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MARKUPS ACROSS SPACE AND TIME

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ABSTRACT

In this paper, we provide direct evidence on the behavior of markups in the retail sector across space and time. Markups are measured using gross margins. We consider three levels of aggregation: the retail sector as a whole, the firm level, and the product level. We find that: (1) markups are relatively stable over time and mildly procyclical; (2) there is large regional dispersion in markups; (3) there is positive cross-sectional correlation between local income and local markups; and (4) differences in markups across regions are explained by differences in assortment within each goods category, not by deviations from uniform pricing. We propose an endogenous assortment model consistent with these facts.

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1 Introduction

Are markups procyclical, acyclical or countercyclical? The answer to this question is central to many important issues in macroeconomics, ranging from the slope of the Phillips curve and the size of the fiscal multiplier (Hall (2009)) to the cyclical movements of the share of labor in income (Kaplan and Zoch (2020)). More generally, the cyclical properties of markups are important for understanding how firms and consumers interact and how these interactions shape consumption dynamics.

The presumption that markups are countercyclical has a long-standing tradition in macroeconomics. Examples of models with countercyclical markups include Rotemberg and Woodford's (1992) imperfect competition model and textbook New-Keynesian models with sticky prices and flexible costs (see e.g. Woodford (2003) and Gali (2015)).

The cyclical properties of markups are difficult to study empirically because marginal costs are generally not observable. Most empirical studies use structural approaches that rely on assumptions about production functions and market structure to infer marginal costs.[1] This literature, reviewed in depth by Nekarda and Ramey (2020), is divided in its conclusions, in part because different studies resort to different structural assumptions.

In this paper, we provide direct empirical evidence on the cyclical properties of markups for the retail industry. We focus on the retail sector because its predominant variable cost, the cost of goods sold, can be used as a proxy for marginal cost. Moreover, estimates of the frequency of price changes and other statistics based on retail prices have often been used to evaluate the importance of nominal rigidities and to calibrate macroeconomic models (see e.g. Bils and Klenow (2004) and Golosov and Lucas (2007)).

We find no evidence in favor of the conventional view that markups are countercyclical. Instead, we find that markups are acyclical or mildly procyclical. We study markups at three levels of aggregation: the retail sector as a whole, the firm level, and the product level. The product-level analysis is based on scanner data from two large retailers, one based in the U.S. and the other in Canada. These scanner data sets have three important advantages. First,

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[1]For example, Bils (1987), Hall (1988), Galeotti and Schiantarelli (1998), Rotemberg and Woodford (1999), Bils and Kahn (2000), Kryvtsov and Midrigan (2012), and Bils, Klenow and Malin (2018) infer the cyclicality of markups from the cyclicality of the cost shares of labor and other inputs. Hall (2014) bases his analysis on the cyclicality of advertising expenses. Collard-Wexler and De Loecker (2015) study the cyclical properties of markups implied by an estimated production function.

they include the price of every transaction, instead of the average price across transactions. Second, they contain the replacement cost of every item, which is a good proxy for marginal cost. Third, the data includes stores located in different regions, which allows us to compute regional markups. We use these data to study the regional distribution of markups as well as the response of markups to local business cycle conditions.[2]

We use the gross margin (sales minus cost of goods sold as a fraction of sales) as a proxy for the markup. Our main empirical finding is that gross margins are relatively stable over time and acyclical or mildly procyclical. In contrast, sales and net operating margins (revenue minus cost of goods sold and other expenses as a fraction of sales) are quite volatile and strongly procyclical. These results are consistent across all three levels of aggregation: for the aggregate retail sector, at the firm level, and at the product level. Our product-level evidence suggests that the marginal replacement cost of goods sold is relatively stable.

Nekarda and Ramey (2020) emphasize the importance of studying the conditional response of markups to various types of shocks. We estimate the conditional response of gross margins and net operating profits to monetary policy shocks and oil shocks. The response of gross margins to these shocks is not statistically significant. In contrast, the response of net operating margins to these shocks is negative and statistically significant.

The relative stability of markups over time contrasts sharply with the large regional dispersion in markups present in our scanner data sets. We find that regions with higher incomes and more expensive houses tend to buy goods with higher markups. These higher markups are not driven by less intense competition (as predicted by models such as Greenhut and Greenhut (1975) and Thisse and Vives (1988)) or regional differences in marginal costs. Also, they do not reflect regional differences in markups charged for the same item. Instead, high-income regions pay higher markups because, for each category (e.g. footwear or toys), they buy an assortment of goods that is different from the assortment offered and sold in low-income regions. Items sold in both high- and low-income regions generally have uniform prices, a finding consistent with the results of Della Vigna and Gentzkow (2019). Our regional evidence suggests that permanent shocks might result in permanent changes in assortment and markups.

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[2]Our approach to estimating local business-cycle effects is similar to that used by Coibion, Gorodnichenko and Hong (2015), Beraja, Hurst and Ospina (2019), and Stroebel and Vavra (2019). These authors study how prices respond to local business-cycle conditions in order to draw inference about the effect of monetary policy on aggregate fluctuations.

Our evidence sheds light on the empirical plausibility of different macroeconomic models. Consider first models with flexible retail prices. Our evidence favors the standard Dixit-Stiglitz model which implies that markups are acyclical. In contrast, models that imply countercyclical markups, such as Ravn, Schmitt-Grohé, and Uribe (2008)'s deep-habit model and Jaimovich and Floetotto (2008)'s entry and exit model, are inconsistent with our evidence.

Models with sticky prices at the retail level and procyclical marginal costs (e.g. Woodford (2003), Golosov and Lucas (2007) and Midrigan (2011)) imply countercyclical markups that are inconsistent with our evidence. In contrast, models with sticky prices at the retail level and acyclical marginal costs (e.g. in Nakamura and Steinsson (2010), Coibion, Gorodnichenko and Hong (2015) and Pasten, Schoenle and Weber (2017)) and models with prices and wage rigidities at the manufacturing level (e.g. Erceg, Henderson, and Levin (2000), Christiano, Eichenbaum and Evans (2005) and Christiano, Eichenbaum and Trabandt (2016)) imply acyclical markups that are consistent with our evidence.

Search models in which people devote time to search for lower prices generate procyclical markups because workers search less in expansions when the opportunity cost of search, the wage rate, is high (see e.g. Alessandria (2009)). When this procyclicality is not pronounced, these models are consistent with our evidence.

Existing macroeconomic models are generally inconsistent with the regional correlation between markups and income that we document. The trade models proposed by Fajgelbaum, Grossman and Helpman (2011) and Bertoletti and Etro (2017), which feature non-homothetic preferences, are consistent with this regional correlation.

We propose a model that draws on insights from the trade literature (Fajgelbaum, Grossman and Helpman (2011)) where the assortment of goods offered by firms to consumers is endogenous. The model is consistent with both our time-series and regional evidence: (1) markups are relatively stable over time and mildly procyclical; (2) there is large regional dispersion in markups; (3) there is a positive cross-sectional correlation between local income and local markups; and (4) differences in markups across regions are explained by differences in assortment, not by deviations from uniform pricing.

In sum, we provide direct empirical evidence on the behavior of markups, as well as a simple theory that is consistent with our findings.

This paper is organized as follows. Section 2 describes the data we use. Section 3 contains our empirical findings. Section 4 discusses the implications of these findings for business cycle and trade models. This section also presents an endogenous assortment model consistent with our empirical evidence. Section 5 concludes.

2 Data

Our analysis focuses on the retail sector, which accounts for roughly 10 percent of aggregate employment. We use three data sets.

Firm level data The first data set, obtained from Compustat, includes quarterly panel data on sales, costs of goods sold, selling, general and administrative expenses, and net profits for retail firms for the period from 1979 to 2014.[3] Our sample has 1,735 retail firms. In the Appendix, we show that the sales growth rates from the Compustat data for the retail sector track closely the sales growth rates implied by the U.S. Census Retail survey data.

Using Compustat data, we construct two margins for each firm f in quarter t:

$$(\text{Gross margin})_{ft} = \frac{\text{Sales}_{ft} - (\text{Cost of goods sold})_{ft}}{\text{Sales}_{ft}}, \tag{1}$$

$$(\text{Net operating profit margin})_{ft} = \frac{\text{Sales}_{ft} - (\text{Cost of goods sold})_{ft} - (\text{Other expenses})_{ft}}{\text{Sales}_{ft}}, \tag{2}$$

$$= (\text{Gross margin})_{ft} - \frac{(\text{Other expenses})_{ft}}{\text{Sales}_{ft}}.$$

Other expenses include overhead expenses, rent, labor costs, and capital and property depreciation. For retail firms, these expenses are predominately fixed or quasi-fixed costs.

Large U.S. retailer data Our second data source is a scanner data set from a large retailer that operates more than 100 stores in different U.S. states. This retailer sells products in the grocery, health and beauty, and general merchandise categories. We have weekly observations

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[3]The cost of goods sold does not include selling, general and administrative expenses. These expenses are reported separately from the cost of goods sold.

on quantities sold, retail and wholesale prices for each item in each of the retailer's stores. An item is a good, defined by its stock keeping unit code (SKU) in a particular store. In total, we have roughly 3.6 million SKU-store pairs across 79 product categories. Our sample period begins in the 1st quarter of 2006 and ends in the 3rd quarter of 2009, so it includes the recession that started in the 4th quarter of 2007 and ended in the 2nd quarter of 2009.

Large Canadian retailer data Our third data source is a scanner data set from a large retailer that operates hundreds of stores in different Canadian provinces. This retailer sells products in 41 product groups, including clothing and footwear, toys, books, videos, and sporting and camping equipment. We have weekly observations on quantities sold, retail and wholesale prices for 15.6 million item-store pairs. The sample begins in the 1st quarter of 2016 and ends in the 4th quarter of 2018, a period during which the Canadian economy experienced a modest expansion.

