3.27	31.79	-4.26	31.31
Reallocation	33.06	37.42	32.02	36.5

Notes: Product switching measures are at the firm by product group by year level. The sample only keeps the continuing Nielsen listed firms in pairs of years. All the rates or ratios are in percentage points.

Table 2.3: Firms' Product Switching Rates

	$Entry_{m,grt}$		$Exit_{m,grt}$		$NetEntry_{m,grt}$		$Reallocation_{m,grt}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UR_{rt}	-0.1621		0.0030		-0.1651		-0.1591	
	(0.1138)		(0.0566)		(0.1397)		(0.1132)	
Small × UR_{rt}		-0.3350**		-0.1253**		-0.2097		-0.4604***
		(0.1413)		(0.0619)		(0.1633)		(0.1445)
Medium × UR_{rt}		-0.1017		0.0073		-0.1090		-0.0943
		(0.1120)		(0.0565)		(0.1377)		(0.1117)
Large × UR_{rt}		-0.0435		0.1373**		-0.1808		0.0939
		(0.1130)		(0.0609)		(0.1406)		(0.1147)
Product group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4867	0.4867	0.3447	0.3447	0.4098	0.4098	0.5131	0.5132
Observations	4700177	4700177	4700177	4700177	4700177	4700177	4700177	4700177

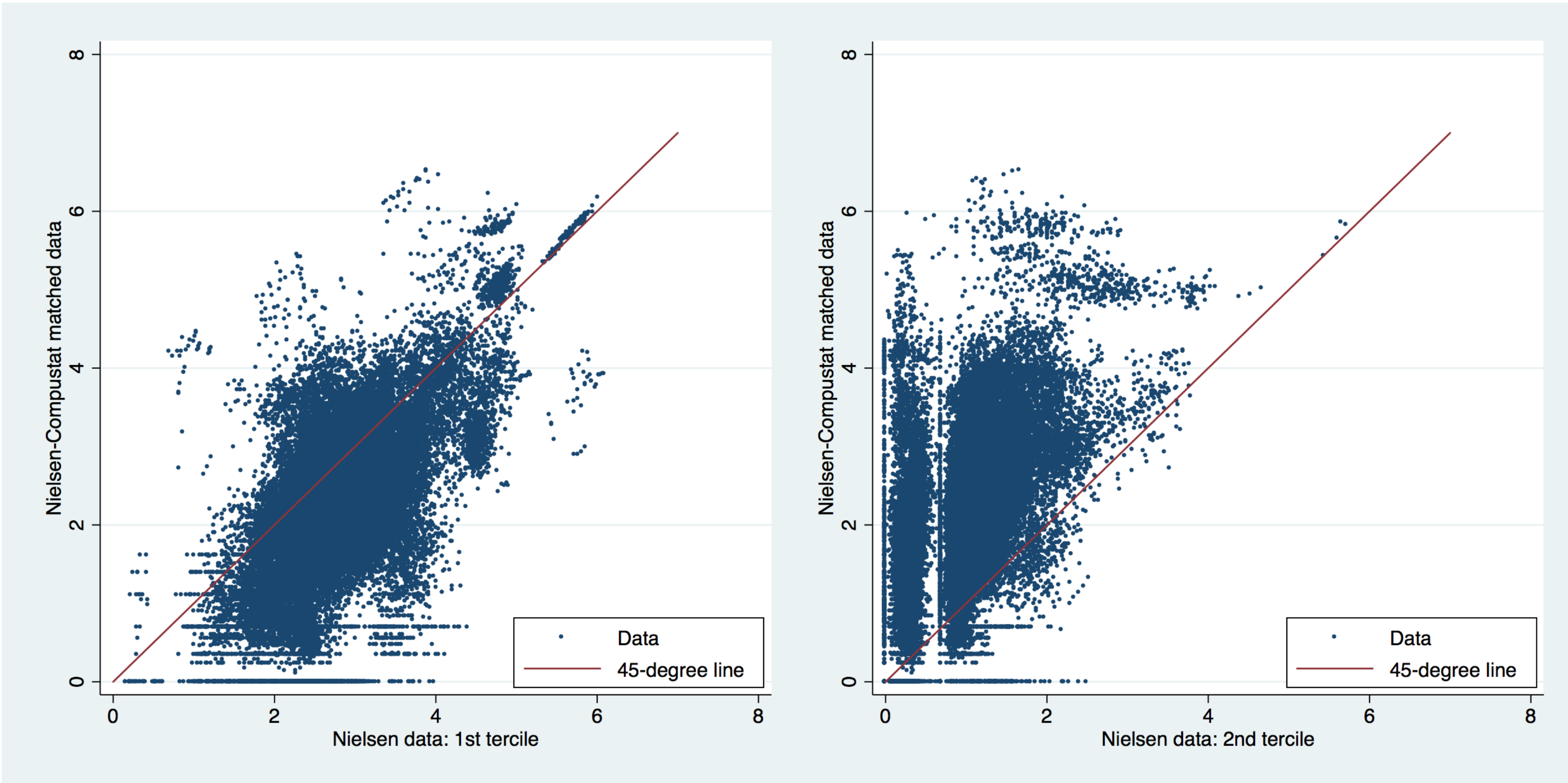
Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Net entry rates equal entry minus exit rates. Reallocation rates equal entry plus exit rates. A firm is "Small" if its lagged log(PS) is in the first tercile or the firm is a new entrants, "Medium" if lagged log(PS) is in the second tercile, and "Large" if lagged log(PS) is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

