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Analysis of Retailer Inventory and Financial Performance

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ANALYSIS OF RETAILER INVENTORY AND FINANCIAL PERFORMANCE

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1. Introduction

Effective inventory management is considered to be of fundamental importance for retailer performance. On one hand, excess inventory generates costs associated with the storage and disposal of unsold merchandise. On the other hand, insufficient inventory decreases customer satisfaction and negatively impacts sales. Due to the costs associated with overstocking and understocking, ordering policy arises as an important determinant of financial performance.

While several studies in operations management and accounting literature have focused on the concurrent relationship between inventory levels and financial metrics, less research has been conducted on the predictive power of inventory on future financial performance. This paper attempts to recreate the regression model and results originally presented in Kesavan and Mani (2013) to analyze the relationship between inventory growth and on-year-ahead earnings for U.S. public retailers.

In addition, this paper aims to build upon Kesavan and Mani (2013)'s findings by applying their model to recent data in order to test whether results vary as a function of different macroeconomic conditions. Specifically, I attempt to study the impact of trade policy changes related to the ongoing economic conflict between the United States and China.

Unlike Kesavan and Mani (2013), I do not find a statistically significant relationship between abnormal inventory growth and future earnings per share for the years 2004-2009. However, when applying the same model to data from 2013 to 2018, I find a significant, inverted-U relationship between the two variables. Although my results vary from Kesavan and Mani (2013), the extension suggests that abnormal inventory growth is impacted by macroeconomic factors that encourage retailers to accumulate excess inventory. My results also suggest that excess inventories have a larger negative impact on future earnings than insufficient inventories, implying that retailers should prioritize strategies that prevent bloated inventory levels above those that lead to decreased service levels

2. Literature Review

2.1. The Link Between Inventory and Financial Performance

The link between inventory and financial performance has received significant attention in both operations management (OM) and accounting literature. A large portion of this line of research has focused on the financial implications of inventory reduction. Several studies explore these implications by analyzing the financial performance of firms before and after they adopt Just in Time (JIT) inventory management, as it is often observed that firms who adopt JIT initiatives report lower inventory levels (Billesbach and Hayen 1994, Huson and Nanda 1995, Biggart and Gargeya 2002). Huson and Nanda (1995), for example, provide strong evidence that firms' earnings per share (EPS) tend to increase in the periods following JIT adoption, even when JIT implementation increases unit manufacturing costs. That is, the cost savings of inventory reduction outweigh the reductions in operating margins, leading to higher net earnings.

More recently, Fullerton et al. (2003) examine the effect of JIT manufacturing implementation on firm profitability, as measured by return on assets (ROA), return on sales, and cash flow margin. Fullerton et al. (2003) find a significant negative correlation between inventory margin (total inventory divided by net sales) and each of the profitability measures.

The inventory-financial performance link is further examined by Cannon (2008), who finds little or no relationship between increased inventory turnover and financial performance. More interestingly, for some of the observed firms in the study, higher inventory turnover worsened financial outcomes. The discrepancy between Cannon (2008) and earlier empirical work can be explained through theoretical OM literature. While Cannon (2008) assumes a linear relationship between inventory level and financial performance, OM literature suggests this relationship follows an inverted-U shape, implying there is an optimal level of inventory leanness, after which further decreasing inventory has a negative impact on firm performance.

Eroglu and Hofer (2011) provide empirical evidence of the inverted-U relationship, while additionally addressing a second shortcoming of prior literature on inventory leanness and financial performance: the aggregation of data points from firms in broadly-defined industry sectors. This approach is problematic as it fails to account for industry-specific characteristics that may affect the inventory-financial performance relationship, such as demand and supply conditions and the nature of the product.

2.2. Inventory Management in the Retail Industry

In order to control for industry-specific characteristics, this paper will focus solely on retail operations. Effective inventory management is of particular importance in the retail sector, as inventory constitutes a significant portion of current and total assets (Gaur 2005). In 2018, retail inventory investment in the United States averaged over $637 billion (U.S. Census Bureau 2019).

OM literature has widely focused on 'ordering policy' in retail operations. This includes order quantity decisions, order timing decisions, and order frequency decisions. These decisions are made under the objective of minimizing the expected costs of being overstocked or understocked due to supply and demand mismatches (Kabak and Schiff 1978). Ordering policy, therefore, aims to manage the tradeoff between excessive and insufficient inventory levels.

This tradeoff can be summarized as the following. Inventory reduction decreases the amount of capital tied up in product storage. It also prevents the accumulation of excess inventory and the cost associated with the disposal of unsold merchandise (Singhal 2005). However, inventory reduction may reduce the service level, leading to customer dissatisfaction and foregone sales (Fitzsimons 2000, Anderson et al. 2006). Inventory accumulation, on the other hand, increases the service level, but concurrently increases inventory-associated costs: the cost of capital (interest and opportunity), as well as the physical cost of storage (facility maintenance, storage taxes, insurance, spoilage etc.) (Singhal 2005).

2.3. Inventory as a Predictor of Retailers' Future Financial Performance

Due to the costs associated with overstocking and understocking, ordering policy arises as an important determinant of retailer performance. Extensive research has been conducted on the contemporaneous relationship between inventory management and financial performance of retailers. Gaur et al. (2005) find a strong negative correlation between inventory turns and gross margin for all but one of the observed retail sectors. Roumiantsev and Netessine (2005) find that inventory *levels* have no correlation to current ROA. However, they also conclude that operational elasticities, defined as a percentage change in the inventory level associated with a one percent change in variables such as sales and lead time changes, consistently explain current profitability. In other words, companies that react faster to changes in demand by adjusting inventories report higher ROA.

While the immediate impact of inventory management on financial performance is well-researched, limited empirical evidence exists on the *predictive* power of inventory on future sales and earnings for retailers. The accounting and finance literature related to this line of work has yielded mixed results. Bernard and Noel (1991) find a strong positive correlation between unexpected inventory increases and one-quarter-ahead sales, and a strong negative correlation between unexpected inventory increases and one-quarter-ahead profit margins for retailers. The increase in sales, however, is found to be temporary and a result of retailers "dumping" excess inventory at reduced prices. The negative impact on profit margins and earnings, on the other hand, is observed consistently over the four subsequent quarters. In contrast to Bernard and Noel (1991), Abarbanell and Bushee (1997) find that annual inventory growth (measured as change in inventory divided by change in sales) is not predictive of one-year-ahead earnings in the retail industry.

Kesavan et al. (2010) focus on the impact of inventory-related information on analysts' sales forecast for U.S. public retailers. They find that incorporating cost of goods sold, inventory level, and gross margin as endogenous variables in a sales forecast significantly improves the accuracy of the forecast. Sales forecast accuracy is paramount in equity research as it is one of the primary inputs in standard firm valuation models. Sales projections are also highly valued by investors. Oftentimes, minor positive (negative) deviations in reported sales from projected sales are associated with significant increases (decreases) in stock prices (Kesavan el al. 2010). Therefore, Kesavan et al. (2010)'s results have relevant implications for both equity analysts and investors.

