Multiproduct Firms and the Business Cycle*

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Abstract

Multiproduct firms account for a large fraction of economic activity and are actively engaged in changing their product mix. In this paper, 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. The changes at the new margin are procyclical on average and heterogeneous across firms. Such product scope changes affect aggregate consumption and output by changing the total number of products available in the market and by affecting firms' markups. This decomposition is 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 implied average markup goes up and further decreases consumption.

Keywords: Multiproduct firms, Oligopolistic competition, Endogenous markups
JEL Classification: E32, L11, L21, L25, L60

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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. 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.[1] I assign UPCs to their manufacturers using a data tool provided by GS1, the registrar of UPCs.[2] 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

[1]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 product as five-digit SIC category; on the contrary, Bernard et al. (2010) use a similar Nielsen data to mine and define product as Universal Product Code, which is a more disaggregated product definition.

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

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.[3]

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.[4] 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.[5] 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

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

[4] 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 differers from the previous studies by using UPC-level data and investigating average firms.

[5] Both aggregate product additions and product additions net of product subtractions are procyclical. Very recently, Argente et al. (2017) 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.

or large firms.[6] 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 medium and large firms respectively.

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 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 demand constraint: the benefit to adding a product is

[6] 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.

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).[7] 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 the 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 scope changes, I compare two steady states - one capturing normal times and the other of recession features that average productivity is lower and productivity dispersion is higher.[8]

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 varieties, 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 others as the productivity dispersion rises, to acquire more market shares. Since firms are oligopolistic competitors, higher market share leads to higher markup. Consequently, the average markup rises. The countercyclical markup intensifies

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

[8]The recession features are supported by literature, e.g., Kehrig (2015).

the increase in the aggregate price of consumption relative to leisure and further decrease 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 2, I review the literature on multiproduct firms and firm dynamics over the business cycle. In section 3, I describe the data and my empirical approach. Section 4 reports the main empirical results and robustness checks. In section 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 6 summarizes.

2 Literature review

My study contributes to the empirical researches 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 explore regional variations and identify 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 an well-documented important factor affecting aggregate dynamics discussed later.

My study is also related to two groups of theoretical studies: the models of multiproduct firms and 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.[9] 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.[10] 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 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

[9]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.

[10]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)

of firms and the 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) argues 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. In contrary, I present empirical patterns first and highlight firm heterogeneity in both data and model.

Firm heterogeneity is 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.

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 similar similar to Nielsen Retail Scanner but collected at the consumers' end is called 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.[11] 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 the manufacture (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 remaining products or UPCs 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.

The Nielsen data also contain transaction locations. I define geographic units as Scantrack

[11] 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.

markets such as Washington D.C.[12] In this way, I can explore regional variations. There are 49 Scantrack markets with transactions of all product groups available.

The Nielsen data lack manufacturer information on UPCs. 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.[13] 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. Although rarely, a company prefix may be recycled after its owner exits the market or stops paying the annual renewal registration fee.[14] To confirm that the data capture the firm dynamics well, I check the annual firm entry and exit rate, which is 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 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.[15]

[12]Scantrack markets are the most disaggregated level of geographic units with counterparts from the representative Consumer Panel Panel. More specifically, to check the representativeness of Nielsen's 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 Consumer Panel is Scantrack market.

[13]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.

[14]GS1 claims that such cases are rare.

[15]Product module is a lower level of aggregation than product group. An example is baby food, junior. 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.