Table 2.4: Probability of Adding/Dropping a Product

	$Dummy(Add)_{m,grt}$		$Dummy(Drop)_{m,grt}$	
	(1)	(2)	(3)	(4)
UR_{rt}	-0.0013		-0.0001	
	(0.0009)		(0.0008)	
Small	0.7201***	0.7279***	0.2641***	0.2775***
	(0.0076)	(0.0081)	(0.0070)	(0.0075)
Medium	0.4961***	0.4997***	0.6030***	0.5989***
	(0.0073)	(0.0075)	(0.0070)	(0.0070)
Large	0.8721***	0.8597***	1.0134***	1.0037***
	(0.0076)	(0.0082)	(0.0072)	(0.0079)
Small × UR_{rt}		-0.0023**		-0.0017*
		(0.0009)		(0.0009)
Medium × UR_{rt}		-0.0018*		0.0004
		(0.0009)		(0.0008)
Large × UR_{rt}		0.0002		0.0011
		(0.0010)		(0.0008)
Product group fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes	Yes
R^2	0.5546	0.5546	0.6386	0.6386
Observations	4700177	4700177	4700177	4700177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. "Dummy(Add)" ("Dummy(Drop)") equals one if any product of the firm is added (dropped). "Small" if new firm or lagged product scope in logs is in the first tercile, "Medium" if lagged product scope in logs is in the second tercile, and "Large" if lagged product scope in logs is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

Figure 2.1: Average Product Scope, the Listed Nielsen firms vs All the Nielsen Firms



Note: Left (right) panel compares the average product scope of the listed Nielsen firms to the average product scope of all the Nielsen firms whose product scope lies in the first (second) tercile. Each point is a product group by Scantrack market by year observation.

Table 2.5: Products and Sales by Firm Types

	Backward looking			Forward looking		
	Contng Firms w/ product switching	Entering firms	Contng Firms w/o product switching	Contng Firms w/ product switching	Exiting firms	Contng Firms w/o product switching
	All years					
Product share	88.9	1.8	14.9	87.5	1.3	16.4
Sales share	92.5	0.8	11.8	91.8	0.3	12.7
	Recession years					
Product share	88.8	1.1	15.1	84.9	1.3	18.6
Sales share	91.9	0.1	12.5	90.0	0.0	14.2

Notes: The table reports the share of the number of products (sales) by different types of firms. The upper panel reports the shares when all years from 2007-2014 are considered. The lower panel is for years 2008-2009. The left side of each panel uses the current period as the benchmark and looks backward. There are three types of firms: Continuing firms with product switching, Entering firms, and Continuing firms without product switching. The right side of each panel uses the current period as the benchmark and looks forward. There are three types of firms: Continuing firms with product switching, Exiting firms, and Continuing firms without product switching. All the shares are averages across product groups and the years.