Kesavan and Mani (2013) build upon previous research by providing evidence of an inverted-U relationship between inventory growth and future earnings. They argue that inventory growth consists of two components: normal and abnormal. The former refers to factors related to a firm's regular economic activity, such as gross margin, capital intensity, store growth, product variety, and competition. The latter refers to significant changes in inventory levels that cannot be explained by the aforementioned factors. Kesavan and Mani (2013) find that the relationship between inventory growth and future earnings arises because of the *abnormal* component.

Positive (negative) abnormal inventory growth (AIG) indicates that a retailer's inventory grew more (less) than expected in a given time period. Positive AIG could signal poor operational performance and lower future earnings due to discounting. Alternatively, it could signal expected demand increases and higher future earnings. On the other hand, negative AIG could signal operational improvements and higher earnings, or expected demand decreases and lower earnings. The relationship between AIG and future earnings per share, therefore, depends on the dominant drivers in an aggregate sample. Kesavan and Mani (2013) explain that an inverted-U relationship will arise between AIG and future EPS if the prevailing driver of positive AIG is poor operational performance, and if the prevailing driver of negative AIG is lower expected demand.

2.4. On the Relationship Between Abnormal Inventory Growth and Stock Performance

Despite the predictive power of inventory-related information, research suggests that analysts consistently fail to incorporate this information in their forecasts. Kesavan et al. (2010), Kesavan and Mani (2013) and Alan et al. (2014) all find that analysts fully or partially ignore information regarding firms' operations that would improve the accuracy of their sales and expenses predictions. Interestingly, Hendricks and Singhal (2009) report that excess inventory announcements are associated with an economically and statistically significant negative stock market reaction. Based on this response, it is clear that analysts fail to anticipate excess inventory announcements, despite having access to historical inventory data that allows them to proactively identify AIG.

Given that inventory growth is not fully absorbed into analyst forecasts, retail stocks may not fully reflect all available financial information, and therefore may be priced incorrectly according to the Efficient Market Hypothesis (Fama 1970). If this is the case, an investment strategy based on inventory growth may yield abnormal rates of return, which can be defined as higher security returns than those generated by benchmarks or those measured by the Capital Asset Pricing Model (Sharpe 1964) or Fama and French (1993)'s Three-Factor Model. Thomas and Zhang (2002) provide some evidence in support of this hypothesis by building upon the previous work of Sloan (1996). Sloan (1996) finds that firms with low levels of accruals, defined as changes in working capital that are scaled by average beginning and ending total assets, experience abnormal future positive stock returns around future earnings announcements. Thomas and Zhang (2002) complement this finding by analyzing the components of accruals and concluding that inventory changes are primarily responsible for the market inefficiency identified by Sloan (1996). This result is especially relevant to the current paper given the high level of inventory investment on behalf of retailers.

Chen et al. (2007) further explore the correlation between inventory and long-term retail stock performance by forming portfolios as a function of a firm's abnormal inventory. They find strong evidence that retailers with bloated inventory yield lower stock returns in the long-run, and some, yet weaker, evidence that retailers with low inventory yield particularly high stock returns. Kesavan and Mani (2013) use sorting and regression approaches to identify whether AIG is an anomaly variable, and find that both methodologies produce the same conclusion: the information content in AIG is a significant determinant of stock performance even when controlling for previously known anomaly variables. Superior or inferior OM performance is also found to correlate with abnormal stock returns by Alan et al. (2014) and Ullrich and Transchel (2017).

This paper attempts to expand the current line of research by testing the robustness of Kesavan and Mani (2013)'s model representing the relationship between AIG and one-year-ahead earnings per share (EPS). While Kesavan and Mani (2013) utilize financial data from 1999 to 2009, I apply their model to more recent data, spanning the period from 2011 to 2018. By applying the model to a set of data collected during a different time period, I attempt to determine whether Kesavan and Mani (2013)'s conclusions remain consistent under various economic conditions.

3. Research Setup

3.1. Data Description

Using SAS, I begin by merging the following annual files from the Compustat Annual Database: Industrial Balance Sheet, Industrial Income Statement, Statement of Cash Flows, Fiscal Market Data, Period Descriptor, Company Descriptor, and Security Header. After combining the files, I narrow the data to the selected period in Kesavan and Mani (2013), 1999-2009. I repeat this process with the respective quarterly files obtained from the Compustat Quarterly Database. Table 1 reports the selected Compustat field names from the annual and quarterly files that are used to calculate the variables described in §3.2.

Table 1: Data Fields for Variables

Variable Name	Compustat field names	Definition
i	KYGVKEY	Firm ID
t	FYYYY	Fiscal year
q	FYYYYQ	Quarter
SIC_{it}	SIC	Standard Industry Classification Code
-	LOC	Location
AP_{itq}	APQ	Quarterly accounts payable
CFO_{it}	OANCF - XIDOC	Operating cash flow
$COGS_{it}$	COGS	Cost of goods sold
$Comps_{it}$	RTLCS	Comparable store sales growth
DO_{it}	DO	Discontinued operations
$EBXI_{it}$	IBC	Income before extraordinary items
EPS_{it}	EPSFX	Earnings per share
FCA_{it}	FCA	Foreign exchange income (loss)
I_{itq}	INVTQ	Quarterly ending inventory
$LIFO_{it}$	LIFR	LIFO reserve
N_{it}	RTLNSE	Number of stores
P_{it}	PRCC_F	Previous fiscal year's ending stock price
PPE_{itq}	PPENTQ	Quarterly net property, plant, and equipment
$RENT_{it}$	MRC1…5	Rental commitments for the next five years
SGA_{it}	XSGA	Selling, general, and administrative expenses
SR_{it}	REVT	Total revenue
TA_{it}	AT	Total assets
$xsga\_dc_{it}$	XSGA_DC	Observations that combine SGA with COGS

Starting with the merged annual file, I focus my analysis on retail companies by removing firms whose Standard Industrial Classification (SIC) code is not between 5200 and 5999. The resulting sample contains retailers across eight sub-sectors as classified by the U.S. Department of Commerce: lumber and other building materials dealers (SIC 52), general merchandise stores (SIC 53), food stores (SIC 54), eating and drinking places (SIC 55), apparel and accessory stores (SIC 56), home furnishing stores (SIC 57), automotive dealers and service stations (SIC 58), and miscellaneous retail (SIC 59).

Following Kesavan and Mani (2013), I make several adjustments to the annual file. First, I exclude retailers in the sectors eating and drinking places and automotive dealers and service stations because a significant portion of their operations are service-related. I also exclude jewelry retailers (SIC 5944) because their inventory levels may be affected by commodity prices and other macroeconomic factors not captured by the model. Next, I remove observations in which firms did not report the number of stores in their chain (in such cases, the *RTLNSE* variable reports a missing value). In addition, some retailers report parts of their selling, general and administrative expenses (SGA) as cost of goods sold (COGS). I drop these retailers from my analysis using the variable *XSGA_DC*, which is populated as "4" in such cases. I then remove foreign retailers by eliminating firms whose *LOC* variable does not equal "USA".