Our scanner data sets have two key features that distinguish them from a number of other scanner data sets.[4] First, they contain the price of every transaction instead of the average price across transactions. Second, the cost data measures the replacement cost, which is a good proxy for marginal cost. Moreover, the replacement cost is available at the store level, rather than as a national average. This property allows us to compute the gross margin as the difference between the price and the replacement cost for each item and store at each point in time.

Using these two scanner data sets, we construct the percentage gross margin for each item, i, at store s, in county k, at time t:

$$(\text{Gross margin})_{iskt} = \frac{\text{Price}_{iskt} - (\text{Replacement cost})_{iskt}}{\text{Price}_{iskt}}. \tag{3}$$

Since the real GDP data we use to measure economic activity is available quarterly, we construct gross margins at a quarterly frequency by expenditure-weighting weekly gross margins.

We define the growth rate of the gross margin from $t-1$ to t for the subset of products

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[4]Data from this retailer have been used in other studies, including Anderson, Jaimovich and Simester (2015), McShane, Chen and Anderson (2016), and Anderson, Malin, Nakamura, Simester, and Steinsson (2017).

that are in stock at time t and $t-1$ as:

$$g_{kt} \equiv \frac{\sum_s \sum_{i \in I_{i,t-1,t}} \omega_{iskt-1} \times \text{Gross margin}_{iskt}}{\sum_s \sum_{j \in I_{j,t-1,t}} \omega_{jskt-1} \times \text{Gross margin}_{jsk,t-1}},$$

where

$$\omega_{isk,t-1} = \frac{\text{Cost of goods sold}_{isk,t-1}}{\text{Total cost of goods sold}_{k,t-1}}.$$

and the cost of goods sold of an item is its replacement cost times quantity sold.

We compute the chained gross margin as

$$\text{Gross margin}_{kt} = \prod_{d=1}^{t} g_{kd} \times \text{Gross margin}_{k0},$$

where Gross margin$_{k0}$ denotes the weighted-average of the gross margin in region k in period 0 computed using the cost of goods sold as weights. We use this measure of the gross margin, whose construction resembles the Laspeyres index, to study the margin cyclicality generated by changes in the margins of individual items. This measure abstracts from changes in margin resulting from product substitution between time $t-1$ and t.[5]

We also use data on the unemployment rate, real GDP growth, and estimates of monetary policy and oil price shocks. The monetary-policy shocks are identified from high-frequency Federal Funds futures data.[6] Oil-price shocks are identified using the approach proposed by Ramey and Vine (2010). We provide additional details on the process used to estimate these shocks in the Appendix. We also use, in the Appendix, a simple model to discuss the conditions under which the gross marginal cost is likely to be a good proxy for marginal cost.

3 Business cycle properties

This section documents the cyclical properties of gross margins, operating margins, sales, and cost of goods sold. We discuss the comovement and volatility of these series for the aggregate retail sector, at the firm level, and at the product level.

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[5]We thank Mark Bils for suggesting that we use this measure of the gross margin.

[6]See Kuttner (2001) and Gurkaynak, Sack, and Swanson (2005) for details on the construction of these shocks.

3.1   Aggregate retail sector evidence

We construct aggregate measures of our variables for the retail sector using aggregate sales and aggregate costs. Table 1 summarizes the elasticity of different variables with respect to real GDP. This elasticity is estimated by regressing the year-on-year logarithmic difference of each variable on the year-on-year logarithmic difference of real GDP.

We see that gross margins are roughly acyclical or mildly procyclical. In contrast, sales and cost of goods sold are highly procyclical. These properties suggest that firms do not change markups in response to business-cycle fluctuations. Rather, the business cycle affects primarily their quantities sold and the cost charged by suppliers, which is why sales and cost of goods sold are highly procyclical.

Table 2 shows that gross margins are relatively stable when compared to other variables. At a quarterly frequency, operating profit margins are 3.4 times more volatile than gross margins, while sales and costs are roughly 2.6 times more volatile than gross margins. The high volatility of operating profit margins compared to the volatility of gross margins suggests that fixed costs might be an important driver of profitability. Figure 1, which depicts the log-differences from the prior year of gross margins and operating margins, illustrates the different volatility of these two variables.

3.2   Firm-level evidence

To study the cyclical properties of firm-level variables, we regress each variable on the year-on-year log-difference in real GDP using firm fixed effects. These fixed effects control for any permanent differences across firms, including differences in the degree of vertical integration between the retail and manufacturing operations.

Table 3 reports our elasticity estimates. The elasticity of the gross margin is small and statistically insignificant, while the elasticities of operating profits, sales and cost of goods sold are positive and statistically significant. Consistent with the aggregate evidence, the firm-level evidence suggests that business cycles primarily affect costs and quantities sold, rather than gross margins.

To study the volatility of a given variable at the firm level, we estimate the standard deviation of this variable for each firm and then compute the equally-weighted average of

this statistic across firms. We report our results in Table 4. The operating profit margin is the most volatile variable in our sample while the gross margin is the least volatile.

Finally, we study the conditional response of the gross margin and the operating profit margin to high-frequency monetary-policy shocks and oil-price shocks.[7] We estimate this response by running the following regression separately for the gross margin and the net operating profit margin:

$$\Delta \ln m_{it} = \beta_0 + \sum_k \beta_k \epsilon_{t-k} + \lambda_{q(t)} + \lambda_r + \eta_{it},$$

where $\Delta \ln m_{it}$ is the year-on-year log-difference in the margin of firm i at time t. The variable ϵ_{t-k} is the aggregate shock at time $t - k$. The variables $\lambda_{q(t)}$, λ_r, and λ_i are fixed effects for the calendar quarter, recession, and firm.

Figure 2 depicts the implied impulse response functions. We see that the response of the gross margin is statistically insignificant for both monetary and oil-price shocks. In contrast, net operating profit margins fall in a statistically significant manner in response to both shocks.

Collectively, these results are at odds with the properties of simple New-Keynesian models, which generally predict that gross margins rise in response to monetary shocks and fall in response to oil-price shocks. Monetary shocks are contractionary, so they produce a fall in marginal costs. Since prices are relatively stable, the gross margin rises. Oil-price shocks are also contractionary, but they produce a rise in marginal costs and a fall in the gross margin. In our data, the gross margin does not respond to either monetary or oil-price shocks.

3.3   Product-level evidence

There are two potential sources of measurement error in our aggregate data for the retail sector. First, gross margins are constructed using average costs instead of marginal costs. Second, changes in inventories can affect the cost of goods sold and potentially influence the cyclical properties of our empirical measure of the gross margin.[8] We now report results

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[7]Our scanner data does not contain enough time periods to allow us to estimate the conditional response of the gross margin to shocks.

[8]In Appendix A2, we present a version of our analysis where we adjust the cost of goods sold for changes in inventories. We still find that the elasticity of gross margins with respect to GDP is statistically insignificant.

that are free of these two potential sources of measurement error. Our analysis is based on scanner data from two large retailers, one based in the U.S. and the other in Canada. These data include transaction prices and replacement costs at the item level. Using this information, we compute gross margins for every product in every store. We aggregate the weekly observations to construct quarterly data.

3.4   Results for U.S. scanner data

We use our U.S. product-level data to show that the gross margins based on the cost of goods sold used in the previous subsections are a good proxy for gross margins based on the marginal replacement cost. We find that the correlation between the two measures of gross margins is 0.96.

Figure 3 shows how the U.S. retailer reacted to the onset of the 2009 recession. This figure plots the distribution for gross margins and for year-on-year log difference in sales and number of unique items for the periods 2006-07 and 2008-09.

Each data point in the distribution is a region-quarter observation. For confidentiality reasons, we do not report the level of the average gross margin. In constructing Figure 3, we normalize the gross margins by subtracting the average gross margin for the period 2006-07 from the gross margins for 2006-07 and 2008-09. As a result, the normalized average gross margin for the period 2006-07 is zero.

We see that the regional distribution of the level of gross margins remained relatively stable with a small shift to the left. In contrast, the distribution of year-on-year log difference in sales is more skewed in the Great Recession than in the 2006-07 period. This result is consistent with Bloom, Guvenen and Salgado (2019) who find that sales growth becomes skewed during recessions.

The distribution of the number of unique items in each store shifted to the left during the recession. In other words, lower sales are associated a smaller assortment and stable gross margins.

Table 5 reports the average, median, 10th and 90th percentiles of the distribution of the three variables in Figure 3 for the expansion and recession periods. The gross-margin

moments are similar across the two periods.[9] In contrast, the sales and number of item moments are all lower in the recession period.

To go beyond these unconditional moments, we now compute the elasticity of the variables of interest with respect to the local rate of unemployment and local real house prices.[10] Our approach is similar to that of Stroebel and Vavra (2019). We estimate the following regression:

$$\Delta \log \text{margins}_{mt} = \beta_0 + \beta_1 \Delta \log(Z_t) + \gamma X_{mt} + \varepsilon_{mt}, \tag{4}$$

where m denotes the region and the variables are yearly log-differences. We consider two possible alternative explanatory variables, Z_t: the local unemployment rate, and house prices instrumented with the housing supply elasticity proposed by Saiz (2010).[11] Since the Saiz (2010) instrument is static, for the regression specification that includes house prices we consider the difference between the period 2005-2006 and 2007-08. For the regression specification that includes the unemployment rate, the regression is estimated at the quarterly frequency and includes region fixed effects. The vector X_{mt} is a set of controls including local area income, racial composition, median age, manufacturing industry share of employment, and share of college-educated workers.

Table 6 reports our results. The elasticity of the gross margin is statistically insignificant with respect to unemployment and local house prices. The price and replacement cost elasticities are also statistically insignificant at a 5 percent confidence level. The elasticity of sales is statistically significant for both the unemployment rate and local house prices, indicating that sales rise during periods when the local economy booms. Finally, the number of unique items carried in the store is procyclical; its elasticity with respect to house prices is statistically significant at a 10 percent confidence level.