Table 2.6: Net Product Entry, the Listed Nielsen Firms

$NetEntry_{m,gt}$	(1)	(2)	(3)
UR_t	-0.5044**	-0.4981**	-0.4988**
	(0.2517)	(0.2517)	(0.2521)
Firm size	0.0228	-0.0581	-0.0781
	(2.2219)	(2.2233)	(2.2535)
Financial constraint		0.0083	0.0083
		(0.0080)	(0.0080)
R&D			-0.0519
			(0.9522)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.0805	0.0806	0.0806
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product net entry rate by product group by year in percentage points. The net entry rate equals entry minus exit rates. The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.7: Product Reallocation, the Listed Nielsen Firms

$Reallocation_{m,gt}$	(1)	(2)	(3)
UR_t	-0.1102	-0.1233	-0.0560
	(0.2668)	(0.2668)	(0.2667)
Firm size	1.0489	1.2167	3.1832
	(2.3555)	(2.3565)	(2.3846)
Financial constraint		-0.0172**	-0.0170**
		(0.0085)	(0.0085)
R&D			5.1035***
			(1.0076)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.2538	0.2542	0.2567
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product reallocation rate by product group by year in percentage points. The reallocation rate equals entry plus exit rates. The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.8: Net Product Entry, the Listed Nielsen Firms

$NetEntry_{m,gt}$	(1)	(2)	(3)
UR_t	-0.4135	-0.4128	-0.4130
	(0.2987)	(0.2987)	(0.2987)
TFP	0.7699	0.7135	0.7159
	(1.3862)	(1.3873)	(1.3879)
Financial constraint		0.0081	0.0081
		(0.0080)	(0.0080)
R&D			-0.0597
			(0.9399)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.0805	0.0806	0.0806
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product net entry rate by product group by year in percentage points. The net entry rate equals entry minus exit rates. The regressors are national unemployment rate (UR), the listed firms' lagged productivity (TFP), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.9: Product Reallocation, the Listed Nielsen Firms

$Reallocation_{m,gt}$	(1)	(2)	(3)
UR_t	-0.4819	-0.4833	-0.4701
	(0.3165)	(0.3165)	(0.3160)
TFP	-3.0022**	-2.8884**	-3.0871**
	(1.4692)	(1.4701)	(1.4684)
Financial constraint		-0.0163*	-0.0159*
		(0.0085)	(0.0085)
R&D			4.9415***
			(0.9944)
Product group fixed effects	Yes	Yes	Yes
R^2	0.2542	0.2546	0.2569
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product reallocation rate by product group by year in percentage points. The reallocation rate equals entry plus exit rates. The regressors are national unemployment rate (UR), the listed firms' lagged productivity (TFP), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.10: Net Product Addition, the Listed Nielsen Firms

$NetAddition_{m,gt}$	(1)	(2)	(3)
UR_t	-0.1455	-0.1438	-0.1504
	(0.2955)	(0.2956)	(0.2960)
Firm size	-2.2122	-2.2345	-2.4275
	(2.6092)	(2.6110)	(2.6464)
Financial constraint		0.0023	0.0023
		(0.0094)	(0.0094)
R&D			-0.5009
			(1.1183)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.0867	0.0868	0.0868
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product net entry rate by product group by year in percentage points. The net entry rate equals product addition minus subtraction rates (all sales-based). The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.11: Product Sales-based Reallocation, the Listed Nielsen Firms

$SalesReallocation_{m,gt}$	(1)	(2)	(3)
UR_t	-0.0633	-0.0790	-0.0122
	(0.2969)	(0.2969)	(0.2969)
Firm size	-0.8939	-0.6932	1.2573
	(2.6215)	(2.6225)	(2.6547)
Financial constraint		-0.0205**	-0.0204**
		(0.0094)	(0.0094)
R&D			5.0622***
			(1.1218)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.2160	0.2165	0.2185
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product reallocation rate by product group by year in percentage points. The reallocation rate equals product addition plus subtraction rates (all sales-based). The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.12: Firm Markup Growth, the Listed Nielsen Firms

$g(Markup)_{m,t}$	(1)	(2)
UR_t	1.0627**	1.1489**
	(0.4564)	(0.4501)
Lagged markup		-0.0184***
		(0.0025)
Observations	2126	2126
Firm fixed effects	Yes	Yes
R^2	0.1541	0.1784
Observations	2126	2126

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. The dependent variable is firm-level markup growth rates in percentage points. The regressors are national unemployment rate (UR) and the lagged markup in percentage points.

Table 2.13: Reallocation and Growth, All the Nielsen Firms

$g(ProductSales)_{m,grt}$	(1)	(2)
UR_{rt}	0.0103	
	(0.0682)	
Reallocation	0.0169***	0.0169***
	(0.0009)	(0.0009)
Small × UR_{rt}		-0.1341*
		(0.0757)
Medium × UR_{rt}		0.0104
		(0.0700)
Large × UR_{rt}		0.0854
		(0.0692)
Product group fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm size fixed effects	Yes	Yes
R^2	0.0640	0.0640
Observations	3002664	3002664

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Only continuing firms in 3 consecutive years are considered. The dependent variable is firm-level product sales growth rate by product group by year by region in percentage points. The control variable "Reallocation" is the lagged within-firm product reallocation rate. The other regressor is the regional unemployment rate (UR). A firm is "Small" if its lagged lagged product scope in logs is in the first tercile, "Medium" if lagged product scope in logs is in the second tercile, and "Large" if lagged lagged product scope in logs is in the largest tercile.