Kesavan and Mani (2013) also remove firm-years in which a retailer was involved in a merger or acquisition (M&A) using the Compustat annual footnote code because these transactions can have a significant impact on inventory levels. However, I was unable to find the aforementioned Compustat annual footnote code and instead relied on the Compustat field name *AQC* to produce similar results. This variation may partially explain the discrepancy between my resulting data sample and that of Kesavan and Mani (2013). After removing firm-years with non-missing *AQC* values, I reduce the sample by only keeping retailers that reported at least five years of consecutive data.

Finally, I identify firm-years when retailers' financial performance was impacted by changes in foreign exchange rates and/or discontinued operations such as divestiture of a core business. To preserve sample size, Kesavan and Mani (2013) do not drop all firm-years with populated *DO* and *FCA* variables, but instead divide the former by total revenue (*SR*) and the latter by net income (*IBC*) and remove observations that are more than three standard deviations away from the mean.

After making the above adjustments, I use the merged quarterly file to calculate annual averages of the *APQ, INVTQ* and *PPENTQ* variables. To do so, I simply sum each variable's quarterly values in a given fiscal year, and divide the sum by four to arrive at the arithmetic mean. I use the annual average for these variables instead of the value reported at the end of the fourth quarter because the retail industry is subject to cyclical trends that may skew results.

I then merge the annual file and quarterly file, remove observations with missing data, and combine SIC 52 and SIC 57 because SIC 52 has a small number of firms and is most similar to SIC 57. The resulting overall sample, displayed in Table 2, contains 1,708 observations and 183 retailers for the period 1999-2009. I derive the test sample by narrowing the overall sample to the period between 2004 and 2009, which contains 876 observations and 170 retailers.

Table 2: Description of Initial and Test Data Sets by Retail Sectors, 1999-2009

		Overall sample 1999-2009		Test sample 2004-2009	
Retail sector	SIC code	No. of firms	No. of obs.	No. of firms	No. of obs.
Lumber and other building materials	52	26	232	23	116
Home furnishing stores	57				
General merchandise stores	53	27	271	27	141
Food stores	54	26	238	24	110
Apparel and accessory stores	56	55	536	52	281
Miscellaneous retail	59	49	431	44	228
Total		183	1,708	170	876

3.2. Description of Variables

Prior to defining the variables used in their model, Kesavan and Mani (2013) make several adjustments to the values obtained from Compustat. To ensure that all retailers have similar inventory evaluations, irrespective of whether they use first-in, first-out (FIFO) or last-in, first-out (FIFO) methods of valuing inventory, the authors add the LIFO reserve (defined as the difference between FIFO inventory and LIFO inventory) to the ending inventory and subtract the annual change in LIFO reserve from the cost of sales. Furthermore, to adjust PPE uniformly based on the value of capitalized leases and operating leases, Kesavan and Mani (2013) compute the present value of rental commitments ($RENT_{it}$) for the coming five years using a discount rate of d = 8% and add it to PPE. Finally, the authors normalize some of the variables by the number of stores to control for scale effects.

Considering these adjustments, the data from the Compustat annual and quarterly databases is used to calculate the following explanatory variables for each firm i in fiscal year t and fiscal quarter q:

Average cost-of-sales per store: $CS_{it} = [COGS_{it} - LIFO_{it} + LIFO_{it\text{-}1}] / N_{it}$
Average inventory per store: $IS_{it} = [\, \frac{1}{4} \Sigma^{4}_{q=1} I_{itq} + LIFO_{it} \,] / N_{it}$
Gross margin: $GM_{it} = SR_{it} / [COGS_{it} - LIFO_{it} + LIFO_{it\text{-}1}]$
Average SGA per store: $SGAS_{it} = [SGA_{it}] / N_{it}$
Store growth: $G_{it} = [N_{it}] / N_{it\text{-}1}$
Accounts-payable-to-inventory ratio: $PI_{it} = [\, \frac{1}{4} \Sigma^{4}_{q=1} AP_{itq} \,] / [\, \frac{1}{4} \Sigma^{4}_{q=1} I_{itq} + LIFO_{it} \,]$
Average capital investment per store: $CAPS_{it} = [\, \frac{1}{4} \Sigma^{4}_{q=1} PPE_{itq} + \Sigma^{5}_{r=1} (RENT_{itr} / (1{+}d)^{r})] / N_{it}$
Accruals: $Acc_{it} = [EBXI_{it} - CFO_{it}] / TA_{it\text{-}1}$

The variables obtained after taking the logarithm are denoted by their respective lowercase letters (i.e. cs_{it}, is_{it}, gm_{it}, $sgas_{it}$, $caps_{it}$, g_{it}, and pi_{it}). Table 3 displays summary statistics for all the variables used in my analysis.

As will be explained in §4, the explanatory variables above will be used to calculate expected inventory growth for retailers. I select these variables because they were identified by Kesavan et al. (2010) as predictors of future inventory growth. Cost of sales is used as a proxy for demand measured at cost. The fourth variable, SGA expense, is included because it captures costs that are assumed to lead to increased sales. These include costs related to building brand image, providing customer service, and conducting marketing activities. The fifth variable, store growth, is used as a control variable to account for differences in inventory levels between less mature and more mature stores. The sixth variable, accounts-payable-to-inventory ratio, is included as it has been used in practice for sales forecasting. The seventh variable, capital investment per store, is used to capture retailers' investment in warehouses, information technology, and supply chain infrastructure that could lead to increased efficiencies and, therefore, lower inventories.

Apart from the variables discussed in Kesavan et al. (2010), Kesavan and Mani (2013) include accruals as an additional control variable for reasons that will be discussed in §5.

Table 3: Definitions and Summary Statistics of Variables for 2004-2009

Definitions	Variables	Names in Stata code	Mean	Standard deviation	Min	Max
Average cost-of-sales per store	CS_{it}	CS	5.645	8.867	0.174	67.189
Average inventory per store	IS_{it}	IS	1.159	2.039	0.025	25.958
Gross margin	GM_{it}	GM	1.600	0.296	1.113	3.714
Average SGA per store	$SGAS_{it}$	SGAS	2.091	3.206	0.046	37.262
Store growth	G_{it}	G	1.049	0.133	0.588	2.597
Accounts-payable-to-inventory ratio	PI_{it}	PI	0.477	0.223	0.118	1.607
Accruals	Acc_{it}	acc	-0.083	0.078	-0.484	0.342
Comparable store sales growth	$Comps_{it}$	comps	-0.437	6.731	-25.400	44.700
Change in gross margin	ΔGM_{it}	GMdif	0.000	0.091	-0.274	1.432
Earnings per share	EPS_{it}	EPS	0.886	2.016	-15.410	9.590
Prior fiscal year's ending stock price	PI_{it}	Plag	23.581	21.976	0.060	176.650
Change in earnings per share	ΔEPS_{it}	EPSdif	-0.122	1.943	-15.410	14.360
Change in earnings per share / price	$\Delta EPS1_{it}$	chEPSl1	0.250	2.888	-1.394	60.811