To investigate further the cyclical properties of the gross margin, we divide margin changes into "passive" and "active." We define passive gross-margin changes for a given

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[9]For confidentiality reasons, we do not report the average gross margin, only the difference in the average gross margin between the expansion and recession period.

[10]We thank Emi Nakamura for sharing with us unemployment data for the regions included in our scanner data.

[11]This instrument uses information on the geography of a metropolitan area to measure the ease with which new housing can be constructed. The index assigns a high elasticity of housing supply to areas with a flat topology and without many water bodies, such as lakes and oceans. In low-elasticity areas, it is more difficult for the housing supply to respond to demand shocks, so these shocks produce larger movements in house prices.

product as those that occur when the replacement cost of that product changes but the company does not change the product's price. Active gross-margin changes for a given product are those that result from changes in the price of that product, independently of whether or not the replacement cost changed. We compute these changes at a daily frequency and then aggregate them at a quarterly frequency using the average of the daily changes.

Table 7 summarizes our results obtained using specification (**??**). We find that given that a margin change occurs, the probability that this change is active is acyclical. The behavior of passive margin changes is consistent with the presence of small menu costs. When we use local house prices to measure cyclical conditions, we find that replacement costs are slightly procyclical and gross passive margin changes slightly countercyclical. In contrast, active margins and changes in replacement costs are roughly acyclical. This finding is inconsistent with models where the elasticity of demand varies in a systematic way with the business cycle. When we use unemployment rate to measure cyclical conditions, we find that both active and passive margins are acyclical. Most (91 percent) margin changes are active. Since changes in active margins are acyclical, overall margin changes are also acyclical.

Table 8 shows the standard deviation of year-on-year logarithmic changes in different variables. We see that gross margins, prices and cost of goods sold are relatively stable. In contrast, sales and the number of unique items in store's assortment are quite volatile.

3.5 Results for Canadian scanner data

We run regression (**??**) using the Canadian unemployment rate as an explanatory variable and region fixed effects, where a region is defined as a Census metropolitan area.[12] Table 9 reports our results. Recall that our data covers a period during which Canada experienced a moderate expansion. Quarterly real GDP growth rates ranged from 0.06 to 1.08 percent. While there is not much aggregate variation in growth rates, there is substantial regional variation. Our point estimates indicate that gross margins are slightly procyclical but the gross-margin elasticity statistically insignificant. We also find evidence that sales are strongly procyclical and statistically significant at a 10 percent level. These results obtained for a different country, set of goods, and cyclical period are broadly similar to those obtained for

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[12]The Saiz (2010) instrument is not available for Canada, so we cannot run a version of regression (**??**) using house prices as an explanatory variable.

the U.S.

One advantage of the Canadian data is that changes in oil prices generate substantial regional variation in economic activity. Alberta, Saskatchewan, Newfoundland and Labrador are all highly dependent on oil production. An unexpected rise in oil prices is a negative supply shock for all regions and a positive demand shock for oil-producing regions. In Table 9, we report estimates of β_2 obtained by running the following regression:

$$\Delta \log \text{margins}_{mt} = \beta_0 + \beta_1 \Delta \log(Z_t) + \beta_2 \Delta \log(Z_t) I_m + \gamma X_{mt} + \varepsilon_{mt}, \tag{5}$$

where I_m is equal to one if the region is a major oil producer and zero otherwise. The coefficient β_2 isolates the positive demand shock to oil-producing regions. We find that the gross margins are acyclical while sales and number of items sold are procyclical.

We now turn to the properties of active and passive margins. A fraction 93 percent of gross margin changes are active. Table 10 reports our estimates of β_1 obtained using specification (**??**) and unemployment as the measure of cyclical conditions. This table also reports our estimates of β_2 obtained using specification (**??**) and changes in oil prices as the measure of cyclical conditions. We find that both active and passive changes in gross margins are acyclical. The acyclicality of active margins are inconsistent with models where the elasticity of demand varies in a systematic way with the business cycle.

Table 11 shows the standard deviation of year-on-year logarithmic changes in different variables. As in our U.S. data set, we see that gross margins, prices and cost of goods sold are relatively stable. In contrast, sales and the number of unique items in store's assortment are quite volatile.

3.6   Trends in retail gross margins

Our analysis so far has been focused on business-cycle properties, so our empirical work is based on log-differences in gross margins. We now briefly examine the trends in gross margins present in our data. Figure 4 displays the time series for the average gross margin in the retail sector. We see that this margin has increased by roughly two percentage points in the mid 1980s and increased again by three percentage points from about the mid 1990s onward. These increases are consistent with the trends documented by De Loecker and Eeckhout (2017). However, the trends in our data are much smaller than those estimated by

De Loecker and Eeckhout (2017) who use a structural approach. Our results are consistent Karabarbounis and Neiman (2018) and Traina (2018) who find small long-run trends in markups.

3.7   Summary

In this section, we study the cyclical properties of the retail sector at three levels of aggregation: the sector, firm and product level. Our main findings for sector and firm data are as follows. Gross retail margins are stable over the business cycle and mildly procyclical. In contrast, sales, cost of goods sold, and net operating profits are highly procyclical. Operating profit margins are much more volatile than gross margins which suggests that fixed costs are important.

The evidence at the product level for our large U.S. retailer indicates that the firm reacted to the 2009 recession primarily by reducing the number of unique items in its assortment. Gross margins remained relatively stable, falling slightly. The evidence at the product level for our large Canadian retailer is consistent with the notion that gross margins are acyclical or mildly procyclical and that sales are strongly procyclical.

4   Cross-sectional properties

In this section, we use our scanner data to study the distribution of gross margins across regions. Figure 3 shows that. in the U.S., this regional distribution is relatively similar in the Great Recession and in the expansion that preceded it. Each data point in the distribution is a region-quarter observation. The mean of the distribution is somewhat higher in the expansion period, which is consistent with the notion that margins are slightly procyclical. The same figure shows that there is a large regional dispersion in the gross margins of our large retailer in both the expansion and the recession period.

We can decompose the overall variance of the gross margins into a time-series and a regional component. We denote by v_{mt} the gross margin of region m at time t, computed as a sales-weighted average of all items in stores located in this region. The variance of v_{mt}

can be written as:

$$var\left(v_{mt}\right) = \frac{1}{TM-1} \sum_t \sum_m \left(v_{mt} - v\right)^2$$

$$= \frac{1}{TM-1} \sum_t \sum_m \left(v_{mt} - v_t + v_t - v\right)^2$$

$$\approx \frac{1}{T} \sum_t \underbrace{\frac{\sum_m \left(v_{mt} - v_t\right)^2}{M-1}}_{var_t(v_m)} + \underbrace{\frac{\sum_t \sum_m \left(v_t - v\right)^2}{TM-1}}_{var(v_t)} + 2cov(v_{mt} - v_t, v_t - v),$$

where T is the total number of time periods and M is the total number of regions. The variable v_t is the average gross margin across all regions at time t, computed as a sales-weighted average of all items in all stores. The variable v is the average of v_t across time. The variables $\frac{1}{T} \sum_t var_t\left(v_m\right)$ and $var\left(v_t\right)$ represent the average regional and time-series variance of gross margins, respectively. The variable $cov(v_{mt} - v_t, v_t - v)$ is the covariance between the time-series and the regional component.

Table 12 reports our results. The regional variance in gross margins, $\frac{1}{T} \sum_t var_t\left(v_m\right)$, is 0.103 while the time-series variation, $var(v_t)$, is 0.013. The covariance term, $cov(v_{mt} - v_t, v_t - v)$, is close to zero. This decomposition suggests that most of the variation in gross margins comes from the cross section, not from the time series.

To study the source of regional variation in gross margins, we start with the following equation for the variance of gross margins across different markets conditional on period t, $var_t(v_m)$:

$$var_t(v_m) = var_t\left(\sum_j v_{jm} w_{jm}\right). \tag{6}$$

Here, v_{jm} is the gross margin of product j in market m and w_{jm} is the sales of product j in market m as a fraction of total sales in market m.

Expanding the terms on the right-hand side of equation (**??**), we obtain:

$$var_t(v_m) \quad = \quad \underbrace{var_t\left[\sum_j (v_{jm} - \bar{v}_j)\bar{w}_j\right]}_{\text{differences in gross margins for the same item}}$$

$$+ \quad \underbrace{var_t\left[\sum_j (w_{jm} - \bar{w}_j)\bar{v}_j\right]}_{\text{differences in assortment composition}}$$

$$+var_t\underbrace{\left[\sum_j (v_{jm} - v_j)(w_{jm} - \bar{w}_j)\right]}_{\text{interaction term}} + \text{covariance terms.}$$

The first term on the right-hand side of this equation measures the importance of differences in gross margins for the same item. This term is zero when there is uniform pricing, i.e. prices for the same product are identical across regions. The second term measures the importance of differences in assortment holding fixed the gross margin across regions. This term is zero when all regions have the same assortment composition. The third term measures the importance of the interaction between differences in assortment and differences in gross margins.

Table 13 reports the average over time of the components of this decomposition for the U.S. (panel A) and Canada (panel B). The first column of panels A and B reports results obtained using all items, including items sold in only some of the regions. In both panels, we find that the predominant driver of regional differences in gross margins are differences in assortment composition across regions. In contrast, regional differences in the gross margins of the same items account for very little of the regional variation in gross margins. In other words, when the same item is available in different regions our retailers use roughly uniform pricing.

For robustness, we use our U.S. data to produce results obtained by restricting the sample to items that are sold in all regions.[13] We report these results in the second column of panel A. Here, the regional variation results from regional differences in consumer baskets. The results obtained using this restricted sample are similar to those obtained using the full sample.

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[13]We do not compute the results for a sample of items sold in every market in Canada because the number of these items is relatively small.