Table 2.14: Reallocation and Growth, the listed Nielsen Firms

$g(ProductSales)_{m,gt}$	(1)	(2)
UR_t	-0.4122	-0.1996
	(0.4791)	(0.4746)
Firm size	-4.8903	-4.4985
	(3.9973)	(3.9564)
Financial constraint	-0.0126	-0.0146
	(0.0133)	(0.0131)
R&D	4.1787***	3.4389**
	(1.4444)	(1.4311)
Reallocation		0.1833***
		(0.0161)
Firm fixed effects	Yes	Yes
Product group fixed effects	Yes	Yes
R^2	0.1858	0.2026
Observations	6504	6504

Notes: $*p < 0.1, **\,p < 0.05, ***p < 0.01$. Only continuing firms in 3 consecutive years are considered. The dependent variable is firm-level product sales growth rate by product group by year in percentage points. The control variable "Reallocation" is the lagged within-firm product reallocation rate. The other regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.15: Own-product Improvement vs Business Stealing, All the Nielsen Firms

$Exit_{m,grt}$	(1)	(2)
UR_t	0.0412	
	(0.0768)	
Entry	0.0634***	0.0635***
	(0.0018)	(0.0018)
Rivals' entry	0.0032	0.0032
	(0.0059)	(0.0059)
Small × UR_{rt}		-0.1465*
		(0.0814)
Medium × UR_{rt}		0.0361
		(0.0777)
Large × UR_{rt}		0.1441*
		(0.0778)
Product group fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Firm size fixed effects	Yes	Yes
R^2	0.3803	0.3804
Observations	3002664	3002664

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Only continuing firms in 3 consecutive years are considered. The dependent variable is firm-level product exit rate by product group by year by region in percentage points. The control variable "Entry" is the lagged within-firm product entry rate, and "Rivals' entry" is the lagged weighted product entry rate of the firm's rivals by their relative product scope sizes. Another regressor is the regional unemployment rate (UR). A firm is "Small" if its lagged product scope in logs is in the first tercile, "Medium" if lagged product scope in logs is in the second tercile, and "Large" if lagged product scope in logs is in the largest tercile.

Table 2.16: Own-product Improvement vs Business Stealing, the listed Nielsen Firms

$Exit_{m,gt}$	(1)	(2)
UR_t	0.1567	0.2358
	(0.2802)	(0.2836)
Firm size	1.1302	1.4285
	(2.3378)	(2.3268)
Financial constraint	-0.0058	-0.0078
	(0.0078)	(0.0077)
$R\&D$	2.5697***	2.4038***
	(0.8448)	(0.8410)
Entry		0.1071***
		(0.0135)
Rivals' entry		-0.0426
		(0.0492)
Firm fixed effects	Yes	Yes
Product group fixed effects	Yes	Yes
R^2	0.1850	0.1932
Observations	6504	6504

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms in 3 consecutive years are considered. The dependent variable is firm-level product exit rate by product group by year in percentage points. The control variable "Entry" is the lagged within-firm product entry rate, and "Rivals' entry" is the lagged weighted product entry rate of the firm's rivals by their relative product scope sizes. The other regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

2.8 Appendix

Appendix A. More Empirical Results

A1. All the Nielsen Firms: Product Switching

Table 2.17: Probability of Adding/Dropping a Product

	$Dummy(Add)_{m,grt}$		$Dummy(Drop)_{m,grt}$	
	(1)	(2)	(3)	(4)
UR_{rt}	-0.0011		-0.0001	
	(0.0007)		(0.0009)	
Small	0.4404***	0.4427***	0.3173***	0.3313***
	(0.0074)	(0.0074)	(0.0079)	(0.0086)
Medium	0.5642***	0.5709***	0.6341***	0.6324***
	(0.0074)	(0.0076)	(0.0079)	(0.0076)
Large	0.9358***	0.9267***	1.0438***	1.0366***
	(0.0078)	(0.0081)	(0.0081)	(0.0087)
Small × UR_{rt}		-0.0014**		-0.0018*
		(0.0007)		(0.0010)
Medium × UR_{rt}		-0.0019**		0.0001
		(0.0007)		(0.0009)
Large × UR_{rt}		0.0000		0.0007
		(0.0008)		(0.0010)
Product group fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm size fixed effects	Yes	Yes	Yes	Yes
R^2	0.5309	0.5309	0.6438	0.6438
Observations	4035742	4035742	4035742	4035742

