How Stable is the Intertemporal Shift of Seasonal Fluctuations in Retail Sales?

Thesis

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Abstract

Seasonality is a characterizing aspect of the retail sector. Besides increasing sales, the intertemporal shift is possibly an important aspect of a retail sales season. The intertemporal shift occurs when the increase in sales is partly the result of consumers speeding up or delaying their purchase. In this thesis, the intertemporal shift is divided into two aspects. First, the intertemporal pattern, which represents how seasonal months interrelate. Second, the intertemporal effect, this estimates to what extent the intertemporal shift controls for the seasonal spike in sales. The main research question in this thesis is: "*How stable is the intertemporal shift of seasonal fluctuations in retail sales?"*

In order to answer this question, a joint use of four inequality measures is interpreted. These include the Gini coefficient, Theil T1, Theil T0 and Coefficient of Variation. For each type of measurement, a within- and between seasonal inequality index can be calculated. The within seasonal inequality calculates how the seasonal months are related. The between seasonal inequality highlights the differences between seasons. The latter estimates to what extent the intertemporal shift controls for the seasonal spike in sales. This approach has the following main advantages; first, it adds robustness to the results. Second, there are clear differences between the inequality measurements, so interpreting discrepancies help to better understand the intertemporal shift.

In this thesis, twelve retail sectors are studied. Both aspects of the intertemporal shift are only stable for the home furniture sector. Comparing the inequality measures showed that almost all series have a declining trend. This means that the monthly sales are becoming more equal over time. However, this declining trend occurs for the most part in the seasonal months. Hence, for most retail sectors, the intertemporal effect is declining and the seasonal months are becoming more equal in their sales.

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1. Introduction

Seasonality is one of the most characterizing aspects of retail sales. Retail sales gain a lot of attention during their peak seasons, because of its economic significance. This attention does not only include the general increase or decrease compared to previous years. Each year, several news items are dedicated to the performance of sectors, products and which outlet is visited most. The Christmas season is typically a peak selling period for each retail sector all around the world. Sales increase drastically as people go shopping for gifts, supplies, and decorations to celebrate. This increase is further influenced by consumers taking advantage of the sales promotions, product introductions and the advertisements offered by retailers during the Christmas season.

In the U.S. the “Christmas shopping season” generally starts with Black Friday, on the fourth Friday of November, and ends when Christmas is over. Consumptions increase drastically in this period. Consumer consumption makes up about 70% of the gross domestic product in the US. Christmas sales take up a big share, as a quarter of all personal spending takes place each year during this period (Amadeo, 2018).

The question that remains is to what extent does the holiday sales actually influence the economy? There are economists who argue that holiday performance is a zero-sum game for the consumer economy. As Jim Sullivan, chief U.S. economist for High-Frequency Economics, states the more a person spends on holiday items in November and December, the less will be spend on other items in January and February (Light, 2016).

Therefore, given the magnitude of the holiday sales, the general increase/decrease in sales may not tell the whole story of the seasonality in retail. An important part of the story could be the intertemporal choice of consumers. Intertemporal choice is the process where a decision at a certain point in time influences the possibilities available at other points in time (Loewenstein & Thaler, 1989). These choices are motivated by the relative value a person attaches to various payoffs at multiple points in time (Loewenstein & Thaler, 1989).

When a large number of people make similar intertemporal choices in their retail consumption, a shift in sales is noticeable. This intertemporal shift occurs when the peak, or part of the peak, in sales comes from people delaying or speeding up their purchases, causing the seasonal sales peak. However, not much is known about the intertemporal shift of seasonal fluctuations.

In this thesis, the phenomenon of the intertemporal shift is divided into two parts. The first is the pattern, which evaluates how seasonal months interrelate. Second is the effect of the intertemporal shift. The effect indicates to what extent the intertemporal shift controls for the seasonal spike in sales.

The Christmas period is generally a peak selling season for all retail sectors. Some retail products also have a summer season. Understanding the full story of the seasonality in retail sales is not only important for the national economy. There could also be implications on the industrial or managerial level. With a better knowledge of the intertemporal shift, retailers could put together their advertisement strategy more efficiently and target the consumers on critical points in time in their decision making. The delay or speeding up of a product introduction could turn out to be effective. Furthermore, there could be less uncertainty in managing the storage for products. Therefore, this thesis deals with the intertemporal shift of seasonality with the following main research question:

How stable is the intertemporal shift of seasonal fluctuations in retail sales?

This main question can be divided into four sub-questions. The first sub-question deals with the stability of the intertemporal pattern of a retail sector. Assessing the stability of the intertemporal pattern shows the stability of the structure of a season and how the months interrelate. Therefore, the first sub-questions is:

Is the intertemporal pattern stable over time?

The second sub-question estimates the stability of the relative magnitude of the intertemporal effect of a retail sector. As mentioned earlier, there is some discussion about the effect and stability of the intertemporal effect. Answering this question gives an estimation of the relative magnitude of the intertemporal effect and whether this is stable. in other words, is the extent to which the intertemporal shift controls for the seasonal spike in sales stable? Hence, the second sub-question is:

Is the intertemporal effect stable over time?

The third sub-question deals with diversity within the retail sector. Each retail sector has its own characteristics with various product types. However, less is known on how the intertemporal sales pattern compares between the sectors. Hence, the third sub-question is:

Does the intertemporal pattern differ between types of products?

Finally, the fourth sub-question is used to answer whether the intertemporal effect can be compared across retail sectors. Therefore, the final sub-question is:

Does the intertemporal effect differ between types of product?

This thesis makes use of inequality measures. To my knowledge, a variation of this approach has not been used in any retail study. On the one hand, inequality measures can be used to determine the seasonality on the annual level. On the other hand, through decomposition methods, it is possible to determine the within- and between season component of the inequality coefficient. This approach does not estimate the stability of a season, but also on how monthly sales interact with each other; both within- and between seasons. In this thesis, three different types of inequality measures are used: (1) the Gini coefficient, (2) Theil index, and (3) Coefficient of Variation. The joint use of these measurements gives some reliability to the outcomes. The measurements differ in how they weigh changes in different parts of the distribution. Thus, various aspects of the sales series are highlighted, giving a better comprehension of the seasonal pattern.

This thesis is structured as follows: the second section reviews the theoretical background of seasonality in retail sales and the measures being used. The third section presents the data being used and the annual seasons for each sector. The fourth section explains the methodology. In the fifth section, the results of this thesis are described. The sixth section discusses these results. Finally, the seventh section includes the conclusion of this thesis.

2. Theoretical Framework

The theoretical framework is split into three parts. First, the general approach of dealing with seasonality in the retail literature is described. Second, the background of the proposed method is given. Finally, the intertemporal shift is predicted per sector.

2.1. Existing Literature on Seasonality in Retail Sales

Because of its economic significance, retail sales have been a widely discussed topic in various studies from multiple economic disciplines. Understanding and quantifying the aspects of seasonality can be of great importance to all strategic and planning decisions. For each type of manager, the ability to better deal with seasonality can be valuable, not only in marketing. Since this thesis deals with sales patterns, the theory is most closely related to the marketing literature.

2.1.1. Marketing Literature

With regards to seasonality, the current marketing literature mainly focusses on factors that influence demand and how these manifest in a seasonal period. Another topic that gained attention in the marketing literature is the ability to boost sales in a seasonal period by understanding customer preferences. For example, the effect of promotions on demand has been well studied over time. Where an increase in sales not only comes from new customers, or from the competition. A large part of the sales comes from customers that would have bought the product at another time if there was no promotion (Presendorfer, 2002; Hendel & Nevo, 2004; Gong et al., 2015).

Promotions and other business activities are not the only cause of seasonality. Seasonality is also often institutional. This is related to cultural and social factors that influence human behavior (Bar-On, 1999). Retail sales are affected by many factors of consumer behavior as well as macroeconomic influences. An exploration of these factors is beyond the scope of this thesis. Nonetheless, understanding how to deal with seasonality is an important step in order to deal with the intertemporal sales shift phenomenon.