We now investigate which variables might explain the regional variation in gross margins. Column 1 of Table 14 shows that gross margins in our U.S. data are positively correlated with measures of income or wealth. These measures include the logarithm of household income and the logarithm of median house value. In contrast, gross margins are uncorrelated with a measure of competition (the Herfindahl index) and a proxy for higher transportation costs (a dummy variable that takes the value one for counties classified by the census as rural).

We find that there is indeed a positive cross-sectional correlation between local income and local gross margins. But these differences in gross margins across regions are explained by differences in assortment, not by deviations from uniform pricing. These results are consistent with the evidence in Della Vigna and Gentzkow (2019). They are also consistent with recent work by Neiman and Vavra (2018) that shows that households concentrate their spending on different goods. We add to these results by providing direct evidence on differences in gross margins and assortment across regions.

Column 2 of Table 14 shows that gross margins in our Canadian data are also positively correlated with measures of income or wealth. These measures include the logarithm of household income and the logarithm of median house value. We also find a positive correlation between the unique number of items sold in a region and regional household income. This correlation is 0.42 for the Canadian retailer and 0.17 for the U.S. retailer.

5 Macroeconomic and trade models

In this section, we evaluate several business cycle and trade models in light of our evidence. We then present an endogenous assortment model that is broadly consistent with our time-series and cross-section evidence.

5.1 Business cycle models

As discussed in the introduction, our evidence favors models that generate acyclical or weakly procyclical retail markups. This class of models includes the standard Dixit-Stiglitz model which has flexible prices at the retail level. It also includes models with acyclical marginal costs and sticky prices at the retail level (e.g. in Nakamura and Steinsson (2010), Coibion, Gorodnichenko and Hong (2015) and Pasten, Schoenle and Weber (2017)) and models with

prices and wage rigidities at the manufacturing level (e.g. Erceg, Henderson, and Levin (2000), Christiano, Eichenbaum and Evans (2005) and Christiano, Eichenbaum and Trabandt (2016)). However, none of these models are consistent with our finding that markups and income are correlated in the cross section.

5.2 Trade models

Trade models with non-homothetic preferences generate a positive correlation between markups and income. Bertoletti and Etro (2017) consider a version of the Dixit-Stiglitz model of monopolistic competition with a non-homothetic aggregator. Fajgelbaum, Grossman and Helpman (2011) propose a model with non-homothetic preferences in which households consume an homogeneous good and a single unit of a differentiated good. Households choose the quantity of the homogeneous good and the quality of the differentiated good. We discuss the properties of these two models in turn. Both models are static so income and consumption expenditures coincide.

5.2.1 The Bertoletti and Etro model

Bertoletti and Etro (2017) write the household's indirect utility function as:

$$\int_0^n \mu(p_i/Y)di,$$

where p_i denotes the price of differentiated good i and Y represents income. The authors show that when $\mu(.)$ takes an exponential form,

$$\mu(p_i/Y) = \exp\left[-\tau\left(p_i/Y\right)\right],$$

the markup of price over marginal cost (c) is given by:

$$\frac{p_i}{c} = 1 + \frac{Y}{\tau c}.$$

When $\mu(.)$ takes an addilog form,

$$\mu(p_i/Y) = \left[a - (p_i/Y)\right]^{1+\gamma},$$

the markup of price over marginal cost (c) is given by:

$$\frac{p_i}{c} = \frac{\gamma + a(Y/c)}{1 + \gamma}.$$

Consistent with our time-series evidence, as long as the cyclicality of income and marginal costs is similar, markups are roughly acyclical. The model is also consistent with our cross-sectional evidence. Suppose that marginal costs are similar across regions but there is dispersion in income levels. Then, higher income regions pay higher markups.

However, this model is inconsistent with the nature of the regional variation in markups present in our data. Our evidence suggests that markups vary with income or wealth because rich and poor regions buy different assortments. In contrast, the Bertoletti and Etro (2017) model implies that regions with different levels of income have different markups for the same item.

5.2.2 The Fajgelbaum, Grossman and Helpman model

The model proposed by Fajgelbaum, Grossman and Helpman (2011) is fully consistent with our cross-sectional evidence under the assumption that there is less substitutability between brands of higher quality than between brands of lower quality. Under this assumption, the model implies that regions with higher income pay higher markups but consume higher quality items. So variations in markups are driven by differences in assortment, just like in our scanner data.

Unfortunately, the Fajgelbaum, Grossman and Helpman (2011) model is inconsistent with our time-series evidence. The markup over marginal cost (c_i) for an item of quality q_i and brand j is:

$$\frac{p_{ij}}{c_i} = 1 + \frac{\theta_i}{q_i c_i},$$

where θ_i is the dissimilarity parameter. This formula implies that, when marginal costs are procyclical, the model generates countercyclical markups for each item i.

A version of the Fajgelbaum, Grossman and Helpman with sticky wages might be consistent with both the time-series and cross-sectional evidence. But such a model would have complex borrowing and lending across agents that would greatly reduce its tractability. Instead of exploring such a model, we consider a version of the Dixit-Stiglitz model that

embodies a central insight from Fajgelbaum, Grossman and Helpman (2011): higher quality consumption bundles are made of less substitutable components.

5.3   An endogenous assortment model

We consider a model in which the assortment of goods available to the consumers is endogenous. In equilibrium, producers who sell in higher-income regions offer consumers higher-quality goods that have higher markups.

Our economy is populated by a representative household who maximizes its lifetime utility given by:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\log \left(C_t^\alpha Z_t^{1-\alpha} \right) + \theta_t \log(1 - N_t) \right].$$

(7)

The symbol E_0 denotes the expectation conditional on the information set available at time zero. The variables N_t and Z_t denote hours worked and consumption of an homogenous good, respectively. We interpret the homogeneous good as representing staple goods that are sold in all regions. The variable θ_t represents a shock to the labor supply.

A consumption bundle C_t with quality q_t is a composite built with an assortment of n_t differentiated goods combined according to a Dixit-Stiglitz aggregator:

$$C_t = q_t^\gamma \left[\int_0^{n_t} x_{iqt}^{1/v(q_t)} di \right]^{v(q_t)},$$

where x_{iqt} is the quantity consumed of variety i with quality q at time t. We assume that $v(q_t)$ is an increasing function of q_t. So, as in Fajgelbaum, Grossman and Helpman (2011), higher-quality consumption bundles are produced with an assortment of more differentiated inputs.

For tractability, we consider the simple case in which $v(q_t)$ is a linear function, so v_t is equal to the quality of the inputs ($v_t = q_t$) and the consumption aggregator is given by:

$$C_t = v_t^\gamma \left[\int_0^n x_{ivt}^{1/v_t} di \right]^{v_t}.$$

We assume that $\gamma > 1$ which implies that, other things equal, households prefer higher quality baskets.[14] We also assume that there's a minimum consumption size for each variety.

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[14]See Jaimovich, Rebelo, Wong, and Zhang (2019) and Faber and Fally (2020) for evidence that higher-income households consume higher-quality goods.

For convenience, we normalize this minimum size to one:

$$x_{ivt} \geq 1.$$

In the absence of a minimum consumption size, households would want to consume infinitesimal amounts of goods with infinite quality.

We can solve the household's problem in two steps. The first step is to find the efficient consumption of varieties, minimizing total expenditure, for a given level of C_t, $\bar{C}_t$:

$$\min_{x_{ivt}, v_t} \int_0^{n_t} p_{ivt} x_{ivt} di,$$

subject to:

$$\bar{C}_t = v_t^\gamma \left[\int_0^n x_{ivt}^{1/v_t} di \right]^{v_t}.$$

Households choose the quality of the consumption bundle, q_t, and the amount consumed of each individual variety with quality q_t, x_{ivt}. The first-order condition for the optimal choice of x_{ivt} is:

$$\frac{x_{ivt}}{x_{jvt}} = \left[\frac{p_{ivt}}{p_{jvt}} \right]^{v_t/(1-v_t)}.$$

The elasticity of substitution between any two varieties is $-v_t/(1 - v_t) \geq 0$. An increase in v reduces the elasticity of substitution, so goods are less substitutable. As v_t goes to ∞, the elasticity converges to one which corresponds to the Cobb-Douglas case.

The optimal allocation of the differentiated consumption goods satisfies the condition,

$$p_{ivt} = v_t^{\gamma/v_t} P_t C_t^{(v_t-1)/v_t} x_{ivt}^{(1-v_t)/v_t}.$$

Here, P_t is the price index associated with the bundle C_t:

$$P_t = v_t^{-\gamma} \left[\int_0^n p_{ivt}^{1/(1-v_t)} di \right]^{1-v_t}. \tag{8}$$

The second step in solving the household's problem is to maximize lifetime utility subject to the household's budget constraint. The household's income, Y_t, is given by the sum of labor income and firm profits:

$$Y_t = w_t N_t + \int_0^{n_t} \pi_{it} di.$$

The household budget constraint is:

$$Y_t = P_t C_t + Z_t.$$

We choose the homogeneous good as the numeraire, so its price is one. The first-order conditions for this problem are:

$$\frac{\theta_t}{1 - N_t} = (1 - \alpha)\frac{w_t}{Z_t},$$
$$P_t C_t = \alpha Y_t,$$
$$Z_t = (1 - \alpha)Y_t.$$

Production   Each intermediate good of quality v_t is produced with labor:

$$x_{ivt} = A_t(1 + g)^t N_{ivt},$$

where A_t is a stationary shock to productivity and g is the long-run growth rate of productivity.

The monopolist of variety i supplies the level of quality, v_t, demanded by consumers. Its problem is to maximize profits given by:

$$\pi_{it} = p_{ivt} x_{ivt} - \frac{w_t}{A_t(1 + g)^t} x_{ivt} - \Psi, \tag{9}$$

where Ψ denotes a fixed cost denominated in units of the homogeneous good that the firm must incur in every period of operation.