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Only continuing firms are considered. "Dummy(Add)" ("Dummy(Drop)") equals one if any product of the firm is added (dropped). "Small" if lagged product scope in logs is in the first tercile, "Medium" if lagged product scope in logs is in the second tercile, and "Large" if lagged product scope in logs is in the largest tercile. For firm-level analysis, I identify firms within the product group by Scantrack market by year cells. The dependent variables are product scope in logs (columns (1) and (3)) and product scope growth (column (2)). The main regressor is the regional unemployment rate.

A2. The Listed Nielsen Firms: Product Entry and Exit Respectively

We have observed that the business cycle and the firm factors can both affect firms' net entry and reallocation rates, but their importances differ. The underlying times series of the net entry and reallocation rates are the firm-level gross product entry and exit rates. The tables 2.18 and 2.19 report the results using the continuing listed firms sample.

The entry rates are procyclical, while the exit rates are countercyclical. Both contribute to the procyclicality of the net entry rates, shown in Table 2.6. In addition, a higher R&D ratio implies both higher entry and exit rates. Naturally, the sum of the two, the reallocation rates, also increase when the R&D ratio rises up. In contrary, the tighter the financial constraint, the higher the entry and exit rates. So the financial constraint has a negative impact on firms' reallocation rates.

Table 2.18: Product Entry, the Listed Nielsen Firms

$Entry_{m,grt}$	(1)	(2)	(3)
UR_t	-0.3073*	-0.3107*	-0.2774
	(0.1801)	(0.1801)	(0.1802)
Firm size	0.5359	0.5793	1.5526
	(1.5900)	(1.5910)	(1.6112)
Financial constraint		-0.0044	-0.0044
		(0.0057)	(0.0057)
R&D			2.5258***
			(0.6808)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.1853	0.1854	0.1868
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product entry rate by product group by year in percentage points. The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.19: Product Exit, the Listed Nielsen Firms

$Exit_{m,grt}$	(1)	(2)	(3)
UR_t	0.1971	0.1874	0.2214
	(0.1866)	(0.1866)	(0.1867)
Firm size	0.5130	0.6374	1.6306
	(1.6476)	(1.6482)	(1.6692)
Financial constraint		-0.0127**	-0.0126**
		(0.0059)	(0.0059)
R&D			2.5777***
			(0.7053)
Firm fixed effects	Yes	Yes	Yes
Product group fixed effects	Yes	Yes	Yes
R^2	0.1772	0.1777	0.1791
Observations	8120	8120	8120

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Only continuing firms are considered. The dependent variable is firm-level product exit rate by product group by year in percentage points. The regressors are national unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

A3.The Listed Nielsen Firms: Product Scope and Sales

As a bridge of Chapter 1 and 2, I investigate the cyclicality and other influential factors of the list Nielsen firms' product scope levels. Consistent with the Chapter 1 analysis, the data used in this subsection is firm by product group by region by year.

As shown in the main context, the listed Nielsen firms have large product scope on average. From the analysis of Chapter 1, the large firms are the most resilient in the business cycle: their product scope are acyclical while the medium-sized and small firms' product scope are procyclical; at the same time, while the sales of all the firms are procyclical and decrease in the recession, the large firms experience the least sales loss, all else equal.

Table 2.20 reports the regression results for firm product scope, using the Chapter 1's firm-level regression specification. The firms' product scope is acyclical. The product scope (by product groups and regions) can be affected by firm size, financial constraint and the R&D ratio. Among these, the positive impact of firm size is in accordance with the model implication in Chapter 1.

Aside from the firm product scope results, another test that I can conduct is to look at the firms' sales cyclicality while controlling for the firm fundamentals. From Table 2.21, when the unemployment rate increases by 1 point, the firm sales decreases by -0.02%. Although the adjustment is significant, its magnitude is small and in line with small correlation between the large firms' sales and the unemployment rate in Chapter 1. Controlling for the business cycle, firm size, financial constraint and R&D ratio also affect firms' sales.