2.1.2. Modeling Retail Sales Seasonality

Seasonality is often a component of a study that models aggregate retail sales. These type of studies are mainly focused on forecasting retail sales. The analysis of seasonality is mostly used to improve the forecasting accuracy, rather than analyzing the seasonal component itself. A comparative study of linear and nonlinear models for aggregate retail sales forecasting has been done by Chu and Zhang (2003). The linear models studied are: regression with dummy variables, regression with trigonometric variables and ARIMA models. The non-linear models are: ANN’s in which the adjustment of seasonal effect have been studied with the use of dummy- or trigonometric variables.

In the literature, there is no consensus on what method is most effective in describing the pattern of a time series. Since each time series model captures a different aspect of the time series data, most researchers choose to use multiple models to find a more robust forecast of the retail sales (Aye et al., 2015). Moreover, because time series data rarely show similar patterns for multiple products, it depends on the data what time series analysis should be used.

Retail sales data often show strong seasonal fluctuations. Which approach deals best with a certain seasonal component is largely unresolved (Zhang and Kline, 2007). In the context of time series modeling, a group of longitudinal studies can be highlighted that involve decomposition and isolate the seasonal Component (Aye et al., 2015; Ramos et al., 2015). These studies focus on forecasting retail sales for various types of products in different countries.

2.1.3. Limitations in Conventional Time Series Analysis

Besides the time-consuming necessity of constructing a sophisticated analysis for each data set, the conventional approach has more limitations for answering the research questions in this thesis. Since modeling the pattern is prone to many errors, it may be difficult to draw conclusions from these types of models.

Furthermore, the most appropriate analysis can differ for each time series, if there is a ”best” analysis. It could, therefore, be difficult to compare different sales years or products. A possible solution could be to use a single model with seasonal dummies. However, this method could also suffer from an incomplete representation of the seasonal pattern in the time series.

Another limitation of conventional time series analysis for this thesis is that these approaches measure the magnitude of the sales. This leaves out an important part; the intertemporal shift of sales. In this thesis, it is important to acknowledge that people make temporal choices. Therefore, the inability of estimating the interaction of months within a particular season would be a limitation in order to assess the intertemporal effects of seasons.

2.2. Measuring Seasonality

Seasonality is a phenomenon that can be found in many fields of research. Each seasonal activity can have different patterns and implications. First, it needs to be clear what is understood by seasonality. Seasonality indicates that specific and regular intervals occur in less than a year. In this respect, retail sales show strong seasonal variations (Aye et al., 2015). This means that retail seasonality is a temporal imbalance of sales. Hence, seasonality is in some sense a distributional imbalance that can be measured synthetically (Duro, 2016). Where seasonal activity is the result of consumers delaying and/or speeding up their purchases.

Taking this as a reference, it is necessary to apply synthetic distribution indices to the annual distribution of retail sales (Duro, 2016). The main use of this type of method is the possibility to, not only measure, but also decompose seasonal concentrations of retail sales. To my knowledge, there are no studies in the retail sales literature that use this type of measurement of seasonality. However, in other fields of study, a variation of this method is being used to measure seasonality. Mainly in tourism, environmental- and ecological studies measuring and decomposing seasonality gained some attention.

Regarding decomposing inequality analyses, a few studies can be highlighted. A variation of this approach is used in studies measuring seasonality in tourism destinations and the effects of counter-seasonal policies (Fernández-Morales, 2003; Fernández-Morales & Mayorga-Toledano, 2008; Duro, 2016; Rosselló & Sansó, 2017). Furthermore, in the literature of environmental and ecological studies, a decomposition technique has also been used to determine seasonal concentration (Sun et al., 2010; Liuzzo et al., 2016).

2.2.1. Inequality Measurements

There are multiple suitable synthetic measures that measure inequality. The most widely used measurement is the Gini coefficient. Other methods include, for instance, indices from the Theil family or the Coefficient of Variation (CV). However, no single measurement is preferred, because each measurement differs in weighing the changes in different parts of the distribution (Kawachi & Kennedy, 1997; Rosselló & Sansó, 2017).

Each inequality index as distance function can be interpreted differently. They differ in the way each method aggregates the differences into a single measurement. As a result, some indices may in some cases strongly disagree in their pattern or even the sign of their evolution. This makes it difficult, if not impossible, to directly compare measurements (Morduch &

Sicular, 2002; Duro, 2012; Rosselló & Sansó, 2017). Therefore, a choice has to be made between either explaining the evaluation for a single measurement or dealing with multiple indicators in order to obtain a broad overview of the situation. There is no argument suggesting a particular measurement is better than another. It seems therefore reasonable to use multiple measurements that are sufficient and heterogeneous in treating the observations. This makes the analysis more robust and avoids biased conclusions. Therefore, given the different characteristics of each measurement, a joint use of the Gini coefficient, Theil T1, Theil 0 and CV is used in this thesis. This provides a broader qualitative range and prevents over-extending the number of measurements. The combination is chosen based on the fact that the Gini coefficient is more sensitive to variations in months other than the peak. The Theil indices are more sensitive to changes in the peak months and the CV is neutral.

2.2.2. Properties of inequality measures

Following the literature, an inequality index should have five basic properties: independence of scale, independence of population, principle of transfer, decomposability and the particular sensitivity for an index to the part of the distribution where changes take place (Theil, 1967; Sen & Foster, 1973; Cowell, 2011; Duro, 2012). Indices that satisfy these five requirements include CV, Gini coefficient and indices of the Theil family (Theil, 1967; Adams et al., 2008).

Besides dealing with the specific sensitivity of each measurement, it is important in this analysis to explore the possibilities of decomposing the indices. In this respect, there are two possibilities emphasized in the literature on inequality measurement (Cowell, 2011). First, some of the indices may be decomposed by group. In the retail sales, a group would be formed by consecutive months. In other words, a group is a retail season. Decomposing by groups identifies a component of an inter-group and an intra-group (Shorrocks, 1984). This measurement of the within- and between seasons components provides an indication of the stability of the season (Dagum, 1997).

Second, there is a possibility to decompose an index by markets (e.g. states). This could indicate the total contributions to an inequality measurement of an individual market. Furthermore, the potential effect of increasing/decreasing markets can be captured in this decomposition. In this sense, it is necessary that the role of each factor measuring seasonality is expressed additively. This allows identifying different market segments, including their contribution to the annual seasonal concentration. Furthermore, the openness to marketing factors aimed to influence seasonality (Jeffrey & Barden, 1999; Fernández-Morales & Mayorga-Toledano, 2008; Fernández-Morales et al., 2016).

2.2.3. The Use and Advantages of Inequality Measures

In order to isolate the intertemporal shift of sales in the retail sector, this thesis uses the techniques and methodological elements of decomposing inequality measurements applied in studies mentioned earlier. By first treating an annual season as a group of months, the seasonality of this period can be estimated. Decomposing the inequality index, the seasonality and weights of months within a season can be measured. The combination of the inequality indices and seasonal decompositions could perhaps indicate an intertemporal shift in retail sales. Moreover, the stability of the intertemporal shift in retail sales can be estimated. Comparing yearly outcomes provide some robustness and reliability to this study.

The main advantages of inequality measures over conventional time series analyses for this thesis are threefold. First, using inequality measurements allows treating months and seasons separately. Second, the ability to decompose the inequality measurements gives insight into how months and seasons interact. Third, the measurements are comparable over the years and between products. Fourth, this approach directly uses the respective sales data. While a conventional time series analysis uses an indirect measurement. These advantages make it possible to test for stability in the intertemporal pattern and intertemporal effect in sectors. Therefore, the first hypotheses are:

H1a: Inequality measures can find intertemporal patterns.