The optimal price is given by the usual markup equation:

$$p_{ivt} = v_t \frac{w_t}{A_t(1 + g)^t}.$$

Producers of the homogeneous good   The homogeneous good is produced by competitive producers using labor and the following production function:

$$Y_t^Z = (1 + g)^t N_{zt}.$$

We assume that there is a continuum of measure one of homogeneous-good producers. The problem of the representative producer is to maximize:

$$\pi_{zt} = Z_t \left[1 - \frac{w_t}{(1 + g)^t} \right].$$

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Real income It is useful to define real income, $\tilde{Y}_t$, measured in terms of the consumption basket of differentiated and homogeneous goods purchased by the households:

$$\tilde{Y}_t = \frac{Y_t}{P_t^\alpha}. \tag{10}$$

Recall that α is the share of the bundle of differentiated goods in household expenditure.

Equilibrium In equilibrium, households maximize their utility, (**??**), taking the wage rate and prices as given. Monopolists maximize profits taking the wage rate, the aggregate consumption bundle, C_t, and the aggregate price of the bundle of consumption varieties, P_t, as given. Producers of the homogeneous good maximize profits, taking prices as given. The labor market clears:

$$N_{zt} + \int_0^{n_t} N_{ivt} di = N_t.$$

The market for the homogeneous good clears:

$$Y_t^Z = Z_t + n_t \Psi.$$

The market for differentiated goods clears. Using the household budget constraint, we can rewrite C_t in a symmetric equilibrium as:

$$C_t = v_t^{\gamma-1} n_t^{v_t-1} \alpha Y_t A_t.$$

Since $\gamma > 1$, the household's utility is monotonically increasing in v_t. The value of x_{vt} is given by:

$$x_{vt} = \frac{\alpha A_t Y_t}{v_t n_t}. \tag{11}$$

Since utility is increasing in v_t, the constraint $x_{vt} \geq 1$ is binding. Setting $x_{vt} = 1$ in equation (**??**), we obtain the optimal value of v_t:

$$v_t = \frac{\alpha A_t Y_t}{n_t}. \tag{12}$$

The following proposition, proved in the Appendix, summarizes the properties of the equilibrium.

Proposition 1. *The equilibrium of this economy is described by the following equations:*

$$w_t = (1+g)^t,$$

$$Y_t = \frac{(1+g_t)^t}{1+\theta_t},$$

$$n_t = \frac{\alpha A_t (1+g_t)^t}{(1+\Psi A_t)(1+\theta_t)},$$

$$x_{ivt} = 1,$$

$$p_{ivt} = \Psi + 1/A_t,$$

$$N_t = \frac{1}{1+\theta_t},$$

$$v_t = 1 + \Psi A_t.$$

$$\tilde{Y}_t = \frac{A_t^\alpha \left(\frac{\alpha}{\Psi+1/A_t} \frac{1}{1+\theta_t} \right)^{\alpha\Psi A_t}}{(1+\Psi A_t)^{(1-\gamma)\alpha}} \frac{1}{1+\theta_t} \left[(1+g)^{1+\alpha\Psi A_t} \right]^t$$

Real income, $\tilde{Y}_t$, is an increasing function of A_t and a decreasing function of θ_t.

To study the model's steady-state properties, suppose that A_t and θ_t are constant. The price of each differentiated good, hours worked and the markup are also constant. Real wages, household income measured in units of the homogeneous good, and the number of firms producing differentiated goods grow at a constant rate g.

Real income measured in terms of the consumption basket, $\tilde{Y}_t$, grows at a gross rate of $(1+g)^{1+\alpha\Psi A_t}$. The reason this gross rate is higher than $1+g$ is as follows. Equation (??) shows that the price index for differentiated goods is proportional to n_t^{1-v} which, in equilibrium, equals $n_t^{-\Psi A_t}$. The number of firms grows at a gross rate $1+g$, increasing variety and changing the effective price of the basket of differentiated goods at a gross rate $(1+g)^{-\Psi A_t}$. Since differentiated goods have a weight of α in the overall consumer basket, growth in variety results in a fall in the basket price and a rise in real income of $(1+g)^{\alpha\Psi A_t}$.

When the fixed cost Ψ is zero, the equilibrium value of v_t is one. In this case, differentiated goods are perfect substitutes so the net markup is zero–price equals marginal cost.

Model implications   To assess the model's regional implications, we compare regions that have different productivity levels and thus different levels of real income. Higher productivity regions have higher markups and a higher number of varieties available. This implication is

consistent with the finding we report on Section 4: gross margins and the number of varieties are positively correlated with income. Another potential source of cross-sectional variation is differences in the fixed cost, Ψ. Regions with higher fixed costs have higher markups than regions with low fixed costs.

To assess the model's cyclical properties, we consider the effects of temporary shocks to productivity and labor supply. Consider first the effect of an increase in A_t. Households increase the quality of the varieties they consume and, as a result, the markup for differentiated goods increases.[15] Profits would rise if the number of firms stayed constant. In equilibrium, the number of firms rises until profits are zero so that the free entry-condition is satisfied.

The elasticity of the markup with respect to productivity is:

$$\frac{dv_t}{v} = \frac{A\Psi}{1 + A\Psi} \frac{dA_t}{A}.$$

This elasticity approaches zero as the fixed cost Ψ approaches zero. For low values of Ψ the model implies that markups are mildly procyclical. Permanent increases in A_t would give rise to permanent changes in markups such as those displayed in Figure 4. So, a secular rise in A_t produces a secular increase in the markup that is consistent with the findings of De Loecker, Eeckout and Unger (2020).

Now consider an increase in θ_t. This shock leads to a fall in the supply of labor, in real income, and in the number of firms that produce differentiated goods. But the markup remains constant.

In sum, the model implies that markups are mildly procyclical. They do not respond to labor supply shocks and are procyclical with respect to changes in productivity. The model is consistent with dispersion in markups across regions. Regions with higher incomes driven by higher productivity choose higher quality goods and pay higher markups.

A natural way to introduce nominal rigidities in this model would be to assume that wages are sticky and that each firm has to pay a cost to change the quality of the goods it produces. During recessions it might be optimal for the firm to keep quality constant.

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[15]See Bils and Klenow (2011) for evidence that quality demand is strongly correlated with household income.

This sticky assortment is likely to amplify the effect of recessions by limiting the extent to which households can reduce the quality of what they buy.[16] In the time series, we would observe stability in assortment, price and gross margins. In the cross section, we would observe differences in assortment and in markups resulting from the fact that cross sectional differences in income are large and permanent.

6   Conclusion

In this paper, we use gross margins as proxies for markups to study the behavior of markups in the retail sector across space and time. We find that gross margins are relatively stable over time and mildly procyclical. At the same time, there is a large regional dispersion in gross margins. Rich regions pay higher markups than poor regions. Goods that are common to both regions have the same markups. But higher income regions consume higher-markup goods that are not available in low-income regions.

We study an endogenous assortment model that is consistent with these basic facts. This model embodies a central insight from the trade model proposed by Fajgelbaum, Grossman and Helpman (2011): higher quality consumption bundles are made of less substitutable components.

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[16]See, Jaimovich, Rebelo and Wong (2019) for an analysis of quality choices during recessions.

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A   Appendix

A.1   Monetary policy and oil shocks

In section 3.2, we study the conditional response of firms' gross and net operating margins to high-frequency monetary policy shocks and oil-price shocks. This appendix discusses how these shocks are identified.

Monetary policy shocks are identified using high-frequency data on the Federal Funds futures contracts. This approach has been used by Kuttner (2001), Cochrane and Piazessi (2002), Nakamura and Steinsson (2018), Gorodnichenko and Weber (2016), and others. The future rate reflects the market expectations of the average effective Federal Funds rate during that month. It therefore provides a market-based measure of the anticipated path of the Federal Funds rate.

A current period monetary policy shock is defined as:

$$\epsilon_t = \frac{D}{D-t} \left(ff^0_{t+\triangle^+} - ff^0_{t-\triangle^-} \right) \tag{13}$$

where t is the time when the FOMC issues an announcement, $ff^0_{t+\triangle^+}$ is the Federal Funds futures rate shortly after t, $ff^0_{t-\triangle^-}$ is the Federal Funds futures rate just before t, and D is the number of days in the month. The $D/(D-t)$ term adjusts for the fact that the Federal Funds futures settle on the average effective overnight Federal Funds rate.

We consider a 60-minute time window around the announcement that starts $\triangle^- = 15$ minutes before the announcement. Examining a narrow window around the announcement ensures that the only relevant shock during that time period (if any) is the monetary policy

shock. Following Cochrane and Piazessi (2002) and others, we aggregate up the identified shocks to obtain a quarterly measure of the monetary policy shock.

Oil-price shocks are identified using the approach proposed by Ramey and Vine (2010), updated to the recent period. We estimate a VAR system with monthly data

$$Y_t = A(L)Y_{t-1} + U_t.$$

The vector Y_t includes the following variables (in order): nominal price of oil, the CPI, nominal wages of private production workers, industrial production, civilian hours, and the federal funds rate. The function $A(L)$ is a matrix of polynomials in the lag operator L, and U is a vector of disturbances. All variables, except the federal funds rate, are in logs. We include a linear time trend and 6 lags of the variables. The shock to oil prices is identified using a standard Cholesky decomposition. The shocks are aggregated to a quarterly frequency to match the frequency of our firm level data.

A.2 Correcting gross margins for changes in inventories

One potential source of measurement error in our aggregate retail and firm level data stems from the possibility that the cost of goods sold might reflect goods purchased in previous periods and stored as inventory. As a result, the cost of goods sold does not measure the true marginal replacement cost.

We deal with this issue in Section 3.4 by using actual replacement cost for a retailer. Here, we use instead a perpetual inventory approach to correct the cost of goods sold for changes in inventories.