4. Methodology

I begin by using the variables above to calculate expected inventory growth for retailers. I use the expectation model described by Kesavan and Mani (2013) to predict logged inventory per store for a retailer *i* in a given fiscal year *t* as depending on firm-fixed effects (J_i), inventory per store in the previous fiscal year ($is_{it\text{-}1}$), contemporaneous and lagged cost of goods sold per store (cs_{it} , $cs_{it\text{-}1}$), gross margin (gm_{it}), lagged accounts payable-to-inventory ratio ($pi_{it\text{-}1}$), store growth (g_{it}), and lagged capital investment per store ($caps_{it\text{-}1}$). The model results in the following equation, referred to as Equation (1a):

$$is_{it} = J_i + \boldsymbol{\beta}_2 \mathrm{x'}_{\mathrm{it}} + \eta_{it}$$

where $\mathrm{x'}_{it}$ is a column vector of all right-hand side explanatory variables; $\mathrm{x'}_{it} = (1, cs_{it}, gm_{it}, cs_{it\text{-}1}, is_{it\text{-}1}, pi_{it\text{-}1}, g_{it}, caps_{it\text{-}1})$; $\boldsymbol{\beta}_2$ is the row vector of corresponding coefficients, $\boldsymbol{\beta}_2 = (\beta_{20}, \beta_{21}, \beta_{22}, \beta_{23}, \beta_{24}, \beta_{25}, \beta_{26}, \beta_{27})$; and η_{it} is the error term. Equation (1a) is then first differenced to obtain the following growth model, referred to as Equation (1b):

$$\boldsymbol{\Delta} is_{it} = \boldsymbol{\Delta}\mathrm{x'}_{it}\, \boldsymbol{\beta}_2 + \boldsymbol{\Delta}\eta_{it}$$

where $\boldsymbol{\Delta}$ denotes the change in each logged variable in fiscal year *t* from fiscal year *t* -1. For example, for fiscal year $t = 2009$, $\boldsymbol{\Delta} cs = cs_{2009} - cs_{2008}$ and $\boldsymbol{\Delta} cs_{it\text{-}1} = cs_{2008} - cs_{2007}$.

Model (1b) could be used to calculate coefficients $\boldsymbol{\beta}_2$ for each specific retailer. However, to estimate such a model one would need several decades worth of annual data. Because my dataset only contains a maximum of ten fiscal years for a given retailer (1999-2009), I estimate the coefficients at the segment level, i.e., I assume that coefficients $\boldsymbol{\beta}_2$ are identical for all retailers within a given segment. This modification yields the following model, referred to as Equation (1c):

$$\boldsymbol{\Delta} is_{it} = \boldsymbol{\Delta}\mathrm{x'}_{it}\, \boldsymbol{\beta}_{2,s(i)} + \boldsymbol{\Delta}\eta_{it}$$

where $s(i)$ denotes the corresponding segment-specific coefficients for firm *i*.

In Stata, I use the *regress* command to generate sample results for Equations (1c), which are displayed in Table 4. In addition, I use the *robust* command to control for heteroskedasticity and panel-specific autocorrelation in the data. Like Kesavan and Mani (2013), I calculate the regression coefficients using data from 2002-2007 for each retail segment. After performing the regression, I use the *predict* command in Stata to generate the expected logged inventory growth for each retailer, which I denote as $E(\boldsymbol{\Delta} is_{it})$. The expected value is then compared to the actual inventory growth per store in order to measure AIG. I denote actual inventory growth per store as $\{IS_{it} / IS_{it\text{-}1} - 1\}$ and expected inventory growth per store as $\{\exp(E(\boldsymbol{\Delta} is_{it})) - 1\}$. Taking the difference between actual and expected growth, I calculate AIG as the following:

$$AIG_{it} = (\{IS_{it} / IS_{it\text{-}1} - 1\} - \{\exp(E(\boldsymbol{\Delta} is_{it})) - 1\})$$

I use the coefficients from Equation (1c) in Table 4 to calculate AIG for all retailers in my test sample (t = 2004,...,2009). For each retailer, $AIG_{it} > 0$ implies that the retailer's inventory per store growth is abnormally high compared to the norm of the segment to which the retailer belongs. On the other hand, $AIG_{it} < 0$ implies that the retailer's inventory per store growth is abnormally low compared to the overall sector.

My initial results contain n = 555 observation and AIG values that range from -55.50% to 85.15%, with a mean of 0.53%. To ensure that the relationship between AIG and one-year-ahead earnings is not driven by outliers, I eliminate AIG values that are more than three standard deviations away from the mean.

I find that, in the resulting sample of n = 528 observation, 52% of retailers have positive AIG and 48% have negative AIG. The average AIG across the five retail segments is 0.93% (SIC 53), 1.77% (SIC 54), 0.35% (SIC 56), -1.95% (SIC 57), -0.67% (SIC 59). Summary statistics for the overall sample are displayed in Table 5. Figure 1(a) presents the histogram for AIG for the same period.

Table 5: Definitions and Summary Statistics of IG, EIG, AIG, and ACGM for 2004-2009

Definitions	Variables	Mean	Standard deviation	Min	Max
Actual inventory growth	$\{IS_{it}/IS_{it-1} -1\}$	-0.18	10.40	-36.23	81.25
Expected inventory growth	$\{\exp(E(\Delta is_{it})) -1\}$	-0.26	8.13	-24.22	51.75
Abnormal inventory growth	$\mathrm{AIG}_{\mathrm{it}}$	0.08	8.69	-30.68	33.37
Abnormal change in gross margin	$\mathrm{ACGM}_{\mathrm{it}}$	-0.20	1.33	-5.33	17.47

Notes: Descriptive statistics are based on sample size n = 528 observations and are in percentage terms.

After measuring AIG, I compute abnormal change in gross margin (*ACGM*). I calculate this variable because Kesavan et al. (2010) showed that historical gross margin information improves the accuracy of sales forecasts, which in turn improve the accuracy of EPS forecasts. Following the same method as Equation (1c), I first difference the gross margin equation to obtain the following growth model, referred to as Equation (2):

$$\boldsymbol{\Delta} gm_{it} = \boldsymbol{\Delta}\mathrm{x}'_{it}\,\boldsymbol{\beta}_{3,s(i)}+\boldsymbol{\Delta v}_{it}$$

where $\boldsymbol{\Delta}\mathrm{x}'_{it} = (1, \boldsymbol{\Delta} cs_{it}, \boldsymbol{\Delta} is_{it}, \boldsymbol{\Delta} gm_{it-1},)$; and $\boldsymbol{v}_{it}$ is the error term.

Similar to AIG, I calculate coefficients for Equation (2) using data from 2002-2007, and use the coefficients to predict ACGM for the test sample (t = 2004,...,2009). I denote actual change in gross margin as $\{GM_{it} / GM_{it-1} -1\}$ and expected change in gross margin as $\{\exp(E(\boldsymbol{\Delta} gm_{it})) -1\}$. Taking the difference between actual and expected change, I calculate ACGM as the following:

$$ACGM_{it} = (\{GM_{it}/GM_{it-1} -1\} - \{\exp(E(\boldsymbol{\Delta} gm_{it})) -1\})$$

Table 4 displays the coefficients from Equation (2), and Table 5 displays summary statistics for ACGM.