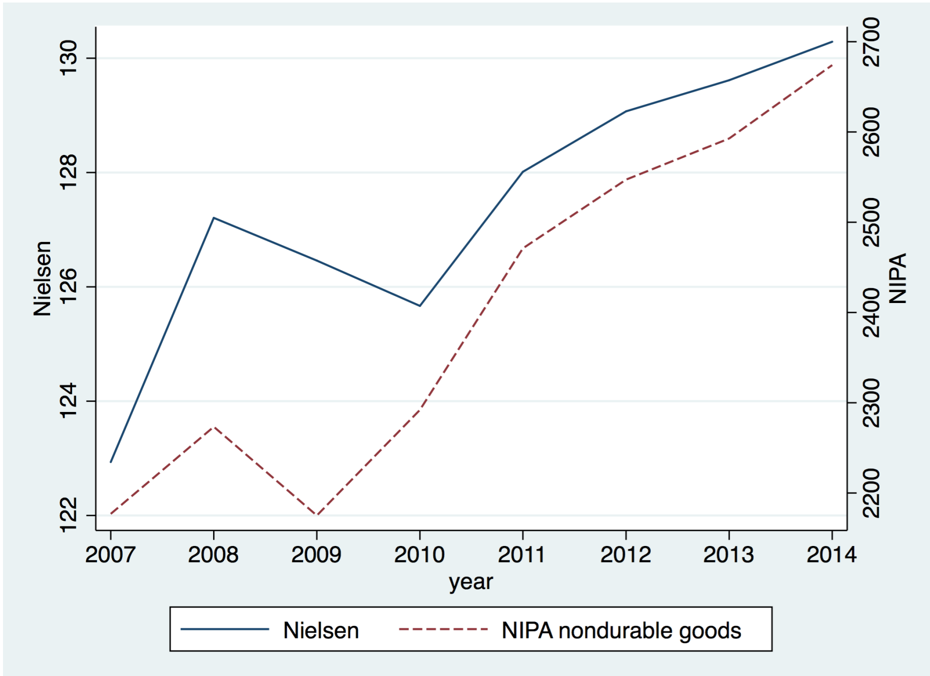
The main measure of interest is firms' product scope (PS), the number of UPCs that a firm offers within a given product group in a given Scantrack market. To document the empirical patterns of firm product scope distribution and its changes over the business cycle, I use two complementary analytical 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.[16] 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.[17]

Total sales of the 115 product groups and 49 Scantrack markets serves as a good proxy of nondurable goods consumption from the National Income and Product Accounts (NIPA) over the sample period. Figure 1 plots the two time series in billions of dollars. The solid line represents Nielsen sales and the dashed 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.

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

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

Figure 1: Total Sales in the Nielsen Data vs. Nondurable Goods Consumption



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

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 is due to firm-side adjustment directly. I also conduct two robustness check in the end.

4.1 Highly skewed distribution

Table 1 shows the summary statistics of the firms by cell data. There are 45,080 Scantrack markets by product group by year cells. The table documents firms' product scope as the number of UPCs and sales as ratios of the total. I also report the total number of firms and total sales to keep track of aggregate activity. The values in the third (fourth) column are averages (standard deviations) 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.