Denote by $\bar{C}_t$ the observed cost of goods sold and by C_t the true cost of goods sold. The observed cost of goods sold is

$$\bar{C}_t = \alpha_t \bar{C}_{t-1} + (1 - \alpha_t)C_t,$$

where
$$\alpha_t = \frac{\text{Starting period inventories}_t}{\text{Sales}_t}.$$

We assume that if $\alpha_t \geq 1$, then

$$\bar{C}_t = C_t/(1 + \pi_t),$$

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where π_t is the rate of change in the producer price index for final goods from the Bureau of Labor Statistics. This equation implies that, if the inventories at the start of the period exceed sales in that period, then the goods sold in that period come from inventories.[17] The observed value of cost of good sold is then assumed to be given by the true cost of goods sold, deflated by the producer price index.

The true cost of goods sold is given by

$$C_t = \frac{\bar{C}_t - \alpha_t \bar{C}_{t-1}}{1 - \alpha_t}, \quad \text{if } \alpha_t < 1$$

and

$$\bar{C}_t = C_t/(1 + \pi_t), \quad \text{if } \alpha_t \geq 1.$$

We assume as starting value $\bar{C}_0 = C_0$ and implement our approach separately for each firm.

The gross margin adjusted for changes in inventories is given by

$$\frac{\text{Sales}_t - C_t}{\text{Sales}_t}.$$

We use this adjusted measure to re-estimate the elasticity of gross margins with respect to real GDP. We regress the year-on-year logarithmic difference of each variable on the year-on-year logarithmic difference of real GDP.

Table 15 shows our results from Section 3, which do not adjust for inventories, as well as the elasticities estimated using gross margins adjusted for changes in inventories. We see that while point estimates are different, the elasticity of gross margins with respect to GDP growth remain statistically insignificant when we use the adjusted gross-margin measures.

A.3 Gross margins as a measure of marginal cost

We use a simple model to clarify the conditions under which the cost of goods sold is a good proxy for marginal cost. Consider a firm that faces a demand function

$$p = \delta q^{-\alpha},$$

where q denotes the quantity sold, p the price charged by the firm, and δ is a random demand shifter drawn from a distribution $g(\delta)$. The firm must choose its capacity. As in Eichenbaum,

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[17]This occurrence is rare, particularly at the annual frequency. The average retailer ratio of inventories to sales is about 12%.

Jaimovich and Rebelo (2011), we assume that this capacity is given by a fixed factor L which we interpret as a composite of labor, equipment and real estate. We denote by w the price of the composite factor.

To sell q units the firm must buy these units at a marginal replacement cost. This cost is c_1 for $q \leq L$ and $c_1 + c_2$ for $q > L$. The firm can sell more than L units, but these additional units have an additional marginal cost, c_2. One particular case of this formulation is where $c_2 = \infty$. In this case, the firm cannot sell more than L units.

The firm's profit, π, is given by:

$$\pi = (p - c_1)q - wL - I(q > L)c_2(q - L),$$

where $I(q > L)$ is an indicator function that takes the value 1 when $q > L$ and zero otherwise. Consider first the case where the firm does not exceed its capacity, $q \leq L$. In that case, the optimal price is given by

$$p_1 = \frac{c_1}{1 - \alpha},$$

and the quantity sold is:

$$q = \left(\delta \frac{1 - \alpha}{c_1} \right)^{1/\alpha}.$$

In order for the condition $q \leq L$ to hold, we need the demand shifter δ to be lower than δ^*, which is given by:

$$\delta^* = \frac{c_1}{1 - \alpha} L^{\alpha}. \tag{14}$$

For $\delta > \delta^*$, the optimal price is given by

$$p_2 = \frac{c_1 + c_2}{1 - \alpha},$$

and the quantity sold is

$$q = \left(\delta \frac{1 - \alpha}{c_1 + c_2} \right)^{1/\alpha}$$

We assume that δ follows a Pareto distribution. The pdf is given by:

$$g(\delta) = \gamma \frac{\bar{\delta}^{\gamma}}{\delta^{\gamma+1}}$$

where $\gamma > 0$ and $\bar{\delta} > 0$ is the minimum of the support. Expected profits can be written as

$$E(\pi) = \int_{\bar{\delta}}^{\delta^*} \frac{\alpha c_1}{1 - \alpha} \left(\delta \frac{1 - \alpha}{c_1} \right)^{1/\alpha} \frac{\gamma \bar{\delta}^{\gamma}}{\delta^{\gamma+1}} d\delta + \int_{\delta^*}^{\infty} \frac{\alpha(c_1 + c_2)}{1 - \alpha} \left(\delta \frac{1 - \alpha}{c_1 + c_2} \right)^{1/\alpha} \frac{\gamma \bar{\delta}^{\gamma}}{\delta^{\gamma+1}} d\delta - w \left(\delta^* \frac{1 - \alpha}{c_1} \right)^{1/\alpha},$$

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Optimizing with respect to δ^* we obtain

$$\delta^* = \left\{ \gamma \frac{\bar{\delta}^\gamma}{w} \frac{\alpha^2}{1-\alpha} c_1 \left[1 - \left(\frac{c_1}{c_1+c_2} \right)^{(1-\alpha)/\alpha} \right] \right\}^{1/\gamma}.$$

The optimal capacity is given by equation (**??**). The probability that the firm exceeds this capacity is

$$1 - \int_{\bar{\delta}}^{\delta^*} g(\delta)d\delta = \left(\frac{\bar{\delta}}{\delta^*} \right)^\gamma = \frac{1}{\gamma} \frac{w}{c_1} \frac{1-\alpha}{\alpha^2} \frac{1}{1 - \left(\frac{c_1}{c_1+c_2} \right)^{(1-\alpha)/\alpha}}.$$

The marginal cost c_1 is a good proxy for the marginal cost whenever the probability of exceeding the capacity L is low. This scenario occurs when the cost of capacity, w, is low or when the probability of large realization of the demand shifter is low (γ is high).

A.4 Proof of proposition 1

Equilibrium in the homogeneous good market requires:

$$w_t = (1+g)^t.$$

The equilibrium price index for consumption of differentiated goods is:

$$P_t = v_t^{-\gamma} n_t^{1-v_t} \frac{v_t}{A_t}.$$

Households choose the same consumption level for all available varieties: $x_{ivt} = x_{vt}$. The consumption bundle is given by:

$$C_t = v_t^\gamma n_t^{v_t} x_{vt}.$$

Using the household budget constraint, we can rewrite C_t as:

$$C_t = v_t^{\gamma-1} n_t^{v-1} \alpha Y_t A_t.$$

Since $\gamma > 1$, the household's utility is monotonically increasing in v_t. The value of x_{vt} is given by:

$$x_{vt} = \frac{\alpha A_t Y_t}{v_t n_t}. \tag{15}$$

Since utility is increasing in v_t, the constraint $x_{vt} \geq 1$ is binding. Setting $x_{vt} = 1$ in equation (**??**), we obtain the optimal value of v_t:

$$v_t = \frac{\alpha A_t Y_t}{n_t}. \tag{16}$$

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The monopolist profits are equal to:

$$\pi_t = \frac{1}{A_t}(v_t - 1) - \Psi.$$

The free entry condition, $\pi_t = 0$, implies that the markup is given by:

$$v_t = 1 + \Psi A_t. \tag{17}$$

Using equation (??) to replace v_t, we obtain:

$$n_t = \frac{\alpha A_t Y_t}{1 + \Psi A_t}. \tag{18}$$

Equilibrium prices are given by:

$$p_{ivt} = \frac{v_t}{A} = \Psi + 1/A_t.$$

Household income is given by:

$$Y_t = (1 + g_t)^t N_t. \tag{19}$$

The equilibrium value of N_t is given by:

$$N_t = N = \frac{1}{1 + \theta_t}. \tag{20}$$

Combining equations (??), (??), and (??), we obtain the following expression for the equilibrium number of monopolistic firms:

$$n_t = \frac{\alpha A_t N (1 + g_t)^t}{1 + A_t \Psi}. \tag{21}$$

To solve for real income, we replace Y_t in equation (??):

$$\tilde{Y}_t = \frac{1}{P_t^\alpha} \frac{1}{1 + \theta_t}(1 + g)^t$$

Replacing P_t:

$$\tilde{Y}_t = \frac{A_t^\alpha \left(\frac{\alpha}{\Psi + 1/A_t} \frac{1}{1 + \theta_t}\right)^{\alpha(v-1)}}{v_t^{(1-\gamma)\alpha}} \frac{1}{1 + \theta_t} \left[(1 + g)^t\right]^{1-\alpha(1-v_t)}.$$

Using the fact that:

$$1 - v_t = -\Psi A_t,$$

we obtain,

$$\tilde{Y}_t = \frac{A_t^\alpha \left(\frac{\alpha}{\Psi + 1/A_t} \frac{1}{1 + \theta_t}\right)^{\alpha \Psi A_t}}{(1 + \Psi A_t)^{(1-\gamma)\alpha}} \frac{1}{1 + \theta_t} \left[(1 + g)^t\right]^{1 + \alpha \Psi A_t}.$$

To see that $\tilde{Y}_t$ is an increasing function of A_t, it is convenient to take logarithms:

$$\log\left(\tilde{Y}_t\right) = \alpha \log(A_t) + \alpha \Psi A_t \log\left(\frac{\alpha}{\Psi + 1/A_t} \frac{1}{1 + \theta_t}\right) + (\gamma - 1)\alpha \log(1 + \Psi A_t) - \log(1 + \theta_t)$$
$$+ [1 + \alpha \Psi A_t] t \log(1 + g).$$

Tables and Graphs

Table 1: Cyclicality of Aggregate Retail Trade Variables

| | Elasticity wrt GDP | | | |
	Quarterly		Annual	
Gross margins	0.162	(0.256)	0.376	(0.616)
Operating profit margins	2.286**	(0.895)	5.233	(3.632)
Sales	8.089***	(0.45)	9.279***	(1.976)
Cost of goods sold	8.104***	(0.43)	9.140***	(2.154)

Notes: Variables are log-difference from prior year. Data is from Compustat and the BLS. Each row is estimated from a separate regression of the dependent variables on GDP. We estimate the elasticities at quarterly and annual frequencies. See text for more details. Standard errors are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Table 2: Volatility of Aggregate Retail Trade Variables

Standard Deviation	Quarterly	Annual
Gross margins	0.017	0.011
Operating profit margins	0.057	0.051
Sales	0.046	0.062
Cost of goods sold	0.045	0.060

Notes: Variables are log-difference from prior year. Data is from Compustat and the BLS. Standard deviations are computed at quarterly and annual frequencies. See text for more details.