H2a: Intertemporal patterns are stable over time.
H2b: Intertemporal effects are stable over time.

2.3. Differences Between Sectors

Consumers use price as a reference point whenever there is chosen between immediate or delayed purchase. Price is used to evaluate the decision and can significantly influence choice (Lowenstein, 1988). In this sense, price promotions could persuade people to delay or speed up their purchase, which would lead to an intertemporal shift. However, retail sectors differ in their price promotion strategies. Retail is an overarching term for multiple retail sectors. Therefore, multiple retail sectors are studied in this thesis. These twelve retail sectors can be found in Table 1.

Table 1 Retail Sectors

NAICS Code	Title	Epithet
443	Electronics and appliance stores	Electronic
445	Food and beverage stores	Food
44831	Jewelry stores	Jewelry
4482	Shoe stores	Shoe
4481	Clothing stores	Clothing
45111	Sporting goods stores	Sports
45112	Hobby, toy, and game stores	Toy
451211	Book stores	Book
4411	Automobile dealers	Car
4421	Furniture stores	Furniture
4422	Home furniture stores	Home Furn
452	General merchandise stores	Gen Merch

All retail sectors have different characteristics. Thus, the pricing strategy also differs between these sectors. Voss and Seiders (2003) examined why price promotion strategies can vary between retail sectors. Pricing and promotions follow from the strategic decisions of retailers (Lal & Rao, 1997). Voss and Seiders (2003) determined three distinct aspects of price promotion strategy.

First, price variation represents the position of price. The range varies from stable prices with consistent prices and few discounts throughout the year to promotional pricing, which features numerous discounts (Hoch et al., 1994; Voss & Seiders, 2003).

Second, price promotion advertising volume is the amount of advertising that mainly focuses on the price and its promotion. This aspect is not necessarily related to price variation. Retailers may also choose to promote stable prices (Voss & Seiders, 2003).

Finally, depth of discount represents the average magnitude of the discount per sales item (Shankar & Krishnamurthi, 1996). This dimension is only relevant with price variation because there is no discount with stable prices. Nonetheless, the average depth of a discount is a discrete decision.

Figure 1 Relationship Between Price Promotion Strategy and the Intertemporal Shift

Voss & Seiders (2003) estimated the retail sector means for these dimensions of price promotion strategy. Table 2 shows whether each dimension is relatively high compared to the other sectors. Furthermore, an indication of the intertemporal shift is included. This shows if a relatively large or small intertemporal shift is expected.

Table 2 Prediction of the Intertemporal Shift

	Price variation	Promotion advertisement	Avg. depth of discount	Intertemporal shift
Electronic	-	+	-	-
Food	+	-	+	+
Jewelry*	+/-	+/-	+/-	-
Shoe*	+	+	+	+
Clothing	+	-	+	+
Sports*	+/-	+/-	+/-	+/-
Toy*	+/-	+	+	+
Book	-	-	-	-
Car*	-	+/-	-	-
Furniture	+	-	-	-
Home Furn	+	-	+	+
Gen Merch	+	+	+	+

Note: * indicates that the sector was not included in the study of Voss & Seider (2003).

Not all retail sectors were included in the study of Voss & Seider (2003). These dimensions follow from a combination of knowledge about the particular sector and the conceptual framework of Voss & Seider (2003).

Voss & Seider (2003) studied aspects that influence retail price promotion. In this thesis, only the sector characteristics are applicable.

Assortment perishability relates to the shelf life of products. Goods with a longer shelf life have lower levels of perishability. Conversely, goods that do not have a long shelf life have higher levels of perishability. When product innovation is frequent, products are physically perishable. When seasonality plays an important role, perishability increases. Assortment perishability positively influences all three dimensions of price promotion strategy (Voss & Seider, 2003)

Assortment heterogeneity represents how products differ within a sector. Sectors with higher levels of heterogeneity lead to lower direct price competition, higher margins on prices, and more variability in prices (Chamberlin, 1965). Heterogeneity of supply is related to heterogeneity in demand (Dickson, 1992). These different demand patterns lead to imbalances in the sector as retailers shift to serve more segments (Dickson, 1992). This dynamism in the market could translate into price dynamism because retailers are likely to lower prices when markets change. Hence, as assortment heterogeneity increases, price variation and average discount increase (Voss & Seider, 2003).

The effect of assortment heterogeneity depends on whether heterogeneity is predominantly within- or cross-retailer (Voss & Seider, 2003). Heterogeneity within the retailer occurs when there is higher concentration among manufactures, which have wide, large and deep assortments. For example, electronics stores sell mostly the same products, provided by the same manufactures. Cross-retailer heterogeneity occurs when there is concentration among both the retailer and the manufacturer. For example, clothing stores only sell a limited amount of brands that are different from other clothing stores.

Therefore, price promotional activity is higher in sectors that are characterized by high perishability and homogenous cross-retailers compared to sectors characterized by high perishability and heterogeneous cross-retailers (Voss & Seider, 2013). Table 3 represents the relative values for the perishability and heterogeneity of the goods and the heterogeneity among retailers. A strong price promotion strategy is therefore more likely for sectors with high levels of assortment perishability and heterogeneity and low levels of retailer heterogeneity. The interpretation of Table 4 is added to the missing sectors in Table 2.

Table 3 The Effect of Sector Differences on Price Promotion Strategies

	Price variation	Price promotion advertisement	Avg. depth of discount
Assortment perishability	Positive effect	Positive effect	Positive effect
Assortment heterogeneity	Positive effect	No effect	Positive effect
Ass. Perishability x Ass. Heterogeneity	Negative interaction	Negative interaction	Negative interaction

Note. Adapted from “Exploring the effect of retail sector and firm characteristics on retail price promotion strategy” by G.B. Voss and K. Seiders, 2003, *Journal of Retailing, 79*(1), 46.

Table 4 Sector Characteristics

	Assortment		Retailer Heterogeneity	
	Perishability	Heterogeneity	Within	Cross
Jewelry	-	+	+	-
Shoe	+	+	+	-
Sports	+/-	-	+	-
Toy	+	+	+	-
Car	-	+	+/-	+

Table 2 shows that the predicted intertemporal shift differs between sectors. Both the intertemporal pattern and intertemporal effect contribute to the interpretation of the intertemporal shift. The previous hypotheses indicated whether the intertemporal shift is stable. As a result, this shift can be compared for the final hypotheses. Therefore, the final hypotheses are:

H3a: The intertemporal pattern differs between sectors.

H3b: The intertemporal effect differs between sectors.

3. Data

This thesis focuses on the unadjusted retail trade data compiled by the US Bureau of the Census. All data is monthly and covers the period from January 1992 to December 2017. The retail economy consists of different aspects, 12 retail sectors are included in this thesis. These 12 series all correspond to different facets of the retail economy. Because of these different facets, it can be expected that the intertemporal pattern differs over various types of products. The twelve retail series highlighted in this thesis are summarized in Table 1 (see section 2.3.).

The data is monthly because seasonality can be influenced by calendar changes. However, weekly data would be too short for an interval. For example, Easter does not have a specific date.

A summary of the seasonal pattern is provided in Table 5. First, in the second column, the average sales of monthly observations in the series data are shown. Furthermore, the table also gives the averages of a particular month relative to the total average. Generally, the retail sector seems highly seasonal.

Some aspects should be highlighted. The most obvious is the spike in retail sales occurring in December for about all sectors. The peak through November and December is almost invariably the highest. Another interesting point is that after a peak period, the following month shows a trough. This could be the result of an intertemporal effect.

This table only gives a first impression of the seasonal patterns. However, interpreting these tables gives an estimation of where the seasons are in the distribution.