Table 4: Estimation Results of Equations (1c) and (2) for Each Retail Segment, 2002-2007

		Retail industry segment				
Equation	Variables	Apparel and accessory stores	Food stores	General merchandise stores	Home furnishing stores	Miscellaneous retail
Equation (1c)	*Intercept*	-0.005	0.002	0.002	-0.001	-0.001
		(0.005)	(0.008)	(0.008)	(0.009)	(0.007)
	$\Delta is_{it\text{-}1}$	0.141**	-0.177	0.132	-0.005	0.113
		(0.061)	(0.140)	(0.092)	(0.099)	(0.084)
	Δcs_{it}	0.717***	0.371***	1.035***	0.763***	0.807***
		(0.061)	(0.084)	(0.082)	(0.103)	(0.073)
	Δgm_{it}	0.568***	1.401***	0.011	0.617**	0.817***
		(0.099)	(0.342)	(0.331)	(0.314)	(0.173)
	$\Delta cs_{it\text{-}1}$	0.146**	0.281***	-0.215*	0.231*	0.062
		(0.074)	(0.085)	(0.130)	(0.121)	(0.100)
	$\Delta pi_{it\text{-}1}$	0.055*	0.031	0.018	0.107**	0.077*
		(0.033)	(0.062)	(0.055)	(0.054)	(0.044)
	Δg_{it}	-0.201***	-0.175**	-0.126***	-0.179**	-0.184***
		(0.044)	(0.077)	(0.036)	(0.085)	(0.064)
	$\Delta caps_{it\text{-}1}$	0.095*	0.111	-0.079*	0.000	-0.059
		(0.054)	(0.116)	(0.045)	(0.097)	(0.052)
Equation (2)	*Intercept*	0.006*	-0.002	0.000	-0.002	-0.001
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
	$\Delta gm_{it\text{-}1}$	-0.252***	-0.082***	0.027	-0.075**	-0.135***
		(0.037)	(0.019)	(0.036)	(0.030)	(0.030)
	Δcs_{it}	0.169***	0.083***	-0.004	0.069***	0.122***
		(0.032)	(0.019)	(0.025)	(0.027)	(0.025)
	Δis_{it}	0.070	0.010	0.282***	-0.040	0.091
		(0.058)	(0.083)	(0.108)	(0.089)	(0.072)
	n	273	129	108	113	204

Notes: Robust standard errors are displayed in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Unlike Kesavan and Mani (2013), I find that some of the dependent variables' coefficients ($\boldsymbol{\Delta}pi_{it\text{-}1}$, $\boldsymbol{\Delta}caps_{it\text{-}1}$) for Equation (1c) are not significant for many of the retail segments. I do find that coefficients for $\boldsymbol{\Delta}gm_{it}$ are positive and significant and those of $\boldsymbol{\Delta}g_{it}$ are negative and significant for the majority of the retail segments, supporting Kesavan and Mani (2013). I also find that the coefficient of cost of sales is positive and significant, supporting Kesavan et al. (2010)'s findings. Kesavan et al. (2010) provide the following potential explanation for this relationship: assuming cost of sales is a proxy for demand and retailers' optimal inventory stocking quantity increases with demand, an increase in cost of sales will lead to an increase in inventory level.

Interestingly, I find that the coefficient of lagged change in inventory is only significant for the apparel and accessory stores retail segment. Furthermore, this coefficient is positive for three out of the five retail segments in my analysis, which differs from Kesavan and Mani (2013)'s negative coefficient across all sectors.

5. Results

The following section will discuss my findings on the relationship between AIG and one-year ahead EPS. The relationship is tested through six models, whose results are displayed in Table 6. The dependent variable in all six models is the change in earnings per share deflated by the previous year's ending stock price, denoted as $\boldsymbol{\Delta}EPS1_{it}$. For example, for fiscal year t = 2009, $\boldsymbol{\Delta}EPS1_{it}$ = [EPS_{2009} - EPS_{2008}] / P_{2008}. The change in EPS is normalized to homogenize firms whose stock price ranges broadly in magnitude.

Model 1 is constructed by regressing $\boldsymbol{\Delta}EPS1$ on lagged $\boldsymbol{\Delta}EPS1$ ($\boldsymbol{\Delta}EPS1_{it\text{-}1}$) and lagged accruals ($Acc_{it\text{-}1}$). Lagged accruals are used as a control variable because their inventory component has been found to predict earnings in accounting literature (Sloan 2006). Therefore, the model attempts to determine whether AIG contains additional information that improves the predictability of earnings. In addition to lagged $\boldsymbol{\Delta}EPS1$ and lagged accruals, Model 1 contains a full set of year dummies (α_t^{eps}) to account for macroeconomic conditions that might impact earnings of all retailers. This yields the following equation for Model 1 of Equation (3):

$$\boldsymbol{\Delta}EPS1_{it} = \alpha_t^{eps} + \alpha_1^{eps}\,\boldsymbol{\Delta}EPS1_{it\text{-}1} + \alpha_2^{eps}Acc_{it\text{-}1} + \varepsilon_{it}^{eps}$$

where ε_{it}^{eps} is the error term.

Building upon Model 1, Model 2 adds lagged AIG ($AIG_{it\text{-}1}$) and lagged AIG squared ($AIG^2_{it\text{-}1}$). The squared term is included to test whether the relationship between AIG and earnings per share follows the inverted-U shape discussed in §2.1. Next, Model 3 adds lagged ACGM ($ACGM_{it\text{-}1}$) as a control variable. Finally, two versions of Model 4 are defined. The first, Model 4(a), adds segment dummies (α_o^{eps}). The second, Model 4(b), adds lagged change in accruals ($\boldsymbol{\Delta}Acc_{it\text{-}1}$) as an additional control variable. These additions give us the following full model to test the relationship between AIG and one-year-ahead EPS:

$$\Delta EPS1_{it} = a_o^{eps} + a_t^{eps} + a_1^{eps}\ \Delta EPS1_{it\text{-}1} + a_2^{eps} Acc_{it\text{-}1} + a_3^{eps} AIG_{it\text{-}1} + a_4^{eps} AIG^2_{it\text{-}1} + a_5^{eps} \Delta Acc_{it\text{-}1} + a_6 ACGM_{it\text{-}1} + \varepsilon_{it}^{eps}$$

As with Equations (1c) - (2), I use the *regress* command in Stata to generate regression coefficients, and use the *robust* command to control for heteroskedasticity and panel-specific autocorrelation.