Table 2.20: Cyclicality of Firms' Product Scope, the Listed Nielsen Firms

$\log(\mathrm{PS})_{m,grt}$	(1)	(2)	(3)
UR_{rt}	0.0018	0.0018	0.0018
	(0.0022)	(0.0023)	(0.0022)
Firm size	0.1576***	0.1582***	0.1542***
	(0.0029)	(0.0028)	(0.0030)
Financial constraint		-0.0009***	-0.0009***
		(0.0001)	(0.0001)
R&D			0.0110***
			(0.0012)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R^2	0.1763	0.1767	0.1770
Observations	271135	271135	271135

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. The dependent variable is firm product scope by product group by region by year in logs. The regressors are regional unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types or regions (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Table 2.21: Cyclicality of Firm Sales, the Listed Nielsen Firms

$\log(\text{Sales})_{m,grt}$	(1)	(2)	(3)
UR_{rt}	-0.0185**	-0.0186**	-0.0188**
	(0.0089)	(0.0088)	(0.0087)
Firm size	0.1649***	0.1665***	0.1162***
	(0.0138)	(0.0138)	(0.0150)
Financial constraint		-0.0023***	-0.0019***
		(0.0002)	(0.0002)
R&D			0.1362***
			(0.0060)
Product group fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R^2	0.1413	0.1417	0.1511
Observations	271135	271135	271135

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. The dependent variable is firm sales by product group by region by year in logs. The regressors are regional unemployment rate (UR), the lagged total sales of the listed firms without distinguishing product types or regions (Firm size), the listed-firms' lagged Kaplan-Zingales indices (Financial constraint), and the listed firms' lagged ratios of the research and development expenses out of the total sales in percentage points (R&D).

Appendix B. Data Details

Appendix B1. Standardization of Compustat Firm Names

The table is an extended version of Table 16 in the appendix of Schoenle (2017).

Table 2.22: Standardization of Firm Names

Term	Standardized term
ASSOCIATION	ASSN
BROTHERS	BROS
BUILDING	BLDG
COMPANY	CO
CORPORATION	CORP
CP	CORP
DISTRIBUTION	DISTR
DIVISION	DIV
FOUNDRY	FDRY
GROUP	GRP
INCORPORATED	INC
INCORP	INC
INCORPORATION	INC
INDUSTRIES	IND
INTERNATIONAL	INTL
INTLL	INTL
MANF	MFG
MANUFACTURING	MFG
NORTH AMERICA	NA
SERVICES	SVCS
THE	

Appendix B2. Constructing Compustat Variables

The Compustat firm fundamental controls include firm size, financial constraint condition, the Research and Development expenses out of the total sales, markup and productivity. The Compustat terms used in the data construction are listed in the following table:

Table 2.23: Compustat Terms for Data Construction

Compustat Term	Definition
AT	Total Assets
CAPX	Capital Expenditures
CEQ	Ordinary Equity - Total
CHE	Cash and Short-Term Investments
COGS	Cost of Goods Sold
DLC	Debt in Current Liabilities - Total
DLTT	Long-Term Debt - Total
DP	Depreciation and Amortization
DPACT	Depreciation, Depletion and Amortization (Accumulated)
DVC	Dividends Common/Ordinary
DVP	Dividends - Preferred/Preference
EMP	Number of Employees
IB	Income Before Extraordinary Items
OIBDP	Operating Income Before Depreciation
PPEGT	Property, Plant and Equipment - Total
SALE	Net Sales
SEQ	Total Parent Stockholders' Equity
TXDB	Deferred Taxes
XRD	Research and Development Expense

- Firm size is defined as $log(SALE)$.

- The financial constraint condition is measured by the Kaplan-Zingales index, proposed in Kaplan and Zingales (1997). The index formula is

$$\begin{aligned}\text{Kaplan-Zingales}_{m,t} &= 1.002CF_{m,t} - 39.368Dididents_{m,t} - 1.315Cash_{m,t} \\ &+ 3.139Leverage + 0.283Q_{m,t}\end{aligned} \tag{2.6}$$

The first term CF is the the ratio of cash flow ($IB_{m,t}$+$DP_{m,t}$) over lagged total assets ($AT_{m,t-1}$), the second term is the ratio of total dividends ($DVC_{m,t} + DVP_{m,t}$) over lagged total assets ($AT_{m,t-1}$). The third term is the ratio of cash and short-term investments ($CHE_{m,t}$) over lagged total assets ($AT_{m,t-1}$). The fourth term is the leverage, defined as the ratio of total debts ($DLTT_{m,t} + DLC_{m,t}$) over total equity ($SEQ_{m,t}$). The last term is Tobin's Q, defined as the ratio of the market value of equity from CRSP minus the book value of equity and deferred taxed ($CEQ_{m,t} + TXDB_{m,t}$) over the total assets ($AT_{m,t}$).