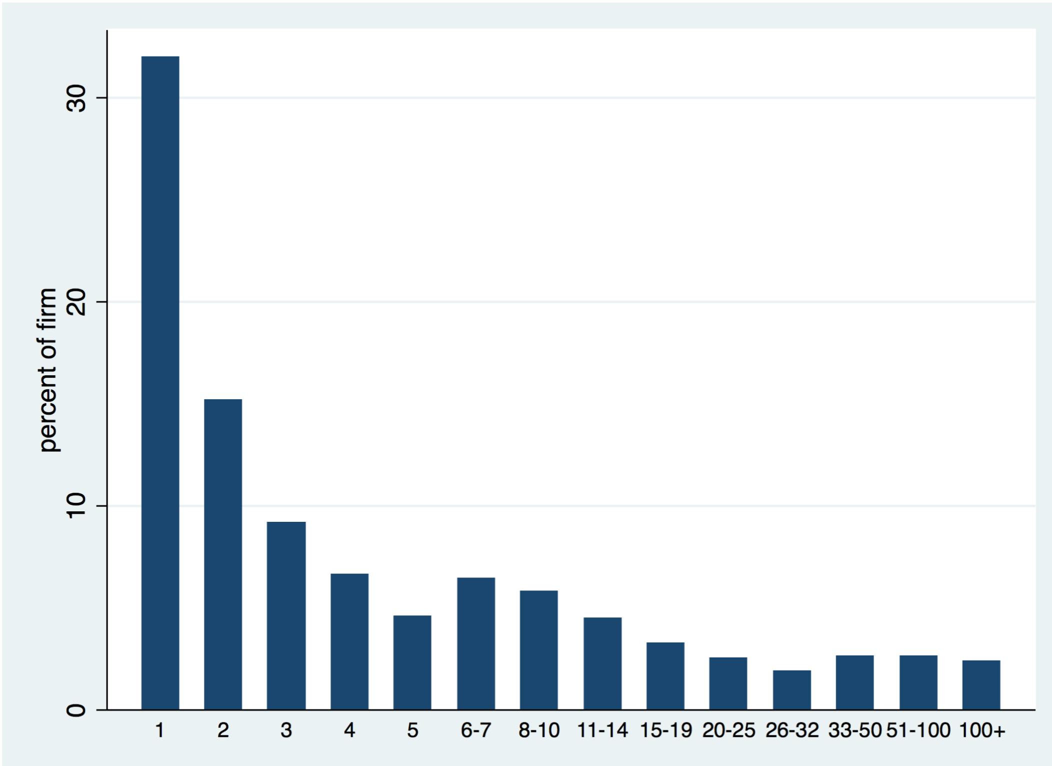
Table 1: Summary Statistics

	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: Observation are at 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.

The skewness of the distribution of firms' product scope is confirmed in the histogram shown in Figure 2. About 67% of firms have more than one product. The largest firms have more than 100 products.

Figure 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.

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 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. Specially, 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 entry (exit) rate of manufacturing firms is 30.7%–42.7% (30.8%–39%) between census years for 1963–1982, which put the annual entry (exit) rate at the range of 10%. If the entry and exit firm ratios are overestimated, the product scope adjustment margin is even more important than the firm entry and exit margin. 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 2: Ratio of Firm Number to the total Number of Firms by Firm Type

	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 ratios reported are the averages across product group by Scantrack market by year observations.

Table 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.[18] 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), 2.42% (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 4 also reports the decomposition by pair of years, which

[18] The growth rates in this study are all constructed in 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.

is 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 firm entry and exit margin.[19]

Table 3: Decomposition of Total Sales Growth

	Total	Entrants	Exiters	Continuing firms		
				Expanding PS	Shrinking PS	PS unchanged
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. The growth rates by firm type are weighted by their sales shares. The growth rates reported are averaged across product groups and Scantrack markets.

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 regional unemployment rate. 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:

$$y_{grt} = \alpha_g + \psi_r + \omega_t + \beta UR_{rt} + \epsilon_{grt}, \tag{1}$$

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

where y_{grt} is the growth rate of firms' average product scope in a given cell of product scope g, Scantrack market r, and year t. I choose the growth rate as the main dependent variable because the product scopes 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.[20] 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 the correlation between growth in average product scope and the business cycle indicator, but does not necessarily establish a causal relationship.

Column (1) of Table 4 shows the baseline regression result for the growth rate of average product scope. 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.[21]

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

[21] 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.

Table 4: Cyclicality of Average Product Scope: Cell-based Approach

	(1) $\bar{PS}$ growth$_{grt}$	(2) $\bar{PS}$ growth$_{grt}$
UR_{rt}	-0.2328***	
	(0.0660)	
ΔUR_{rt}		-0.2545***
		(0.0632)
Product scope growth 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 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 regional unemployment rate, and the alternative in column (2) is its change.

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

$$y_{m,grt} = \alpha_g + \psi_r + \omega_t + \beta UR_{rt} + \text{control}_{m,grt} + \epsilon_{mgrt}, \tag{2}$$

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.[22] A firm is "Small" if it is an entrant or its lagged product scope in logs is in the first tertile. A "Medium" ("Large") firm's lagged product scope in logs is in the second (largest) tertile. Specifically, the first tertile means less than the 34th percentile and the second tertile means less than the 67th percentile. Typically, a 34th percentile firm has one product, while a 67th percentile firm has five. As robustness check, the results using a sales-based firm size indicator is discussed section 4.5.