Table 5 Summary Statistics of Monthly Retail Sales For Different Sectors

Sector	Overall average	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Electronic	€ 7,561.39	-7.2%	-9.7%	-5.9%	-14.6%	-9.1%	-7.1%	-6.2%	-1.6%	-7.6%	-7.9%	14.9%	61.9%
Food	€ 43,168.13	-3.8%	-9.4%	-1.1%	-3.0%	2.8%	-0.1%	3.1%	1.8%	-2.1%	0.3%	0.9%	10.8%
Jewelry	€ 2,130.32	-34.4%	-4.7%	-22.4%	-19.2%	2.7%	-15.1%	-19.1%	-14.7%	-20.5%	-16.1%	5.9%	157.5%
Shoe	€ 2,155.88	-26.4%	-13.8%	1.0%	0.8%	0.6%	-6.0%	-2.2%	24.6%	-6.9%	-6.4%	0.0%	34.6%
Clothing	€ 11,506.79	-26.5%	-21.3%	-3.3%	-4.2%	-1.3%	-6.4%	-5.6%	3.1%	-6.5%	0.2%	13.7%	58.1%
Sports	€ 2,603.20	-23.9%	-22.9%	-2.6%	-4.3%	-0.2%	8.2%	4.0%	11.1%	-8.1%	-14.1%	-2.9%	55.8%
Toy	€ 1,324.26	-30.6%	-27.9%	-16.8%	-20.6%	-23.0%	-22.9%	-21.1%	-22.0%	-20.2%	-7.7%	53.6%	159.2%
Book	€ 1,118.14	49.8%	-21.6%	-23.8%	-27.1%	-17.1%	-17.7%	-19.7%	52.5%	12.6%	-21.5%	-17.7%	51.3%
Car	€ 57,196.73	-12.7%	-8.0%	7.1%	1.2%	6.2%	4.7%	5.9%	8.5%	-1.7%	-1.5%	-7.7%	-2.1%
Furniture	€ 4,078.43	-6.5%	-5.6%	2.4%	-5.9%	-0.1%	-2.1%	-0.2%	3.7%	0.3%	-0.9%	6.3%	8.7%
Home Fur	€ 3,366.18	-15.7%	-18.4%	-5.9%	-8.5%	-2.8%	-2.6%	0.1%	4.8%	-1.9%	1.9%	14.0%	35.0%
Gen Merch	€ 41,026.83	-17.3%	-15.1%	-5.2%	-6.5%	-0.4%	-3.4%	-4.6%	-0.1%	-8.5%	-1.7%	12.9%	49.8%

3.1. Testing for Seasonality

This thesis attempts to investigate the intertemporal shift of seasonal fluctuations in retail sales by examining the seasonal distribution of sales across multiple sectors in the US. The previous section shows that sales patterns can strongly differ across retail sectors. Most of the series show signs of a present seasonal pattern. Therefore, to identify and strengthen the use of a particular season, these periods are first tested for significance. A simple method for defining the seasons in a time series is considering the months that are systematically over or under the trend-cycle of the series (Lim & McAleer, 2001).

To identify the trend and cyclical components of a time series, the data first has to be smoothened. Smoothing the data involves a form of local averaging of data. Thus, the nonsystematic components of individual observations cancel each other out. Moving average is the most common smoothing technique (Crowder, 1989).

With straightforward calculations, this technique is convenient in its computation. In order to use this approach, it has to be assumed that the seasonal structure remains constant over time. Hence, the peaks and troughs generally occur in the same period each year. It is also assumed that a moving average satisfyingly expresses the trend and cyclical components in the series data. The following transformation calculates a centered 12-month moving average of retail sales:

$$\mathrm{MA_t} = \frac{[\mathrm{A_{t+6}} + 2\sum_{\mathrm{k=1}}^{11}(\mathrm{A_{t+6-k}}) + \mathrm{A_{t-6}}]}{24} \tag{1}$$

$\mathrm{MA_t}$= the centered moving average of retail sales for month t.

$\mathrm{A_t}$ = the retail sales in month t.

k = number of lags.

Dividing the original retail sales by the corresponding moving average for each month obtains the ratio-to-moving averages. These ratios intend to eliminate the trend and cyclical component. This results in a data series containing seasonal and irregular movement.

$$\mathrm{P_t} = \frac{\mathrm{A_t}}{\mathrm{MA_t}} \tag{2}$$

These calculated ratios are then averaged by month in which the lowest- and highest ratio are excluded. By doing this, the irregular movements are eliminated before isolating the seasons. The monthly averaged ratio are displayed in Table 6.

Table 6 Average Monthly factors for different sectors

Sector	Jan.	Feb.	Mar.	Apr.	Mei.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Electronic	0.940	0.910	0.948	0.860	0.912	0.931	0.938	0.982	0.920	0.916	1.132	1.611
Food	0.973	0.913	0.997	0.975	1.031	1.001	1.031	1.015	0.974	0.994	0.998	1.096
Jewelry	0.659	0.954	0.776	0.809	1.027	0.850	0.807	0.850	0.787	0.831	1.052	2.579
Shoe	0.747	0.862	1.015	1.017	1.017	0.949	0.978	1.237	0.930	0.933	0.988	1.326
Clothing	0.744	0.791	0.971	0.962	0.988	0.934	0.938	1.030	0.932	0.996	1.126	1.580
Sports	0.777	0.779	0.980	0.971	1.007	1.085	1.038	1.106	0.914	0.847	0.949	1.546
Toy	0.693	0.721	0.835	0.794	0.768	0.769	0.789	0.776	0.790	0.916	1.532	2.589
Book	1.502	0.786	0.762	0.730	0.830	0.822	0.799	1.524	1.125	0.784	0.822	1.508
Car	0.889	0.933	1.085	1.025	1.069	1.054	1.059	1.083	0.973	0.974	0.905	0.952
Furniture	0.947	0.950	1.029	0.947	1.002	0.978	0.997	1.034	0.996	0.984	1.054	1.078
Home Fur	0.854	0.826	0.949	0.926	0.977	0.974	1.002	1.043	0.976	1.013	1.128	1.329
Gen Merch	0.829	0.849	0.952	0.939	0.999	0.966	0.948	0.993	0.907	0.974	1.122	1.506

The results in Table 6 should be interpreted as follow: the difference between 1 and the respective factor is the change in percentages compared to the mean. For example, for the electronics sector, the factor for December is 1.611, so this is 61.1% higher than the mean. Likewise, for February the factor is 0.91, so this is 9% lower than the mean.

The results of Table 6 can be compared to Table 5. These two tables show similar results, which justifies the use of factors calculated with the moving average technique. Now, these monthly averaged indices can be used to test which months are seasonally significant. Months are seasonally significant if the respective index mean statistically differs from the means of the other months. This would mean that the seasonal factors increase/decrease retail sales above/below the trend and cyclical components.

First, a one-way ANOVA tests whether there are significant differences between the means of months. The conventional 5% significance level is used. The hypotheses of an ANOVA are the following:

H0: u1=u2=u3…=u12

Ha: Means are not all equal.

If the null hypothesis is accepted, the distribution does not show any significant differences between the months. In this case, the seasonal effect is assumed to be zero. If the null hypothesis is rejected, months do significantly differ from each other.

The results of this test show that the null hypothesis is rejected for all sectors (see Appendix 9.1.). Hence, the means of the months are not equal for all retail sectors. However, this does not necessarily mean that the seasonal effect is large or that whether months can be grouped together.

3.2. Identifying Seasons

The seasonal structure, or intertemporal demand shift, indicates to what degree a month contributes to the seasonal peak in another month (Peers et al., 2012). Therefore, it is assumed that seasonal activity is the result of consumers delaying or speeding up their purchases. Hence, the peak, or trough of a particular month, is the sum of the intertemporal choices consumers made in other months.

Taking this into respect, a set of focal months has to be identified. A focal month is a month that is significantly different from all other months. To determine this, the differences between months should be analyzed. The ANOVA tells if there are differences between months. A post-hoc of the ANOVA tells which months actually differ from each other. Therefore, the Bonferroni post-hoc test is used to identify significant differences (see Appendix 9.2.).