- The research and development expense ratio is the research and development expense over the total sales, i.e. $XRD/SALE$.

- Markup is defined as the price to cost margin using the Compustat terms SALE and COGS, following Gorodnichenko and Weber (2016). Specially, markup equals $(SALE - COGS)/COGS$.

- Productivity is the Solow residual (Total factor productivity, or TFP) estimated using the semi-parametric method of Olley and Pakes (1996). The Implementation of the estimation is from İmrohoroğlu and Tüzel (2014). The Compustat terms used in the estimation are AT, CAPX, DP, DPACT, EMP, OIBDP, PPEGT, and SALE. The Compustat data is supplemented with price indices: wages, GDP deflater (for output) and investment deflater (for investment, capital).

Table 2.24: Summary Statistics, the Listed Nielsen Firms

	Mean	Std. Dev.
Firm size	8.22	2.12
Financial constraint	1.72	35.79
R&D	2.66	4.90
TFP	-0.09	0.62
Markup growth	-0.06	35.19

Notes: The Compustat observations are at firm by product group by year level. The sample only keeps the continuing Nielsen listed firms in pairs of years. All the rates or ratios are in percentage points.

Bibliography

Acemoglu, D. (2003). Labor-and capital-augmenting technical change. *Journal of the European Economic Association*, 1(1):1–37.

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and Kerr, W. R. (2013). Innovation, reallocation and growth. Working Paper 18993, National Bureau of Economic Research.

Aghion, P., Akcigit, U., and Howitt, P. (2014). What do we learn from schumpeterian growth theory? In *Handbook of economic growth*, volume 2, pages 515–563. Elsevier.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–51.

Argente, D., Lee, M., and Moreira, S. (2018). Innovation and product reallocation in the great recession. *Journal of Monetary Economics*, 93:1 – 20.

Axarloglou, K. (2003). The Cyclicality of New Product Introductions. *The Journal of Business*, 76(1):29–48.

Berger, P. G. and Ofek, E. (1995). Diversification's Effect on Firm Value. *Journal of Financial Economics*, 37(1):39–65.

Bernard, A. B. and Okubo, T. (2016). Product switching and the business cycle. Working Paper 22649, National Bureau of Economic Research.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2010). Multiple-product firms and product switching. *American Economic Review*, 100(1):70–97.

Bilbiie, F. O., Ghironi, F., and Melitz, M. J. (2012). Endogenous Entry, Product Variety, and Business Cycles. *Journal of Political Economy*, 120(2):304 – 345.

Broda, C. and Weinstein, D. E. (2010). Product creation and destruction: Evidence and price implications. *American Economic Review*, 100(3):691–723.

Burstein, A., Atkeson, A., et al. (2015). Aggregate implications of innovation policy. In *2015 Meeting Papers*, number 640. Society for Economic Dynamics.

Chatterjee, S. and Cooper, R. (2014). Entry And Exit, Product Variety, And The Business Cycle. *Economic Inquiry*, 52(4):1466–1484.

Clementi, G. L. and Palazzo, B. (2013). Entry, exit, firm dynamics, and aggregate fluctuations. Working Paper 19217, National Bureau of Economic Research.

Coibion, O., Gorodnichenko, Y., and Hong, G. H. (2015). The cyclicality of sales, regular and effective prices: Business cycle and policy implications. *American economic review*, 105(3):993–1029.

De Loecker, J. and Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review*, 102(6):2437–71.

Decker, R., D'Erasmo, P., and Moscoso Boedo, H. J. (2014). Market exposure and endogenous firm volatility over the business cycle. Working Papers 14-12, Federal Reserve Bank of Philadelphia.

Dunne, T., Roberts, M. J., and Samuelson, L. (1988). Patterns of firm entry and exit in us manufacturing industries. *The RAND journal of Economics*, pages 495–515.

Eckel, C. and Neary, J. P. (2010). Multi-Product Firms and Flexible Manufacturing in the Global Economy. *Review of Economic Studies*, 77(1):188–217.

Ericson, R. and Pakes, A. (1995). Markov-Perfect Industry Dynamics: A Framework for Empirical Work. *Review of Economic Studies*, 62(1):53–82.

Feenstra, R. and Ma, H. (2007). Optimal choice of product scope for multiproduct firms under monopolistic competition. Working Paper 13703, National Bureau of Economic Research.