I run the regression by using both the log level and the growth rate of firms' product scope as the dependent variable for 2008–2014.[23] Columns (1) and (2) of Table 5 summarize

[22] 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).

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

the results. Both the log of firms' product scope and the product scope growth rates are negatively correlated with the unemployment rate.

As documented in firm dynamics literature, firms of different size respond to the same business cycle in different magnitude (Fort et al. (2013)). In my study, this implies that the correlation with the regional unemployment rate differs 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 5 reports the differentiated coefficients. Small firms' product scope is on average positive 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).

Table 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}	-0.009	-0.3225	
	(0.0015)	(0.2148)	
Small $\times$ UR_{rt}			0.0061***
			(0.0016)
Medium $\times$ UR_{rt}			-0.0043***
			(0.0015)
Large $\times$ UR_{rt}			0.0009
			(0.0018)
Product scope growth 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	0.8020	0.2950	0.8021
Observations	4,700,177	4,700,177	4,700,177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rate in percentage. "Small" if firms' lagged log(PS) is in the first tertile or new entrants, "Medium" if lagged log(PS) is in the second tertile, and "Large" if lagged log(PS) is in the largest tertile. 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 group growth (column (2)). The main regressor is regional unemployment rate.

Regression (20) is also applicable for firm-level sales. Table 6 reports the firm-level regression results for firm sales, similar to in Table 5 for firms' product scope. Columns (1) and (2) confirm that firm sales are procyclical on average. 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 regional unemployment rate differently. Column (3) confirms this conjecture. Small firms' sales are moderately procyclical, medium firms' sales are mostly procyclical, and large firms' sales respond the least. Notably, the higher product scope of small firms in bad times, suggested in Table 5, does not necessarily translate into a higher market share of these firms. The large firms are most recession-proof and acquire more market share in recessions than in normal times. Since the large firms are most likely to have high productivity, the data suggests that the most productive firms acquire more market shares in a recession. Table 12 in Appendix A2 directly confirms this conjecture.

Table 6: Cyclicality of Firm Sales: Firm-level Analysis

	(1) $\log(\text{sales})_{m,grt}$	(2) sales $\text{growth}_{m,grt}$	(3) $\log(\text{sales})_{m,grt}$
UR_{rt}	-0.0169***	-0.4686*	
	(0.0060)	(0.2770)	
Small × UR_{rt}			-0.0159***
			(0.0076)
Medium × UR_{rt}			-0.0233***
			(0.0069)
Large × UR_{rt}			-0.0085
			(0.0070)
Product scope growth 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	0.9011	0.1163	0.9011
Observations	4,700,177	4,700,177	4,700,177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rate in percentage. "Small" if firm lagged log(PS) is in the first tertile or new entrants, "Medium" if lagged log(PS) is in the second tertile, and "Large" if lagged log(PS) is in the largest tertile. 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 product group growth (column (2)). The main regressor is regional unemployment rate.

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 consumer demand changes and supply adjustment, 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 the supply side. 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 should be orthogonal to the idiosyncratic conditions of the local market.

I keep the most distinguishable groups of firms in the data: local firms selling in only one region and national firms operating in all 49 regions. 1,585 firms are kept. On average, 62% (38%) of firms are local (national). I extend the above firm-level regression by adding a local firm indicator and its interaction with regional unemployment rate.[24] The result is shown in column (1) of Table 7. The interaction term of the local firm indicator and unemployment rate demonstrates the difference in local and national firms regardless of their size. The negative coefficient suggests that local firms' product scope is more procyclical on average. In other words, firms directly respond to the business cycle by changing their product scope.

Furthermore, column (2) of Table 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 -0.16 for medium-sized and large firms, respectively) suggest that local firms are affected more by the supply side than national firms.