A focal month can be either a peak or a trough. Consecutive focal months are often interpreted as the core of a season. Additionally, if there is a reason to believe other months influence this focal period, these can be added to the season.

3.2.1. Seasons per Sector

From this point out defining the seasons per sector becomes slightly arbitrary. Where a combination of interpreting previous tables, the post hoc test and institutional knowledge attribute to the definition of a season. Because defining a season in this thesis does include some interpretation of the data, a short explanation of the seasons per sector is included.

Electronic; the post hoc test shows that April, August, November, and December are the focal months. However, there are no important significant differences among the remaining months. Therefore, these months do not show any seasonal effect. This can also be seen in both tables, where the remaining months seem similar in their sales. Only November and December are consecutive months that show seasonal influence. Hence, the only season in the electronic subsector is November-December.

Food; This subsector does show significant differences among months. However, besides February and December, the relative differences between months are small. February has the fewest days per year and December includes the holidays, where people, in general, eat more.

Since there is no large seasonal effect in the other months, no grouping of months is formed. This means that there is no season in the food subsector.

Jewelry; the focal months are January and December. Other months that show large differences compared to the remaining months are: February, May, and November. The remaining months do not show large differences between them. February sales are probably the result of Valentine’s Day. January is caught in the middle of two periods. Because Valentine’s Day is an event on itself, this thesis assumes that the intertemporal effect for February is more inter-monthly. Therefore the only season includes: November-January.

Shoes; the focal months are January, February, August, and December. In the remaining months, only September and October show large differences compared to the rest. Therefore the two seasons are: August-October and December-February.

Clothing; the focal months are January, February, November, and December. The other months do not show large differences between them. Therefore the only season is November-December.

Sports; the months in this subsector all show large differences from each other. Therefore the post hoc test shows almost only focal points. Seasons can be identified by averaging the factors and leave out the month that differ the most, until a group of months is left that do not show large differences. This process eventually showed two seasons: June-October and December-February.

Toys; the focal months are November and December. January, February, and October also show a large difference compared to the fairly homogeneous rest of the year. Therefore, the season is October-February.

Books; the focal months are January, August, September, and December. The remainder of the year is fairly equal in monthly sales. Therefore there are two seasons: December & January and August & September.

Cars; no clear focal month can be identified. Therefore, no season in sales can be defined.

Furniture; no clear focal month can be identified. Therefore, no season in sales can be defined.

Home Furniture; the focal months are January, February, November, and December. The other months do not show large differences between them. Therefore the only season is November-December.

General Merchandise; the focal months are January, February, November, and December. The other months do not show large differences between them. Therefore the only season is November-February.

4. Method

This section explains the method that leads to interpretable results. The inequality measurements are explained in more detail. Furthermore, the differences between these measurements are highlighted. Finally, some statistical tests that determine the stability of a time series are introduced. These tests include the Augmented Dickey-Fuller test, Philips Perron and Kwiatkowski, Philips, Schmidt and Shin test**.**

4.1. Inequality Measurement

Inequality measurements for retail sales indicate how much inequality exists between months or seasons in a single year. The activity of seasonal concentration takes a calendar month as the unit of reference. The inequality measures would, therefore, be inter-monthly inequality measures of activity. With respect to measuring inequality, the most widely recognized measure is the Gini Coefficient (Gini, 1912). However, given its characteristics, a joint use of the Gini Coefficient, Theil T1, Theil T0, and CV are analyzed.

First, the overall inequality in the distribution is measured. Furthermore, a distinction will be made in the inequality between and within months. This gives an indication of the overall inequality in the distribution and how this comes into being.

The first step deals with the overall inequality of the distribution. This gives an idea of how seasonal the retail sector is. However, to be able to better understand the inequality measures, these indices should be decomposed. This is explained in the next section (4.2.). First, the mathematics behind each inequality measure is explained.

4.1.1. Gini coefficient

Based on the Lorenz curve, the Gini coefficient measures twice the area between the curve and line of perfect equality. Generally, this coefficient gives a value between 0 and 1. Where 0 means that all monthly sales are equal. An index of 1 occurs if all sales take place in one month. The Gini coefficient for annual retail sales data with a monthly sales distribution of X is defined as:

$$G(X) = \frac{E(|X_1 - X_2|)}{2\mu_x} \tag{3}$$

Where X_1 and X_2 are independent and identically distributed random variables with distribution X and μ_x is the mean of the retail sales distribution. For a given sample from X, Gini proposed his R concentration. This concentration is based on the cumulative proportion of months $p_i = i/n$ and sales $q_i = A_i/A_n$ (Basulto and Busto, 2010).

$$R = \frac{\sum_{i=1}^{n-1}(p_i - q_i)}{\sum_{i=1}^{n-1} p_i}, \forall n \quad (4)$$

This formula ranges from $R = 0$ for total equality, so when all months have the same sales value, to $R = 1$ for maximum concentration, if one month has all the annual sales. Gini's mean difference indicates that:

$$R = \frac{\Delta}{2\frac{A_n}{n}} \quad (5)$$

Where Δ is the mean difference. Pietra (1915) stated that:

$$R = \frac{A}{maxA} = \frac{\Delta}{2\mu} \quad (6)$$

Here the concentration area is given by A and the maximum concentration area is max A. There are extensive contributions based on the work of Gini. Giorgi (2005), describes two expressions to address Gini's mean difference. First, to measure inequality when the mean difference is without repetition is (Jasso, 1979).

$$\Delta_{nr} = \Delta_{no\ rep} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{n(n-1)} \quad (7)$$

Furthermore, Allison (1978), Dagum (1997) and Frosini (2012) define the mean difference with repetition as:

$$\Delta_r = \Delta_{with\ rep} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{n^2} \quad (8)$$

Yitzhaki & Schechtman (2013) state that the former is valid for discrete distributions. The latter provides the answer for continuous distributions. Because of the nature of retail sales, this thesis continues with the latter, Δ_r. So given the distribution, the total Gini ratio being used is formulated through:

$$G = \frac{\Delta}{2\bar{Y}} = \frac{1}{2\bar{Y}}\sum_{i=1}^{n}\sum_{r=1}^{n}|Y_i - Y_r|/n^2 \quad (9)$$

The use of this formula leads to a $(n - 1/n) * 100\%$ of the Gini ratio. So the range on a monthly bases is (0; 0.9167). For example, in the case of evenly distributed monthly sales gives a Gini index of 0. In the case that one month has all the yearly sales, the Gini index is 0.9167. Furthermore, R is independent of size. This makes it possible to compare distributions of different size. For a better interpretation of the Gini index, the boundaries are set to (0, 1).

This is possible with a simple computation of $G/(n-1/n)$. This makes it easier and more intuitive to compare inequality measures.

4.1.2. Theil Index

The Theil index is a statistic measure of inequality. This index is primarily used as an economic inequality index. Inequality measures differ mostly in their sensitivity to changes in different parts of a distribution. In this respect, Theil (1967) introduced a family of inequality measures based on the entropy concept. The Theil indices satisfy the properties of income distribution measurement. For the Theil indices, an entropic distance from the state of equal distribution is measured, where the numerical value is in terms of negative entropy. Therefore, the value is an increasing measure of inequality in the distribution of retail sales (Conceição & Galbraith, 2000; Chongvilaivan & Kim, 2016). The following formula is the general expression of the Theil index:

$$GE_\beta = \frac{1}{\beta(\beta-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{Y_i}{\bar{Y}}\right)^{\beta} - 1\right] \text{ (β is not equal to 0)} \quad (10)$$

Where Y is the mean retail sales. The sensitivity to changes in different places of the distribution is captured by β. This means that β represents the weight that has been given to distances between retail sales at different parts of the time series. The lower the value of the parameter, the more the index is sensitive to changes in the lower tail of the distribution. In contrast, a higher value for β would mean that the index is more sensitive to changes in the higher rankings (Jenkins, 2009). From the family of Theil indices, the two that are being used the most are:

$$\text{Theil T1: } GE(1) = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\bar{y}}\ln\left(\frac{y_i}{\bar{y}}\right) \quad (11)$$

$$\text{Theil T0: } GE(0) = \frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{\bar{y}}{y_i}\right) \quad (12)$$

The Theil measures do not have certain boundaries and can vary between 0 and infinity (Allison, 1978), which could cause some problems directly comparing products. For a Theil index to reach an extreme value, the distribution has to be skewed in an unlikely manner. For example, in a situation where one month has 1000 sales and all other months have sales equal to 1, T1= 2.4 and T0= 3.8. Nonetheless, in this thesis, it is more interesting to interpret the pattern of the Theil indices. Since the monthly factors have been used to estimate the seasons, the Theil indices of a sector are comparable across time.