Figure 1: Time-series of Aggregate Retail Trade Variables

Notes: Variables are log-difference from prior year. Data is from Compustat and the BLS. The data is plotted at a quarterly frequency.

Table 3: Cyclicality of Firm-Level Variables

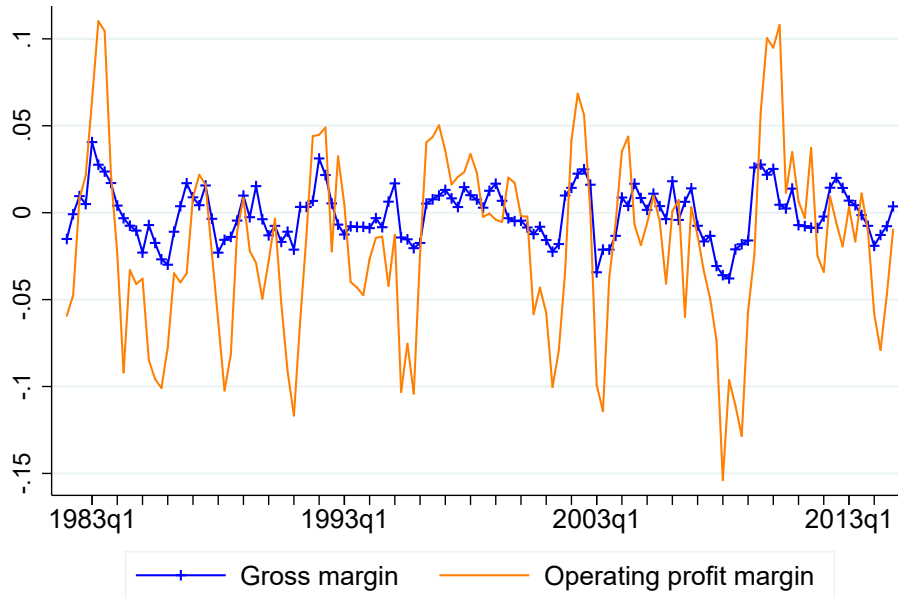|	Elasticity wrt GDP			
	Quarterly		Annual	
Gross margins	0.31	(0.37)	0.15	(0.55)
Operating profit margins	3.03***	(0.96)	3.60***	(1.11)
Sales	3.18***	(0.32)	3.64***	(0.67)
Cost of goods sold	3.09***	(0.32)	3.58***	(0.70)

Notes: Variables are log-difference from prior year. Data is from Compustat and the BLS. Each row is estimated from a separate regression of the dependent variables on GDP. We estimate the elasticities at quarterly and annual frequencies. See text for more details. Standard errors are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Table 4: Volatility of Firm-Level Variables

Standard Deviation	Quarterly	Annual
Gross margins	0.061	0.480
Operating profit margins	0.254	0.699
Sales	0.080	0.364
Cost of goods sold	0.084	0.407

Notes: Variables are log-difference from prior year. Data is from Compustat and the BLS. The standard deviations are computed at quarterly and annual frequencies. See text for more details.

Figure 2: Impulse Response Functions to Monetary Policy and Oil Price Shocks
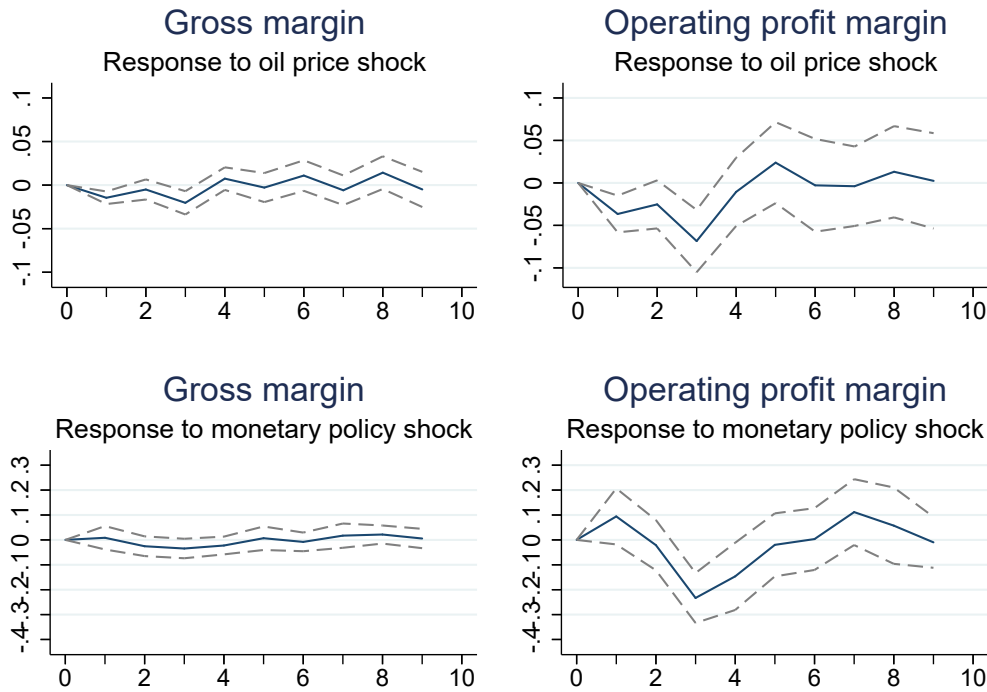
Notes: The figure depicts the impulse response functions of the (log-differenced) gross margins and net operating profit margins to a 1 percentage point monetary policy shock (bottom panel) and an oil price shock (top panel). See text for more information. The data is plotted at a quarterly frequency. Dashed lines are the 90th percentile.

Figure 3: Histograms of Gross Margins, Sales, and Number of Items
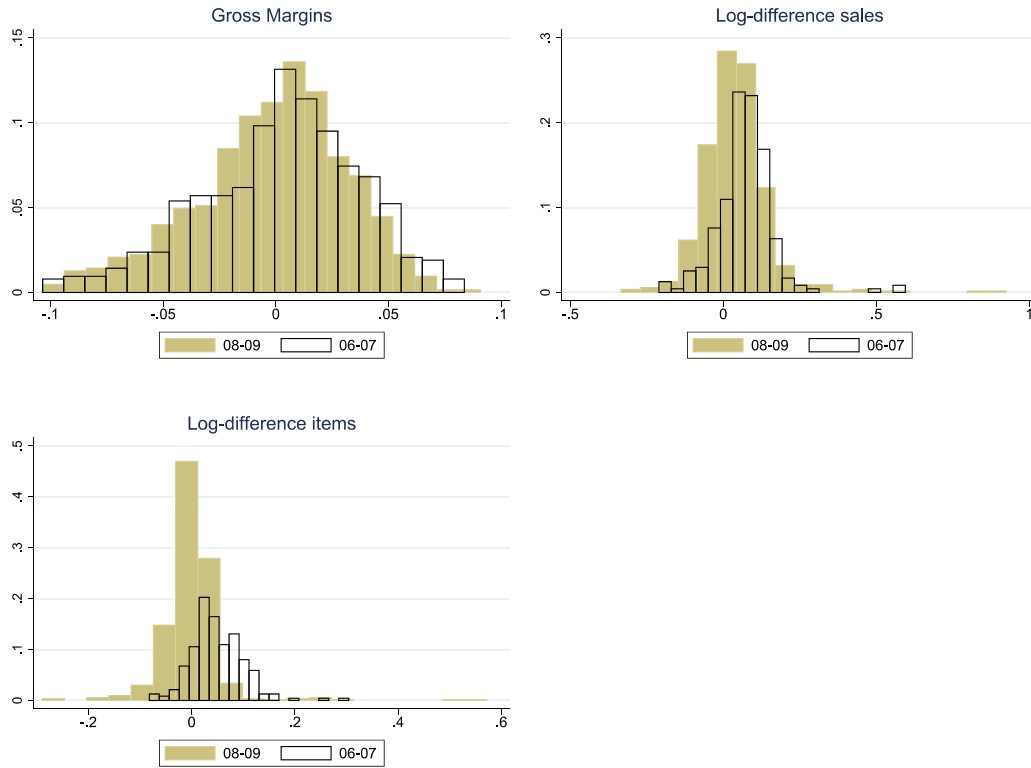
Notes: Data is from a large U.S. retailer. The figure depicts the distributions of gross margins (levels), sales (log-difference from same quarter in the prior year) and number of items (log difference from same quarter in the prior year) for the period 2006-07 and the period 2008-09. Each data point in the distribution is a region-quarter observation. See text for more details. For confidentiality purposes, we normalize the distribution of gross margin by the mean margin in 2006-07. We do so by subtracting the average 2006-07 margin from the 2006-07 distribution so that the average margin of the normalized distribution is zero. We also subtract the average 2006-07 margin from the 2007-08 distribution.