[24] I also run the cell-based regression in equation (1) for national and local firms respectively, finding that local business cycle indicator has a larger impact on local firms than on national firms.

Table 7: Cyclicality of Firms' Product Scope: National vs. Regional Firms

	(1) $\log(\text{PS})_{m,grt}$	(2) $\log(\text{PS})_{m,grt}$
UR_{rt}	-0.0013	
	(0.0023)	
Local$\times\text{UR}_{rt}$	-0.8623***	
	(0.0673)	
Small$\times\text{UR}_{rt}$		0.0018
		(0.0026)
Small$\times$Local$\times$ UR_{rt}		0.0243***
		(0.0057)
Medium$\times\text{UR}_{rt}$		-0.0068***
		(0.0024)
Medium$\times$Local$\times$ UR_{rt}		-0.0118***
		(0.0054)
Large$\times\text{UR}_{rt}$		0.0015
		(0.0026)
Large$\times$Local$\times$ UR_{rt}		-0.1594***
		(0.0345)
Product scope growth 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	0.9115	0.9121
Observations	1,543,563	1,543,563

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

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 firm-level regression. More robustness checks are provided in the Appendix.

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 8 are similar to those in Table 4 in that average product scope is procyclical among continuing firms. Although not explicitly shown, the firm-level estimates are also similar to the previous ones.

Table 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 scope growth 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 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 regional unemployment rate, and the alternative in column (2) is its change.

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 firm size indicator in Section 4.3, a firm is "Small" if it is an entrant or its lagged log sales are in the first tertile. A "Medium" firm's lagged log sales are in the second tertile and a "Large" firm's lagged log sales are in the largest tertile. Table 9 reports similar regression results to those in columns (1) and (2) of Table 5. The procyclicality property 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: medium-sized firms have most procyclical product scope.

Table 9: 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}	-0.0016**	-0.2248	
	(0.0008)	(0.1714)	
Small $\times$ UR_{rt}			0.0010
			(0.0010)
Medium $\times$ UR_{rt}			-0.0036***
			(0.0012)
Large $\times$ UR_{rt}			-0.0022
			(0.0015)
Product scope growth 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	0.7199	0.3217	0.7199
Observations	4,700,177	4,700,177	4,700,177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rate in percentage. 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 group growth (column (2)). The main regressor is regional unemployment rate.

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 abstract from product group or region interactions. Since firms in a given product group and region can have nonnegligible sales shares and make use of the market power to their advantage, I adopt a market structure where firms behave as oligopolists by assuming 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 group changes in a recession and decompose the aggregate impact of such product scope changes, I conduct comparative statics: a normal times steady state versus a steady state of recession features.

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

$$U_t \equiv \ln C_t - \chi \frac{{L_t}^{1+\frac{1}{\xi}}}{1+\frac{1}{\xi}}, \tag{3}$$

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

The household finances her consumption by 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:

$$\chi {L_t}^{\frac{1}{\xi}} = \frac{1}{P_t C_t} \tag{4}$$

$$\frac{1}{P_t C_t} = \beta \mathrm{E}\left[\frac{1+r_{t+1}}{P_{t+1}C_{t+1}}\right]. \tag{5}$$

Since I am interested in consumption, which equates output in equilibrium, and its price, I let the wage rate be the numeraire, i.e. $w_t = 1$ in (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.[25] 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 $\eta > 1$.[26] The total final goods production of a given product group in a given market in period t is

$$Q_t \equiv \left(\sum_{m=1}^{M_t} \lambda_{mt} q_{mt}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{6}$$

with

$$q_{mt} = \left(\sum_{i=1}^{N_{mt}} (q_{mit})^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{7}$$

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 due to (6) is

$$P_t = \left(\sum_{m=1}^{M_t} \left(\frac{p_{mt}}{\lambda_{mt}} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}, \tag{8}$$

[25]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.