4.1.3. Coefficient of Variation

Finally, the Coefficient of Variation (CV) measures the dispersion of a distribution. Where the higher the value for the CV indicates a larger disparity among months. Because neutral sensitivity, the CV is not more sensitive to changes in specific parts of the distribution. The CV can be defined by the ratio between the standard deviation to the mean (Wei et al., 2011). Similar to the Theil index, the CV may vary between 0 and infinity. The CV is mathematically expressed as:

$$CV = \frac{\sigma}{\mu} \tag{13}$$

4.2. Decomposing Inequality Measurements

The Theil indices that are used do not only meet the basic properties, they also allow to be decomposed in additive parts. An aggregative index can be decomposed with two different approaches; by group and by source. In this thesis only the former is applicable. In the previous sections, the series data has been divided into groups in order to analyze what part of total inequality can be explained by the difference between seasons. To further analyze this part of inequality, the aggregate index can be additively decomposed into two parts. The first part represents the between-group component, which describes the average dissimilarity between groups. Second is the within-group component. This measure expresses the internal differences in a season.

In the previous section, the annual level of seasonality is measured. While in this section this level is decomposed to provide a measure of the stability of the seasons. Moreover, the within-and between group components give a better understanding on the presence of an intertemporal shift.

4.2.1. Decomposing the Gini index

The decomposition of the Gini coefficient only holds in cases where groups do not overlap and when the inequality within a group is zero (Zagier, 1983). This method assumes that inside each season the retail sales are evenly distributed, not taking monthly asymmetry into consideration. Because understanding the implications of inequality within a season is important for this thesis, a decomposition of the Gini index into two components (within- and between seasons) does not hold.

However, to test the degree of importance of the within- and between season components can directly be done with the general Gini coefficient formula. The within season inequality is calculated with G, see formula (9) for the months in a particular season.

The between season component can also be identified with the use of G. In this case, the monthly average of a season is used. For example, a season of November, December, and January, with values of 10, 20 and 30 respectively. Calculating the between seasons inequality would use the value of 20 ((10+20+30)/3) for the months November-January. By averaging the monthly sales in a season, this between season component controls for the intertemporal shift. In other words, the monthly sales values of seasonal months are replaced by the average monthly sales of the respective season. This allows to determine the inequality between the average seasonal demand and the rest of the year. This between inequality value shows to what extent the intertemporal shift controls for monthly seasonal fluctuations.

By interpreting both the within- and between inequality component, an estimation on the magnitude of the intertemporal effect can be made. For example, if the intertemporal shift controls for the seasonal spike in sales, the within seasonal inequality is relatively large while the between seasonal inequality component is relatively low. In other words, there are large differences within a season while the monthly average seasonal sales is equal to the average sales in months outside the season. Hence, in combination with a large within season inequality, a small between season inequality shows that intertemporal shift is large.

The relative weights of the within- and between component can be interpreted by dividing the Gini coefficient by their respective $n/(n-1)$. This sets all boundaries to (0,1). Interpreting these results give a good idea of how the annual inequality is influenced.

4.2.2. Decomposing the Theil Index

One advantage of the family of Theil indices is that they are always additively decomposed in two components; within- and between group. The decomposition of both Theil indices is represented by the following mathematical expressions;

$$T(1) = \sum_{i=1}^{N} \frac{y_i}{N\bar{y}} \ln\left(\frac{y_i N}{\bar{y} N}\right) = \sum_{i=1}^{N} \frac{y_i}{Y} \ln(\frac{y_i N}{Y})$$

$$= \sum_j \left(\frac{Y_j}{Y}\right) T_j + \sum_j \left(\frac{Y_j}{Y}\right) \ln\left(\frac{Y_j/Y}{N_j/N}\right) \tag{14}$$

$$T(0) = \sum_{i=1}^{N} \frac{1}{N} \ln\left(\frac{Y}{Y_i N}\right) = \sum_j \left(\frac{N_j}{N}\right) L_j + \sum_j \frac{N_j}{N} \ln\left(\frac{N_j/N}{Y_j/Y}\right) \tag{15}$$

Both decompositions result in a within- and between group component. Bourguignon (1979) showed that both T(1) and T(0) are the only zero-homogeneous decomposable measures. This is important because the weights of the within- and between group inequalities sum to the total inequality value. Where the first part in both equations represents the within group component. The second part in both equations represents the between group component.

4.2.3. Decomposing the Coefficient of Variances

The CV is not decomposable in the between- and within group components. Goerlich (1998) showed that the CV decomposition is ambiguous and the components would not sum up the total inequality index.

However, similar to the approach in section 4.2.1., a within- and between group component can be estimated. By applying the CV formula within a season, the within season inequality can be assessed. Moreover, the between season component can be estimated by averaging the monthly values in a single month and calculate the total inequality.

4.3. Differences Between the Inequality Measures

There are multiple tools that can be used to analyze inequality. Each measurement puts different weights on the changes in different parts of the distribution. The indices could complement each other and explain the main characteristics of seasonality in retail sales. Hence, a joint comparison could contribute to a complete profile of seasonality. This can provide information on the stability and heterogeneity of seasonal effects of retail sales sectors.

The differences in sensitivity can give different insights while comparing the results. The Theil indices give an indication of the influence of the extreme values and how this progressed over time. Meanwhile, the Gini index is more sensitive to changes in the middle of the distribution. Therefore giving an indication of how stable the months are out of the season. By also including the results of the neutral CV, an interpretation of the joint use can give a more unbiased picture of the pattern in retail sales over time. Moreover, giving a better estimation of the quantitative differences between inequalities.

4.4. Application of the Method

In order to better understand the application of the inequality measures, the method is explained with multiple hypotheses. Each inequality measurement produces multiple values.

A joint interpretation of these values leads to answering the hypotheses stated in the theoretical framework.

First, the relation between stability and stationarity should be clear. For a process to be stable, all parameters that measure this process should also be stable. In this thesis, the process of intertemporal effect is measured by multiple time series of inequality measures. A series is considered to be stable if the mean and variance remain constant.

A stationarity test holds the same assumptions. A time series is stationary if the statistical parameters like mean, variance and covariance do not fluctuate over time. If these conditions do not hold, a series is non-stationary (Teverovsky & Taqqu, 1997). Therefore, in this thesis, stationary tests are used to determine whether an inequality series is stable.

The within seasonal inequality series show how unequally the months are distributed within a single season. The intertemporal pattern is stable if the relative proportions between the seasonal months do not fluctuate. In this case, all inequality measurements used in this thesis produce stable series that do not change over time. Therefore, a stable within seasonal inequality series indicates a stable intertemporal pattern. Conversely, an unstable within inequality series indicates that the relative proportions of sales within a season change over time, which result in an unstable pattern. Since four inequality measurements are used in this thesis, the hypotheses that assess the stability of the intertemporal pattern are:

- The Gini within seasonal inequality series is stationary.
- The Theil T1 within seasonal inequality series is stationary.
- The Theil T0 within seasonal inequality series is stationary.
- The CV within seasonal inequality series is stationary.