Table 5: Cross-sectional Distribution of Margins, Sales and Number of Items

	Mean	p10	p50	p90
Margins (levels)				
Difference	-0.005	-0.003	-0.003	-0.007
Log difference in sales				
2006-07	0.072	-0.026	0.072	0.154
2008-09	0.038	-0.074	0.034	0.145
Difference	-0.034	-0.048	-0.037	-0.009
Log difference in number of items				
2006-07	0.050	-0.007	0.044	0.111
2008-09	0.000	-0.053	-0.001	0.043
Difference	-0.050	-0.046	-0.045	-0.068

Notes: Data is from a large U.S. retailer. The table gives key moments from the cross-sectional distribution (across regions) of gross margins, average sales growth and average growth in number of items. We report the average levels of each variable in 2006-07 and 2008-09, and the differences between 2006-07 and 2008-09 for sales growth and growth in number of items. Due to confidentiality reasons, we do not report the *levels* of the margins, and only report how the level of margins changed between 2006-07 and 2008-09.

Table 6: Cyclicality of Store-Item Variables: U.S. Retailer

	Elasticity with respect to local UR		Elasticity with respect to local house prices	
Gross margin	0.001	(0.014)	-0.003	(0.015)
Price	0.001	(0.007)	0.007	(0.019)
Replacement cost	0.000	(0.005)	0.001	(0.001)
Sales	-0.015*	(0.063)	0.21***	(0.080)
Number of items	-0.003	(0.023)	0.151*	(0.086)

Notes: Variables are log-difference from prior year. Data is from a large U.S. retailer. Each entry is a separate regression of the log-differenced variable on the local area change in unemployment rate and house prices. Standard errors are clustered by county. See text for more details.

Table 7: Active and Passive Margin Changes: U.S. Retailer

	Elasticity with respect to local UR		Elasticity with respect to local house prices	
Passive margin changes				
Probability of a passive margin change	-0.0003	(0.001)	-0.013	(0.010)
Size of margin change	-0.0007	(0.001)	-0.002***	(0.001)
Change in replacement cost, given margin change	0.0014	(0.001)	0.011***	(0.004)
Active margin changes				
Probability of an active margin change	0.0003	(0.001)	0.013	(0.010)
Size of margin change	0.0024	(0.004)	-0.003	(0.008)
Change in replacement cost, given margin change	0.0002***	(0.000)	-0.001	(0.000)

Notes: Data is from a large U.S. retailer. Passive margin changes for a given product as those that occur when the replacement cost of that product changes but the company does not change the product's price. Active margin changes are those that result from changes in the price of that product, independently of whether or not the replacement cost changed. We compute these changes at a daily frequency and then aggregate them at a quarterly frequency using the average of the daily changes. Each entry is a separate regression of the variables on the local area change in unemployment rate and house prices. Standard errors are clustered by county. See text for more details.

Table 8: Volatility of Store-Item Variables: U.S. Retailer

	Stdev
Markup	0.026
Price	0.009
Replacement cost	0.005
Sales	0.220
Number of items	0.118

Notes: Variables are log-difference from prior year. Data is from a large U.S. retailer. The standard deviations are computed at a quarterly frequency. See text for more details.

Table 9: Cyclicality of Store-Item Variables: Canadian Retailer

	Elasticity with respect to local UR		Elasticity with respect to change in oil prices	
Gross margin	-0.001	(0.001)	-0.050	(0.034)
Price	-0.003**	(0.001)	0.088*	(0.054)
Replacement cost	-0.004***	(0.001)	0.165***	(0.058)
Sales	-0.007*	(0.004)	0.239***	(0.094)
Number of items	0.002	(0.007)	0.327**	(0.142)

Notes: Data is from a large Canadian retailer. Variables are log-differences from prior year. Each row is a separate regression of the log-differenced variable on the measure of demand. In columns 1 and 2, the variable are regressed on the local area change in unemployment rate. In columns 3 and 4, each entry gives the estimated coefficient of the differential response of oil producing regions and non-oil producing regions to a change in oil prices. See text for more details.

Table 10: Active and Passive Margin Changes: Canadian Retailer

	Elasticity with respect to local UR		Elasticity with respect to change in oil prices	
Passive margin changes				
Probability of margin change	0.001	(0.001)	-0.060	(0.042)
Size of margin change	-0.001	(0.001)	-0.026	(0.018)
Change in replacement cost, given margin change	0.001	(0.001)	0.057	(0.067)
Active margin changes				
Probability of margin change	-0.001	(0.001)	0.060	(0.042)
Size of margin change	-0.001	(0.001)	0.037	(0.029)
Change in replacement cost, given margin change	-0.0001	(0.000)	0.007***	(0.002)

Notes: Data is from a large Canadian retailer. Passive margin changes for a given product as those that occur when the replacement cost of that product changes but the company does not change the product's price. Active margin changes are those that result from changes in the price of that product, independently of whether or not the replacement cost changed. Each entry is a separate regression of the variables. In columns 1 and 2, the variable are regressed on the local area change in unemployment rate. In columns 3 and 4, each entry gives the estimated coefficient of the differential response of oil producing regions and non-oil producing regions to a change in oil prices. See text for more details.

Table 11: Volatility of Store-Item Variables: Canadian Retailer

	StDev
Gross Margin	0.21
Price	0.11
Replacement cost	0.13
Sales	0.47
Number of items	0.62

Notes: Variables are log-difference from prior year. Data is from a large Canadian retailer. The standard deviations are computed at a quarterly frequency. See text for more details.

Table 12: Variance Decomposition of the Cross-sectional Margins

	County-level (%) variance	Contribution to total variance
Panel A: U.S. Retailer		
Total	0.117	1.000
Time variation	0.013	0.112
Spatial variation	0.103	0.886
Covariance term	0.000	0.002
Panel B: Canadian Retailer		
Total	0.061	1.000
Time variation	0.017	0.280
Spatial variation	0.051	0.845
Covariance term	-0.008	-0.124

Notes: Data is from a large U.S. retailer (panel A) and a large Canadian retailer (panel B). The table gives the decomposition of the cross-sectional variance (across regions) into the four components: differences in gross margins for the same item, differences in assortment of composition, the interaction terms, and the covariance terms. See text for more details.

Table 13: Decomposition of the Spatial Variation in Margins

Spatial variation due to:	All items	Item sold everywhere
Panel A: U.S. Retailer		
(i) Differences in gross margins for the same item	14%	10%
(ii) Differences in assortment composition	68%	85%
(iii) Interaction term	1%	1%
(iv) Covariance term	15%	4%
Panel B: Canadian Retailer		
(i) Differences in gross margins for the same item	2%	n.a.
(ii) Differences in assortment composition	61%	n.a.
(iii) Interaction term	3%	n.a.
(iv) Covariance term	34%	n.a.

Notes: Data is from a large U.S. retailer and a large Canadian retailer. Table gives the decomposition of the spatial variance in margins (from page 13, equation 5) into four components. The table reports the average over time of the decomposition. See text for more details.

Table 14: Cross-sectional Variation in Margins and Regional Characteristics

|	U.S. Retailer		Canadian Retailer	
	Estimate	Std error	Estimate	Std error
Log household income	0.17***	(0.06)	0.10**	(0.04)
Log median house value	0.16***	(0.05)	0.01	(0.01)
Herfindahl index	-0.01	(0.05)	n.a.	n.a.
Rural county	0.02	(0.01)	n.a.	n.a.

Notes: Data is from a large U.S. retailer and a large Canadian retailer. Table gives the elasticity of the gross margin with respect to each of the variables. Each regression is estimated separately. Standard errors are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Table 15: Appendix A.2: Cyclicality of Gross Margins, Adjusting for Inventories

| | Gross Margin Elasticity wrt GDP | | | |
	Quarterly		Annual	
Regressions: baseline				
Industry-level regression	0.162	(0.256)	0.376	(0.616)
Firm-level regression	0.310	(0.373)	0.152	(0.548)
Regressions: with inventory adjustment				
Industry-level regression	-0.231	(1.45)	-0.522	(0.924)
Firm-level regression	-0.550	(2.647)	-0.351	(0.678)

Notes: Table gives the elasticity of the gross margin with respect to each of the variables. Each regression is estimated separately. Standard errors are in parentheses. *, **, and *** indicate significance at the 10, 5, and 1 percent levels. The baseline regressions are from Section 3 and correspond to the estimates from Table 1. The regression estimates with inventory adjustment are based on the perpetual inventory approach. See Appendix A2 for details.

Figure 4: Trend in gross margins
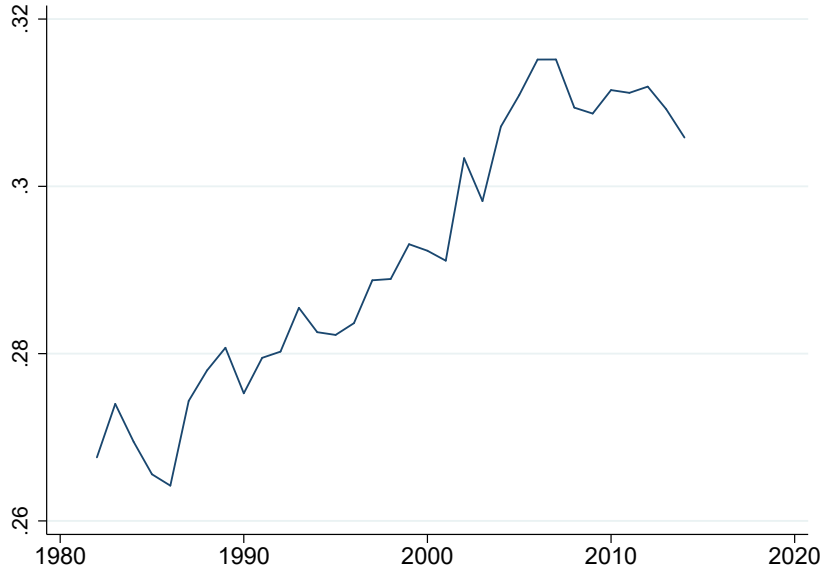
Notes: The figure depicts the average gross margin across firms from Compustat.