Table 6: Relationship Between AIG and One-Year-Ahead Earnings, 2004-2009

	Dependent variable: $\Delta EPS1$				
Independent Variables	Model 1	Model 2	Model 3	Model 4(a)	Model 4(b)
Intercept	-0.677**	-0.625**	-0.620**	-0.666	-0.768*
	(0.296)	(0.307)	(0.307)	(0.443)	(0.455)
$\Delta EPS1_{it\text{-}1}$	0.107**	0.107**	0.105**	0.097**	0.087*
	(0.046)	(0.047)	(0.047)	(0.047)	(0.048)
$AIG_{it\text{-}1}$		-0.277	-0.297	-0.318	-0.164
		(1.449)	(1.451)	(1.458)	(1.465)
$AIG^2_{it\text{-}1}$		-0.502	-0.490	-0.654	-0.670
		(0.801)	(0.802)	(0.809)	(0.809)
$ACGM_{it\text{-}1}$			-5.552	-3.157	-3.191
			(9.826)	(9.876)	(9.875)
$Acc_{it\text{-}1}$	-8.638***	-8.712***	-8.546***	-8.897***	-10.337***
	(1.584)	(1.592)	(1.620)	(1.657)	(2.176)
$\Delta Acc_{it\text{-}1}$					1.864
					(1.825)
Segment dummies	No	No	No	Yes	Yes
n	523	523	523	523	523

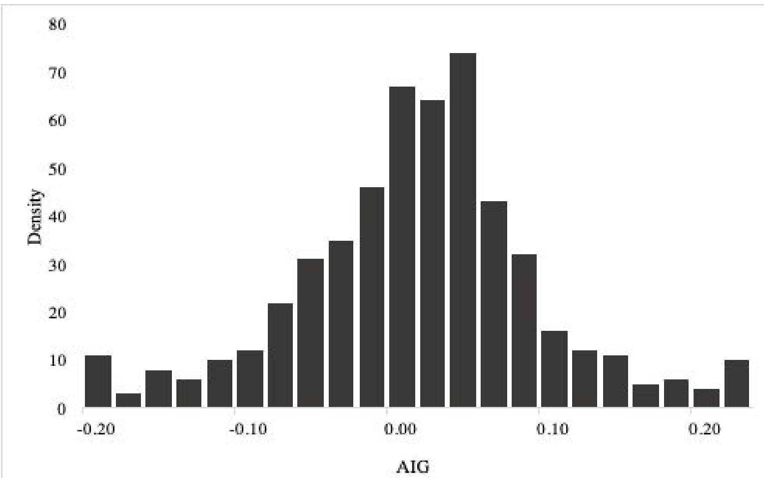
Notes: Robust standard errors are displayed in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

I find that $\Delta EPS1_{it\text{-}1}$ is statistically significant at the 0.05 level for most retail segments, while lagged accruals are significant at the 0.1 level for all segments. The latter confirms previous account literature (Sloan 1996) that identified accruals as predictors of earnings per share. Interestingly, lagged change in accruals is not statistically significant at any level.

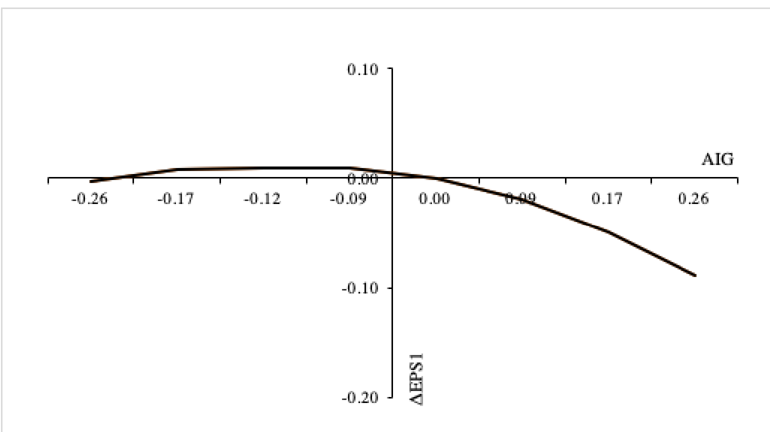
The primary difference between my findings and those of Kesavan and Mani (2013) is that I do not find AIG or AIG^2 to be statistically significant predictors of ΔEPS1 at any level. However, similarly to Kesavan and Mani (2013) I find coefficients for both variables (a_3^{eps}, a_4^{eps})

in Model 4(b) to be negative, indicating an inverted-U relationship between AIG and future earnings.

Figure 1: Histogram of AIG and Relationship Between AIG and One-Year-Ahead Earnings



(a)



(b)

Despite their insignificance, I use coefficients (a_3^{eps}, a_4^{eps}) from Model 4(b) to graphically illustrate the relationship between AIG and **Δ**EPS1 in Figure 1(b). The graph is created using the following methodology. First, I choose AIG values that span observations on each side of the mean. To do so, I calculate the AIG values located at the mean plus and minus one, two, and three standard deviations, which are displayed in Table 7. Similarly to Kesavan and Mani (2013), I also plot the turning point of the curve (- $a_3^{eps}/2a_4^{eps}$), which in my analysis equals -0.1225.

To calculate the respective **Δ**EPS1 for each AIG value, I use coefficients (a_3^{eps}, a_4^{eps}) from Model 4(b). For example, at the mean AIG of .0008, I calculate **Δ**EPS1 in the following way:

$$\Delta\text{EPS1} = (-0.164 * .0008) + (-0.670 * .0008^2) = -0.0001$$

Table 7: Values of AIG and ΔEPS1 Used to Generate Figure 1(b)

AIG Value	-0.2598	-0.1729	-0.1225	-0.0860	0.0008	0.0877	0.1745	0.2614
ΔEPS1 Value	-0.0026	0.0083	0.0100	0.0092	-0.0001	-0.0195	-0.0490	-0.0886

From Table 7 I can draw three distinct insights. First, I find that AIG values in the range of [-0.0860, -0.1729] yield positive **Δ**EPS1 values. This indicates that an abnormal decrease in inventory for retailers in this range lead to an increase in future earnings.

Recall that negative AIG implies that inventory grew less than expected. Theoretically, negative AIG could either have a positive or a negative impact on future earnings. Negative AIG would positively impact future EPS if the inventory reduction was driven by lean inventory practices. That is, if the inventory reduction for retailers either (1) decreased inventory-related costs while having negligible impact on service levels (i.e. revenues), or (2) decreased inventory-related costs by a larger magnitude than it decreased service levels.

On the other hand, negative AIG would negatively impact future EPS if the inventory reduction was driven by supply-chain glitches or management's anticipation of lower future demand. Kesavan and Mani (2013) rely on cost-of-sales as a proxy for demand, which is, in turn, used to predict expected inventory growth. If a retailer's management team has access to information about lower future demand that is not accounted for in cost-of-sales, negative inventory growth could signal lower future sales, and, therefore, lower future earnings.

Because I find that AIG values in the range of [-0.0860, -0.1729] correspond to positive **Δ**EPS1 values, I deduce that the majority of retailers in this region became leaner, and the minority of retailers in this region experienced supply-chain glitches or lower future demand expectations.

The second insight from Table 7 is derived from that observation that AIG values in the range of [0.0008, 0.2614] yield negative **Δ**EPS1 values. This indicates that an abnormal increase in inventory for retailers in this range lead to a decrease in future earnings.

Recall that positive AIG implies that inventory grew more than expected. Like negative AIG, positive AIG can either have a positive or a negative impact on future earnings. Positive AIG would have a positive impact on future earnings if management had private information related to expectations of higher future demand. Additionally, high inventory growth could increase product availability (i.e. service levels), which could lead to higher profitability.

On the other hand, positive AIG would have a negative impact on future earnings if the increase was driven by bloated inventories. Bloated inventories have several potential consequences. First, they can lead to inventory write-downs, leading to depressed selling prices. Second, bloated inventory can restrict cash flow available for new product development. Third, bloated inventories can be a symptom of supply chain glitches and operational inefficiencies.