The between seasonal inequality series indicate to what extent the intertemporal shift controls for the increase of retail sales. A season consists of sales peaks and troughs. The between seasonal inequality value shows to what extent the average monthly sales are higher in a season compared to non-seasonal months. For example, take the case of a retail season that consists of two months, one peak and one trough. If the sales in the peak month are 10 higher and the sales in the trough month are 10 lower compared to the non-seasonal months, there would be no inequality between seasons. Moreover, in this case, the intertemporal shift controls for the increase in sales during the peak month. Hence, a high between inequality value represents a season with a small intertemporal effect. This means, that the between inequality value indicates to what extent the intertemporal shift controls for the sales peak.

Thus, a stable between season inequality series shows the stability of the intertemporal effect. Therefore, the second set of hypotheses is:

- The Gini between seasonal inequality series is stationary.
- The Theil T1 between seasonal inequality series is stationary.
- The Theil T0 between seasonal inequality series is stationary.
- The CV between seasonal inequality series is stationary.

In order to answer whether intertemporal patterns differ between sectors, only sectors with the same structure can be compared. This means that seasons are grouped together by type of season, so with the same number of peak and trough months. Furthermore, seasons can only be compared if the intertemporal pattern is stable. If the intertemporal effect within a season is not stable, it is not possible to compare seasons within the same sector across the timeframe. Hence, it is not possible to compare unstable intertemporal effects across sectors. Only the seasons with the same structure and stable intertemporal patterns can be compared. The hypothesis only includes the Gini coefficient, because a joint use of inequality measures does not has any added value. Moreover, the Gini coefficient always has a value between 0 and 1. This makes it possible to directly compare this coefficient. Therefore the following hypothesis indicates whether the intertemporal pattern is equal between two seasons:

- The mean Gini within inequality series is equal between seasons.

Finally, it is possible to answer whether the intertemporal effect differs between sectors. In order to answer this question, it is not necessary for seasons to have the same structure. The intertemporal effect represents to what extent the intertemporal shift controls for a spike in sales. This does not depend on the structure. For example, the intertemporal shift can fully control the peak sales month in either a season with two or three months. However, only seasons with a stable intertemporal effect can be compared. If this effect fluctuates over time, the intertemporal effect cannot be compared within the same sector. Again, only the Gini coefficient has to be compared. Therefore, the fourth, and final hypothesis is:

- The mean Gini between inequality series is equal between seasons.

4.5. Testing for Stationarity

Through the previous sections, the yearly intertemporal pattern and intertemporal effect per sector can be estimated. This produces multiple time series for each type of inequality measurement. Therefore, determining the stability of the intertemporal effect can be difficult.

As explained in the previous section, testing for stationarity is used to determine stability. First, it is estimated whether the inequality series are stationary. Second, a conclusion is drawn on the stability of these inequality series.

There are various approaches that examine the stationarity of time series data. Generally, the most popular approaches include the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and the Kwiatkowski, Philips, Schmidt and Shin (KPPS) test. Where both ADF and PP test for the presence of a unit-root and KPSS tests for stationarity. These tests complement each other and are used in order to determine the stability of the inequality series.

4.5.1. Unit-Root Test

Unit-root tests like ADF and PP test whether time series possess a unit-root and are non-stationary (Chowdhury & Mavrotas, 2006). The null hypothesis for these tests are defined as: there is a unit-root present in the time series. The alternative hypothesis is therefore stationarity. However, in order to perform the ADF and PP test, certain components have to be specified.

First, it needs to be specified whether the series has a constant, a constant and a trend, or neither. Since the inequality series move around a constant, this specification is included. The trend stationarity will not be determined with the unit-root tests. This is also included in the KPSS test, which is explained in the next section.

Second, in the case of ADF, the appropriate number of lagged difference has to be determined. Too few lags could cause over rejecting the null hypothesis if it is true. Conversely, too many lags diminish the power of ADF to reject the null hypothesis (Harris, 1992). One approach to determine the lags is based on the Akaike Information Criterion (AIC). Doing so, the lag length that minimizes the information criteria is chosen (Hall, 1994).

An in-depth analysis of the ADF and PP tests is beyond the scope of this thesis. Nonetheless, an elaborate explanation on the mathematics of the ADF can be found in the following papers: Hall (1994) and Cheung & Lai (1995). More information on the PP test can be found in Philips & Perron (1988).

Maddala and Wu (1999), describe the main criticism of the ADF and PP test. They argue that the power of these tests is low if the time series is almost non-stationary. This means that ADF would propose problems if the series is stationary, but with a root close to the boundary of non-stationary. Therefore, a more lenient significance level of $p<0.1$ (compared to $p<0.05$) is used with respect to the ADF and PP tests in this thesis.

4.5.2. Stationary Test

Since the unit-root tests lack power, Kwiatkowski, Phillips, Schmidt, and Shin (1992) developed an alternative approach to test whether a time series is stationary. The KPSS test estimates whether a time series is stationary around a mean, or linear trend. Hence, the null hypothesis is that the process is trend stationary. The alternative hypothesis is that the series is not stationary. Thus, in the absence of a unit root, KPPS labels a series as stationary.

With the mention of trend stationary, it is important to understand the different types of stationarity and how to interpret the results. First, strict stationary series satisfy the statistical parameters like mean, variance and covariance to not fluctuate over time. A strict stationary series is in this thesis perceived to be stable. Second, a trend stationary series does not have a unit root, but shows a trend. In this case, the time series stably increases or decreases. Finally, a non-stationary series can often only become stationary after differencing. These series are labeled as not stable.

The ADF, PP and KPSS test are used jointly in order to determine whether the inequality series are stable. Therefore, each possible outcome is described. Since the ADF test and PP test often show the same results, the interpretation of these outcomes is combined in this example.

- Both the ADF and KPSS test conclude that the series is not stationary. This means that the inequality series is not stable.
- Both the ADF and KPSS test conclude that the series is stationary. This means that the inequality series is stable.
- The ADF test concludes the series has a unit root and the KPSS test concludes that the series is stationary. This means that the series is trend stationary. Hence, the inequality is stable with a trend.
- The ADF test concludes that there is no unit-root. However, the KPSS test does not find proof for a stationary series. In this case, the series is not stationary and thus not stable.

5. Results

The methodology has been applied to the data with the use of EViews and Excel. The evolution of the inequality coefficients can be found in Appendix 9.3. The results of the ADF, PP, and KPSS tests are summarized in Table 7, Table 8 and Table 9. The joint interpretation of these results answer the hypotheses stated in the theoretical framework.

The data is monthly distributed for each retail sector. Most retail sectors have a season that includes December and January. Therefore, it is preferable to group these months together in a chronological timeframe. Otherwise, the trend could bias the relations. Hence, the data covers the fiscal years of the period 1993-2017. In the USA, a fiscal year starts in October and ends in September, the next year. Thus, October 2016-September 2017 represents the fiscal year of 2017.

Appendix 9.3. shows the inequality series for each sector. The within inequality series represent the intertemporal patterns. It appears that most inequality measures do not fluctuate much from the mean. In other cases, the within inequality series show a pattern. The inequality measures do find intertemporal patterns. Therefore, hypothesis H1a is accepted. Other tests have to be applied in order to test the stationarity of these series.

The between inequality series represent the intertemporal effect for each sector. Similarly to the within inequality series, the between inequality series show a pattern in most cases. Therefore, hypothesis H1b is accepted. The stationarity has to be tested.

5.1. Testing for Stationarity

Table 7, Table 8, and Table 9 show the results of the stationary tests. These tables also have some missing values. This is the case if there is no respective series to test for stationary. For example, the food sector does not have a season, so it is not possible to assess the between and within seasonal inequality. Another example, the electronics sector has one season, so there is no within inequality series for the summer season.