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

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

$$q_{mit} = \left(\frac{p_{mit}}{p_{mt}}\right)^{-\eta} q_{mt}, \tag{9}$$

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

$$s_{mt} \equiv \frac{p_{mt} q_{mt}}{P_t Q_t} = \left(\frac{p_{mt}}{\lambda_{mt} P_t}\right)^{1-\eta} > 0. \tag{10}$$

5.2 Firms

A large number (compared with the number of firms that can enter the market) of potential firms can live for 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.

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

$$\max_{l_{mit}, p_{mit}, N_{mt}} \pi_{mt} = \sum_{i=1}^{N_{mt}} (p_{mit} q_{mit} - l_{mit}) - N_{mt} f^V, \tag{11}$$

subject to the demand function given in equation (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:

$$p_{mit} = \frac{\eta - (\eta - 1)s_{mt}}{(\eta - 1)(1 - s_{mt})}\mu_{mt} = \frac{\varepsilon_{mt}}{\varepsilon_{mt} - 1}\mu_{mt}, \tag{12}$$

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.[27] 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

$$q^I_{mt}(p^I_{mt} - \mu_{mt}) - s_{mt} q^I_{mt}(p^I_{mt} - \mu_{mt}) = f^V. \tag{13}$$

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 $R(\equiv PC)$ and the firm's sales share:

$$N_{mt} = \frac{s_{mt}(1 - s_{mt})}{\eta - (\eta - 1)s_{mt}} \frac{R_t}{f^V}. \tag{14}$$

The firm's sales share in turn depends on the firm's productivity and productivity and

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

sales share of the marginal firm denoted by subscript 1 (implied by equations (9), (12), and (14)):

$$s_{mt} = s\left(\phi_{mt}, \phi_{1t}, s_{1t}\right) = 1 - \frac{1}{(\eta - 1 + \frac{1}{1-s_{1t}})(\frac{\tilde{\phi}_{mt}}{\tilde{\phi}_{1t}})^{\frac{\eta-1}{\eta}} - \eta + 1}, \tag{15}$$

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

Equation (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 (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 (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.

5.2.2 Entry decision

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

$$\pi_{mt} = \frac{s_{mt}^2 R_t}{\eta - (\eta - 1)s_{mt}}. \tag{16}$$

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 $\left(E[\frac{1}{M^e+1}\sum_{m=1}^{M_e+1}\pi_{mt}] < f^E\right)$.

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 (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 (15);

(3) Firms maximize profits according to equations (12) and (14);

(4) Consumers maximize utility according to equations (4) and (5), and the budget constraint, given the aggregate price index in equation (8);

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

$$C_t = Q_t, \quad L_t = (\alpha(\eta-1)+1)R_t\sum_{m=1}^{M_t}\frac{s_{mt}(1-s_{mt})}{\eta-(\eta-1)s_{mt}} + M_t^E f^E, \quad B_t = 0. \tag{17}$$

5.4 Equilibrium aggregate price index

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

$$\begin{aligned} P_t &= \left(\sum_{m=1}^{M_t}\sum_{i=1}^{N_{mt}}(p_{mit})^{1-\eta}\right)^{\frac{1}{1-\eta}} \\ &= \frac{1}{z_t}\left(\sum_{m=1}^{M_t}N_{mt}\left[\frac{\varepsilon_{mt}}{\varepsilon_{mt}-1}\frac{1}{\phi_{mt}}\right]^{1-\eta}\right)^{\frac{1}{1-\eta}}. \end{aligned} \tag{18}$$

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, 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.

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 10.

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 be the median estimate, 3.9, in Hottman et al. (2016). The lower bound of quality-adjusted productivity is normalized to 1.