Fort, T. C., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2013). How firms respond to business cycles: The role of firm age and firm size. *IMF Economic Review*, 61(3):520–559.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). Aggregate productivity growth. lessons from microeconomic evidence. In *New developments in productivity analysis*, pages 303–372. University of Chicago Press.

Garcia-Macia, D., Hsieh, C.-T., and Klenow, P. J. (2016). How destructive is innovation? Working Paper 22953, National Bureau of Economic Research.

Gorodnichenko, Y. and Weber, M. (2016). Are sticky prices costly? evidence from the stock market. *American Economic Review*, 106(1):165–99.

Grossman, G. M. and Helpman, E. (1991). Quality ladders in the theory of growth. *Review of Economic Studies*, 58(1):43–61.

Hopenhayn, H. A. (1992). Entry, Exit, and Firm Dynamics in Long Run Equilibrium. *Econometrica*, 60(5):1127–50.

Hottman, C. J., Redding, S. J., and Weinstein, D. E. (2016). Quantifying the sources of firm heterogeneity. *The Quarterly Journal of Economics*, 131(3):1291.

İmrohoroğlu, A. and Tüzel, Ş. (2014). Firm-level productivity, risk, and return. *Management Science*, 60(8):2073–2090.

Jaimovich, N. and Floetotto, M. (2008). Firm Dynamics, Markup Variations, and the Business Cycle. *Journal of Monetary Economics*, 55(7):1238–1252.

Jones, C. I. (2016). Life and growth. *Journal of Political Economy*, 124(2):539–578.

Jovanovic, B. (1982). Selection and the Evolution of Industry. *Econometrica*, 50(3):649–70.

Kaplan, S. N. and Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*, 112(1):169–215.

Kehrig, M. (2015). The cyclical nature of the productivity distribution. *Working Paper*.

King, R. G. and Rebelo, S. T. (1999). Resuscitating Real Business Cycles. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1 of *Handbook of Macroeconomics*, chapter 14, pages 927–1007. Elsevier.

Klette, T. J. and Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of Political Economy*, 112(5):986–1018.

Lang, L. H. P. and Stulz, R. M. (1994). Tobin's q, Corporate Diversification, and Firm Performance. *Journal of Political Economy*, 102(6):1248–80.

Lee, Y. and Mukoyama, T. (2012). Entry, exit, and plant-level dynamics over the business cycle. Working paper, Federal Reserve Bank of Cleveland.

Lentz, R. and Mortensen, D. T. (2008). An empirical model of growth through product innovation. *Econometrica*, 76(6):1317–1373.

Lucas Jr, R. E. and Moll, B. (2014). Knowledge growth and the allocation of time. *Journal of Political Economy*, 122(1):1–51.

Maksimovic, V. and Phillips, G. (2002). Do conglomerate firms allocate resources inefficiently across industries? theory and evidence. *The Journal of Finance*, 57(2):721–767.

Mayer, T., Melitz, M. J., and Ottaviano, G. I. (2016). Product Mix and Firm Productivity Responses to Trade Competition. NBER Working Papers 22433, National Bureau of Economic Research, Inc.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725.

Minniti, A. and Turino, F. (2013). Multi-product Firms and Business Cycle Dynamics. *European Economic Review, Elsevier*, 57(C):75–97.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297.

Ottaviano, G. I. (2011). Firm heterogeneity, endogenous entry, and the business cycle. Working Paper 17433, National Bureau of Economic Research.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

Savignac, F. (2008). Impact of financial constraints on innovation: What can be learned from a direct measure? *Economics of Innovation and New Technology*, 17(6):553–569.

Schoenle, R. (2017). International menu costs and price dynamics. *Review of International Economics*, 25(3):578–606.

Schumpeter, J. A. et al. (1939). *Business Cycles*, volume 1. McGraw-Hill New York.

Smets, F. and Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review*, 97(3):586–606.

Srinivasan, S. R., Ramakrishnan, S., and Grasman, S. E. (2005). Identifying the effects of cannibalization on the product portfolio. *Marketing Intelligence & Planning*, 23(4):359–371.

Stokey, N. L. (1988). Learning by doing and the introduction of new goods. *Journal of Political Economy*, 96(4):701–717.

Weintraub, G. Y., Benkard, C. L., and Van Roy, B. (2008). Markov perfect industry dynamics with many firms. *Econometrica*, 76(6):1375–1411.

Yeaple, S. R. (2013). Scale, scope, and the international expansion strategies of multiproduct firms. Working Paper 19166, National Bureau of Economic Research.