Because I find that AIG values in the range of [0.0008, 0.2614] correspond to negative **Δ**EPS1 values, I deduce that the majority of retailers in this region experienced bloated inventory levels, and the minority of retailers in this region experienced high future demand or improvements in product availability.

The third insight from Table 7 is derived from the observation that AIG has a bigger negative impact on **Δ**EPS1 at higher levels of distribution (for example, at the mean plus three times the standard deviation) than at lower levels of distribution (for example, at the mean minus three times the standard deviation). This asymmetry suggests that retailers should prioritize strategies that prevent bloated inventory levels above those that lead to decreased service levels. In other words, my findings imply that retailers with "too much" inventory will financially perform worse than those with "too little" inventory.

6. Model Extension, Limitations, and Conclusion

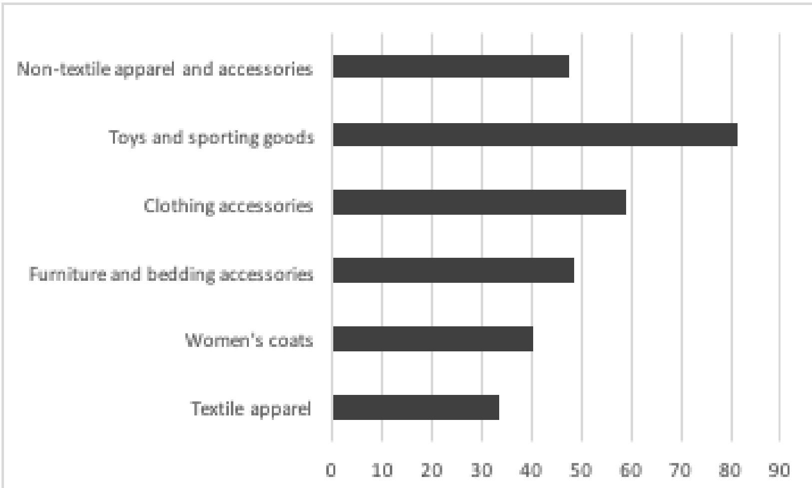
6.1. Description of Changes in Trade Policy

Despite not finding a significant relationship between AIG and future EPS, I attempt to apply the above models to more recent data in order to empirically study the effects of trade policy changes on retailer inventory and earnings. Specifically, I am interested in the effects of the tariffs introduced under President Trump's administration in 2017.

The ongoing economic conflict between the United States and China, spurred by accusations of unfair trading practices and intellectual property theft, has resulted in the implementation of tariffs on hundreds of billions of dollars on American and Chinese goods (Bown 2020). First imposed in July 2018, the duties have ranged broadly in size (from 5% to 25%) and scope, affecting multiple sectors of both economies. Given retailers' reliance upon Chinese suppliers, as shown in Figure 2, I hypothesize that the trade dispute has generated significant supply chain disruptions for companies operating in the sector (Winkler 2018).

In the face of rising input costs, retailers normally have two available options. On one hand, they can choose to pass the cost differential to consumers through higher selling prices. On the other hand, they can absorb the costs and accept lower margins. In the first half of 2018, however, retailers faced an additional alternative. Because the presidential administration announced the trade restrictions a few months before their effective implementation, retailers had a limited window of time to accumulate inventory from Chinese suppliers without incurring the forthcoming tax penalties.

Figure 2: Chinese Share of Total U.S. Imports, 2018



Notes: In percentage terms.

In 2018, several articles in the business press reported cases of retailers making inflated inventory investments ahead of the tariffs' introduction. Reuters, for example, cited Walmart Inc, Target Corp, and TJX Companies among those who raced to purchase chinese products before the end of the year (Naidu and Baertlein 2018). The following extension attempts to determine whether this behavior generated increased abnormal inventory growth, and whether it had a material effect on retailers' profitability.

6.2. Testing Trade Policy Effects on Model Results

In this section, I attempt to determine whether the above changes in trade policy negatively impacted retailer earnings through the mechanism of positive abnormal inventory growth. To do so, I follow the methodology described in §4 to recreate Equations (1c) and (2), but I apply the regression model on data from 2011 to 2016. I retrieve this data from the same Compustat file I originally constructed. Table 8 displays the resulting coefficients for the inventory and gross margin equations.

Continuing to follow my previous methods, I compute AIG and ACGM using the coefficients from the 2013 - 2018 data. To ensure results are not driven by outliers, I eliminate AIG values that are more than three standard deviations above or below the mean. The resulting values are summarized in Table 9.

Table 8: Estimation Results of Equations (1c) and (2) for Each Retail Segment, 2011-2016

		Retail industry segment				
Equation	Variables	Apparel and accessory stores	Food stores	General merchandise stores	Home furnishing stores	Miscellaneous retail
Equation (1c)	*Intercept*	0.022***	0.006	0.017**	0.009	0.010*
		(0.006)	(0.007)	(0.008)	(0.007)	(0.006)
	$\Delta is_{it\text{-}1}$	-0.198**	0.028	0.058	-0.047	0.193*
		(0.096)	(0.124)	(0.190)	(0.122)	(0.116)
	Δcs_{it}	0.770***	0.286*	0.692***	0.682***	0.507***
		(0.085)	(0.146)	(0.105)	(0.121)	(0.111)
	Δgm_{it}	0.329**	-1.687	0.300	0.215	0.389
		(0.138)	(1.064)	(0.397)	(0.377)	(0.293)
	$\Delta cs_{it\text{-}1}$	0.103	0.318*	-0.096	0.134	0.064
		(0.073)	(0.189)	(0.174)	(0.183)	(0.111)
	$\Delta pi_{it\text{-}1}$	-0.022	0.008	0.023	0.056	0.045
		(0.054)	(0.080)	(0.091)	(0.053)	(0.060)
	Δg_{it}	-0.007	-0.585***	0.061	-0.133	-0.324***
		(0.091)	(0.186)	(0.046)	(0.148)	(0.114)
	$\Delta caps_{it\text{-}1}$	0.066	0.035	-0.010	0.094	-0.032
		(0.051)	(0.104)	(0.085)	(0.116)	(0.110)
Equation (2)	*Intercept*	-0.010**	0.002	-0.007**	-0.001	-0.002
		(0.004)	(0.001)	(0.003)	(0.003)	(0.002)
	$\Delta gm_{it\text{-}1}$	-0.069	0.125	0.139	0.383**	0.300***
		(0.106)	(0.117)	(0.111)	(0.158)	(0.108)
	Δcs_{it}	-0.346***	-0.018	0.025	-0.085	-0.034
		(0.110)	(0.031)	(0.045)	(0.071)	(0.034)
	Δis_{it}	0.168*	-0.046	0.031	0.041	0.072**
		(0.089)	(0.034)	(0.050)	(0.088)	(0.029)
	n	201	59	75	88	100

Notes: All regressions are run after controlling for panel specific autocorrelation and heteroskedasticity.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Definitions and Summary Statistics of IG, EIG, AIG, and ACGM for 2013-2018

Definitions	Variables	Mean	Standard deviation	Min	Max
Actual inventory growth	$\{IS_{it}/IS_{it-1} - 1\}$	1.38	7.33	-23.02	36.43
Expected inventory growth	$\{\exp(E(\Delta is_{it})) - 1\}$	-0.86	5.57	-16.49	29.88
Abnormal inventory growth	AIG_{it}	2.24	4.79	-16.23	23.30
Abnormal change in gross margin	ACGM_{it}	-0.33	1.06	-10.05	3.46

Notes: Descriptive statistics are based on sample size n = 357 observations and are in percentage terms.