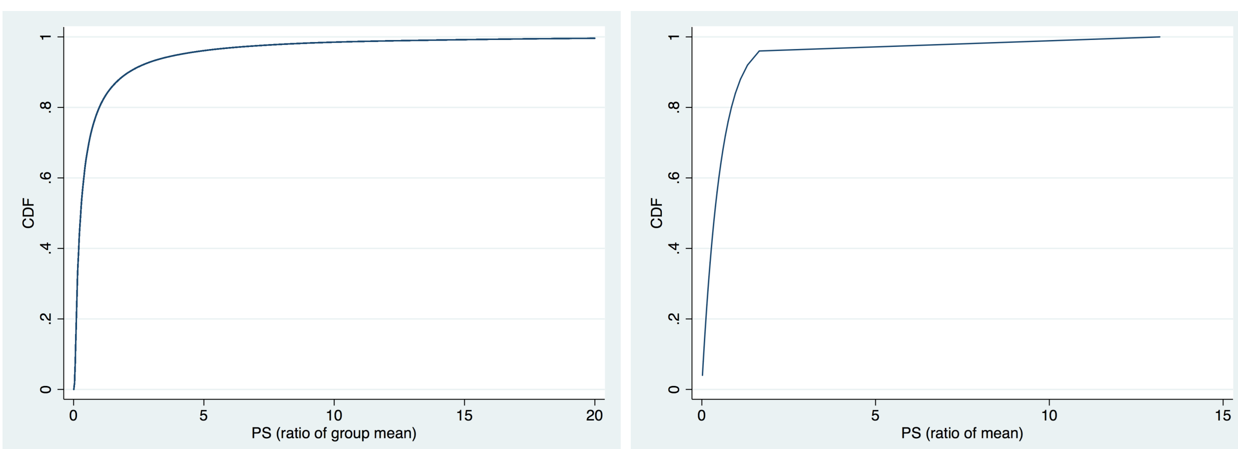
I interpret periods as years and set the discount factor $\beta = 0.96$ so that the annual interest rate is 4% as in King and Rebelo (1999). The preference parameter for labor χ is set to be 8 so that steady-state labor supply is about one-quarter of the available time, as in King and Rebelo (1999). 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 10 shows that the model matches the targets reasonably well.

Table 10: 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	Target	Data	Model
Annual discount factor	β	0.96	Annual interest rate	4%	4%
Preference parameter for labor	χ	8	labor supply	0.25	0.25
Shape parameter of $\tilde{\phi}_m$ dist.	γ	160	Average product scope	13	14
Upper bound of $\tilde{\phi}_m$	$\bar{\lambda}$	1.6	Weighted average product scope	130	117
Fixed cost per product	f^V	0.00015	Median product scope	3	3
Entry cost	f^E	0.000057	Overhead labor ratio	0.5	0.39

Figure 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.

Figure 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.

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.[28] 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 of the calibrated parameter values to a steady state of recession features implied by changes in benchmark parameter values. In recessions, average productivity is lower but productivity dispersion is higher than in normal times (Kehrig (2015)).[29] A simultaneous decrease in the upper and lower bounds of 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.

Table 11 the second column reports the aggregate and firm-level comparative statics. These are my baseline results. While the number of firms doesn't change, product scope affects aggregate output in two ways. First, firms have lower product scope in the steady state of recession features, which means fewer product choices for consumers and a higher aggregate price of consumption relative to leisure (i.e., the aggregate price in (18) is higher). This is the direct impact of procyclical firms' product scope. Second, firms' product scope choices interact with their markups. In the steady state of recession features, the most productive firms acquire more market share by reoptimizing input demand, prices, and product scope. Higher market share implies higher markup. Consequently, the average markup rises, and this further decreases consumption. The firm sales share changes are consistent with the above data observation.

The last column in Table 11 documents the changes in the steady-state values of a

[28] 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.

[29] The Kehrig (2015) findings may be driven by endogenous changes in dispersion in productivity. The way of modeling a shock is not exclusive. The current approach generates the changes in firm sales observed in the data.

multiproduct firms model with fixed product scope. A steady state of recession features is obtained by decreasing productivity range of 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.