Next, I estimate regression coefficients for the five Models in Equation (3) using data from 2013 to 2018. I report these coefficients in Table 10. Lastly, using the updated AIG distribution and coefficients, I construct Figure 3.

Table 10: Relationship Between AIG and One-Year-Ahead Earnings, 2013-2018

	Dependent variable: $\Delta EPS1$				
Independent Variables	Model 1	Model 2	Model 3	Model 4(a)	Model 4(b)
Intercept	-0.028	-0.013	-0.024	0.018	0.022
	(0.031)	(0.029)	(0.031)	(0.058)	(0.058)
$\Delta EPS1_{it-1}$	0.782**	0.808**	0.794**	0.800**	0.776**
	(0.371)	(0.372)	(0.365)	(0.355)	(0.374)
AIG_{it-1}		0.125	0.090	0.077	0.082
		(0.268)	(0.271)	(0.259)	(0.260)
AIG^2_{it-1}		-5.148*	-4.918*	-4.856*	-4.844*
		(2.758)	(2.784)	(2.512)	(2.533)
$ACGM_{it-1}$			2.485*	2.517*	2.531*
			(1.476)	(1.498)	(1.504)
Acc_{it-1}	-0.818*	-0.764*	-0.857*	-0.922**	-0.852*
	(0.434)	(0.431)	(0.447)	(0.460)	(0.463)
ΔAcc_{it-1}					-0.116
					(0.238)
Segment dummies	No	No	No	Yes	Yes
n	357	357	357	357	357

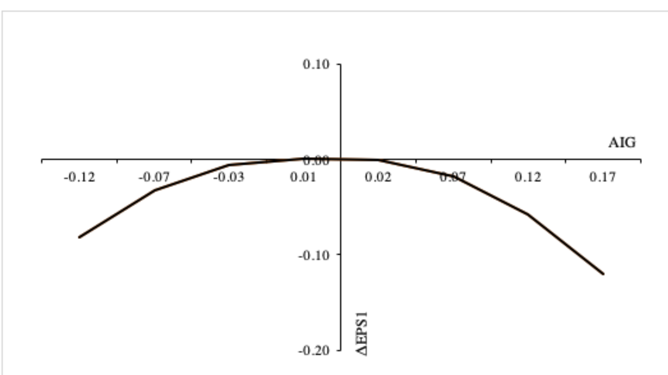
*** p<0.01, ** p<0.05, * p<0.1

The results of the model extension differ significantly both from the results described in §5, as well as those of Kesavan and Mani (2013). Comparing Table 9 to Table 5, I find that the average actual inventory per store growth is 867% higher in the 2013-2018 sample than in the 2004-2009 sample. Additionally, I find that, although AIG has a wider range in the 2004-2009 sample [-30.68, 33.37] than in the 2013-2018 sample [-16.23, 23.30], the mean AIG is 2700% higher in the latter period.

A notable limitation of the methodology I follow is the requirement of at least five years of consecutive data in order to calculate the lagged variables in the regression. Because the tariffs were not implemented until the latter half of the 2013-2018 test sample, it becomes difficult to discern whether the growth in AIG was a direct result of the changes in trade policy. However, I do find that the median AIG increased from 1.08% to 2.33% from 2016 to 2017, which provides some support that the tariffs incentivized retailers to accumulate inventory.

Unlike the results in Table 6, Table 10 shows a significant, negative correlation between the squared AIG term and change in EPS1, which supports an inverted-U relationship between the two variables. The larger magnitude of the squared AIG term increases the steepness of the curve on both sides of the turning point, suggesting that AIG had a stronger negative impact on retailers' earnings during the 2013-2018 period than during the 2004-2009 period. I conclude that the positive AIG region of Figure 3 is dominated by retailers with bloated inventory, while the negative AIG region is dominated by retailers that either anticipated low demand, or retailers that experienced supply chain disruptions. Interestingly, the R-squared value of Model 4(b) in Table 10 (r = 0.2656) is over three times higher that of Model 4(b) in Table 6 (r = 0.0829). This indicates that the model is a more accurate predictor of change in EPS1 during the 2013-2018 period.

Figure 3: Relationship Between AIG and One-Year-Ahead Earnings, 2013-2018



6.3. Limitations

In this section, I explore potential explanations for the differences between my results and those of Kesavan and Mani (2013). First, based on the discrepancies in the summary statistics displayed in Table 2, I conjecture that the data sample I used contained slightly different firm observations. As mentioned in §3.1, I was unable to rely on the Compustat annual footnote code to eliminate retailers that were involved in mergers or acquisitions. Because my overall sample comprises a larger number of firm observations than Kesavan and Mani (2013)'s, I conclude that I may have failed to remove all retails involved in M&A activity during the study period.

Another explanation behind the variance in the summary statistics could be the merging of the Compustat data files. Due to a lack of access to the Wharton Research Data Services (WRDS) database, I used the Center for Research in Security Prices (CRSP) database as my source. To test whether my merged file differed significantly from the WRDS-sourced data, I compared some of the variables in my file to those of a sample from WRDS. While some of the variables were exactly the same between the two datasets, others had slight variations (despite following the same methodology to generate all variables).

Due to the differences in the underlying sample, it becomes difficult to discern whether the incongruence between my regression results and those of Kesavan and Mani (2013) is a result of the data or of my methodology. However, it is unlikely that the two samples differed enough to generate such noticeable dissimilarities in the significance of the regression coefficients, so I believe there may be aspects of my methodology that do not accurately follow that of Kesavan and Mani (2013). The authors do not mention the software commands that were used to generate their coefficient results, so it remains unclear whether my use of the *regress* command in Stata is correct. To ensure the significance of my coefficients was not erroneously affected by the use of the *regress* command, I ran the model using a series of other Stata commands, including *xtreg* and *xtregar*. The resulting AIG coefficients remained insignificant.

6.4. Conclusion

This paper attempts to recreate the regression model originally presented in Kesavan and Mani (2013) to analyze the relationship between AIG and one-year-ahead EPS for U.S. public retailers during the period from 2004 to 2009. My replication does not find a significant statistical relationship between the two variables, indicating variances in the sample selection and methodology of the two papers.

In addition, I discuss a potential extension by applying Kesavan and Mani (2013)'s regression model to recent data, spanning the period of 2016 to 2018. I use this extension to test whether the model yields different results as a function of policy changes introduced over time. Specifically, I focus my analysis on the trade dispute between the U.S. and China due the retail industry's reliance on Chinese exports. I find a significant inverted-U relationship between AIG and future EPS when applying the same regression model to recent data, suggesting that inventory had a greater impact on earnings during this time period compared to that of the 2004-2009 period.

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