Table 11: Differences in Key Outcomes: Recession versus Normal State

	Full model	Fixed product scope
Consumption (output) growth	-3.50	-3.53
Price index growth	3.75	3.77
Labor growth	-0.51	-0.50
Continuing firms: Average product scope growth	-0.62	-
Net firm entry rate	0	-17.39
Average markup change	0.014	0.012

Notes: Two models are considered: full model with endogenous product scope 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 10. The steady state of recession features has lower average productivity level and higher productivity dispersion and is obtained by decreasing the range of firm level productivity such that productivity$\in [1-d, 1.6-d]$ with $d = 0.0378$. Consumption equals output.

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 such firms' product scope is highly skewed. Second, product scope adjustment margin is important. Third, firms' product scope is procyclical on average. 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 steady state of recession features. I find that firms optimally choose lower product scope in the second steady state. Holding fewer product varieties decreases consumption directly because consumers love varieties. 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 and underestimated markups in a recession.

Further robustness checks 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 allows me to separate out major changes in products from minor adjustments that are more volatile but less influential. In addition, 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 "residual firm", which addresses the large impact of firm entry and exit on the firm-level averages.

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Appendix

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:

$$\Delta ln(\bar{N_m})_{grt} = \alpha_g + \phi_r + \mu_t + \beta \Delta ln(R)_{grt} + \epsilon_{grt}, \tag{19}$$

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 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 12 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 12: 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$_{rt}$	0.0008	0.0002	
	(0.0020)	(0.0001)	
Small × UR$_{rt}$			-0.0037
			(0.0044)
Medium × UR$_{rt}$			-0.0079***
			(0.0036)
Large × UR$_{rt}$			0.0144**
			(0.0060)
Product scope growth 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	0.1712	0.0007	0.1713
Observations	4,700,177	4,700,177	4,700,177

Notes: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rate in percentage. "Small" if firm lagged log(PS) is in the first tertile or new entrants, "Medium" if lagged log(PS) is in the second tertile, and "Large" if lagged log(PS) is in the largest tertile. 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 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:

$$y_{m,grt} = \alpha_g + \psi_r + \omega_t + \beta SalesGrowth_{grt}^{\sim m} + \epsilon_{mgrt}, \tag{20}$$

where m denotes the firm, g the product group, r the Scantrack market, and t the year. $SalesGrowth_{grt}^{\sim m}$ 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 13 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 13: Cyclicality of Firms' Average Product Scope: National vs. Regional Firms

	(1) $\log(\text{PS})_{m,grt}$	(2) PS growth$_{m,grt}$
$\text{SalesGrowth}^{\sim m}_{grt}$	0.0297***	0.3947***
	(0.0056)	(0.0179)
Product group fixed effect	Yes	Yes
Scantrack market fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
R^2	0.0447	0.0071
Observations	4,700,009	5,344,269

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level.

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 14 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 14: Cyclicality of Firms' Product Scope: Additional Firm Control

	(1) $\log(\text{PS})_{m,grt}$	(2) $\log(\text{PS})_{m,grt}$	(3) PS growth$_{m,grt}$	(4) PS growth$_{m,grt}$
UR_{rt}	-0.0017	-0.0023	-1.2808***	-1.2808***
	(0.0026)	(0.0026)	(0.3942)	(0.3869)
Product scope growth 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	0.7969	0.7983	0.2937	0.3311
Observations	2,712,215	2,712,215	2,712,215	2,712,215

Note: $*p < 0.1, **p < 0.05, ***p < 0.01$. Standard errors are clustered at the Scantrack market level. Growth rate in percentage.

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:

$$T_{grt} = \frac{1}{M_{grt}} \sum_{m \in M_{grt}} \frac{N_{m,grt}}{\bar{N}_{grt}} log(\frac{N_{m,grt}}{\bar{N}_{grt}}), \tag{21}$$

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 (1) for these measures and their changes. Table 15 summarizes the results.[30] 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.

[30] 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).

Table 15: Changes in Firms' Product Scope Distribution

	(1) Skewness_{grt}	(2) $\Delta(\text{Skewness})_{grt}$	(3) Theil_{grt}	(4) $\Delta(\text{Theil})_{grt}$
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.