Table 7 Results Augmented Dickey-Fuller test

Sector	Gini Total	Gini Between	Gini With Wint	Gini With Sum	CV Total	CV Between	CV With Wint	CV With Sum
Electronic	-3.108**	-3.098**	0.275	-	-2.279	-2.032	0.275	-
Food	-1.987	-	-	-	-2.091	-	-	-
Jewelry	-0.955	-1.054	-1.079	-	-0.931	-0.380	-1.140	-
Shoe	-1.757	-2.810*	-1.145	-	-1.310	-1.036	-1.885	-
Clothing	-2.399	-1.499	-1.457	-	-1.584	-2.402	-1.522	-
Sport	-2.393	-1.522	-2.928*	-3.150**	-2.936*	-0.885	-3.088**	-2.987**
Toy	-1.322	-1.729	-2.149	-	-2.649*	-1.564	-2.937*	-
Book	-1.271	-1.339	-2.922*	-1.479	-1.325	-1.296	-2.922*	-1.479
Car	-3.864***	-	-	-	-3.929***	-	-	-
Furniture	-3.607	-	-	-	-3.333**	-	-	-
Home Furn	-3.031**	-3.315**	-3.303**	-	-2.511	-3.320**	-3.435**	-
Gen Merch	-4.344***	0.525	-4.211***	-	-4.171	0.559	-4.174***	-

Sector	T1 Total	T1 Between	T1 With Wint	T1 With Sum	T0 Total	T0 Between	T0 With Wint	T0 With Sum
Electronic	-2.438	-1.923	0.068	-	-2.555	-1.878	-0.130	-
Food	-2.047	-	-	-	-2.059	-	-	-
Jewelry	-0.886	-0.380	-0.955	-	-0.885	-0.383	-1.071	-
Shoe	-1.381	-0.914	-1.764	-	-1.543	-0.874	-1.849	-
Clothing	-1.618	-1.875	-1.583	-	-1.554	-1.983	-1.507	-
Sport	-2.553	-0.782	-2.930*	-2.883*	-2.562	-0.796	-3.023**	-2.872*
Toy	-2.851*	-1.779	-2.924*	-	-3.430*	-1.801	-2.452	-
Book	-1.199	-1.318	-2.889*	-1.459	-1.221	-1.319	-2.868*	-1.401
Car	-4.012***	-	-	-	-3.982***	-	-	-
Furniture	-3.172**	-	-	-	-3.168**	-	-	-
Home Furn	-2.642*	-3.323**	-2.847*	-	-2.872*	-3.309**	-3.141**	-
Gen Merch	-5.867***	-0.064	-6.559***	-	-6.082***	-0.067	-6.142	-

Note. Value is the t-statistic. *** p<0.01, ** p<0.05, * p<0.1. Some values cannot be determined, because these time series do not exist.

Table 8 Results Philips Perron test

Sector	Gini Total	Gini Between	Gini With Wint	Gini With Sum	CV Total	CV Between	CV With Wint	CV With Sum
Electronic	-3.139**	-3.125**	-0.402	-	-2.322	-2.691*	-0.402	-
Food	-1.987	-	-	-	-2.091	-	-	-
Jewelry	-0.691	-0.761	-0.970	-	-0.658	-0.724	-1.051	-
Shoe	-1.757	-2.843*	-1.145	-	-1.310	-2.420	-1.788	-
Clothing	-1.463	-2.301	-1.461	-	-1.599	-2.301	-1.547	-
Sport	-2.299	-3.787***	-3.483	-3.275**	-2.533	-3.373**	-3.513**	-3.087**
Toy	-1.319	-1.604	-1.883	-	-2.563	-1.437	-2.760*	-
Book	-1.391	-1.462	-2.922*	-1.938	-1.307	-1.415	-2.922*	-1.938
Car	-3.657**	-	-	-	-3.675**	-	-	-
Furniture	-3.629**	-	-	-	-3.286**	-	-	-
Home Furn	-3.067**	-2.854*	-3.229**	-	-2.530	-3.078**	-3.098**	-
Gen Merch	-2.272	-0.533	-2.921*	-	-3.392**	-0.385	-3.046**	-

Sector	T1 Total	T1 Between	T1 With Wint	T1 With Sum	T0 Total	T0 Between	T0 With Wint	T0 With Sum
Electronic	-2.488	-2.707*	-0.452	-	-2.612	-2.719*	-0.642	-
Food	-2.047	-	-	-	-2.059	-	-	-
Jewelry	-0.647	-1.037	-0.855	-	-0.643	-1.033	-0.942	-
Shoe	-1.381	-2.377	-1.807	-	-1.543	-2.398	-1.845	-
Clothing	-1.741	-2.363	-1.667	-	-1.577	-2.389	-1.555	-
Sport	-2.497	-2.636**	-3.431**	-2.965*	-2.408	-3.352**	-3.638**	-2.836*
Toy	-2.671*	-1.678	-3.512**	-	-2.115	-1.698	-2.582	-
Book	-1.313	-1.404	-2.889*	-1.954	-1.330	-1.404	-2.868*	-1.998
Car	-3.904***	-	-	-	-3.955***	-	-	-
Furniture	-3.125**	-	-	-	-3.124**	-	-	-
Home Furn	-2.717*	-2.892*	-2.875*	-	-2.872*	-2.862*	-3.177**	-
Gen Merch	-4.592***	-1.056	-4.607***	-	-4.423***	-1.085	-4.329***	-

Note. Value is the t-statistic. *** p<0.01, ** p<0.05, * p<0.1. Some values cannot be determined, because these time series do not exist.

The interpretation is similar for Table 7 and Table 8. The ADF and PP test both test for the presence of a unit root. If this hypothesis cannot be rejected, the value is insignificant and a unit root is present in the series. Conversely, a significant result rejects the null hypothesis of a unit root is present. In this case, the series is not non-stationary.

Table 9 Results KPSS test

Sector	Gini Total	Gini Between	Gini With Wint	Gini With Sum	CV Total	CV Between	CV With Wint	CV With Sum
Electronic	0.229	0.324	0.652**	-	0.179	0.493**	0.653**	-
Food	0.595**	-	-	-	0.599**	-	-	-
Jewelry	0.558**	0.513**	0.570**	-	0.542**	0.536**	0.540**	-
Shoe	0.184	0.200	0.205	-	0.246	0.386	0.284	-
Clothing	0.653**	0.710**	0.662**	-	0.677**	0.699**	0.673**	-
Sport	0.333	0.792***	0.382	0.110	0.492**	0.777***	0.431	0.132
Toy	0.693**	0.659**	0.701**	-	0.696**	0.668**	0.695**	-
Book	0.538**	0.512**	0.103	0.609**	0.557**	0.535**	0.103	0.609**
Car	0.527**	-	-	-	0.525**	-	-	-
Furniture	0.217	-	-	-	0.290	-	-	-
Home Furn	0.142	0.142	0.213	-	0.285	0.120	0.206	-
Gen Merch	0.707**	0.703**	0.706**	-	0.716**	0.710**	0.710***	-

Sector	T1 Total	T1 Between	T1 With Wint	T1 With Sum	T0 Total	T0 Between	T0 With Wint	T0 With Sum
Electronic	0.155	0.473**	0.639**	-	0.143	0.466**	0.661***	-
Food	0.588**	-	-	-	0.591**	-	-	-
Jewelry	0.542**	0.526**	0.550**	-	0.551**	0.524**	0.571***	-
Shoe	0.216	0.393	0.222	-	0.201	0.379	0.256	-
Clothing	0.673**	0.696**	0.670**	-	0.669**	0.695**	0.664***	-
Sport	0.459	0.754***	0.457	0.131	0.417	0.754***	0.432	0.140
Toy	0.689**	0.665**	0.684**	-	0.690**	0.663**	0.688***	-
Book	0.554**	0.541**	0.094	0.574**	0.550**	0.540**	0.104	0.573**
Car	0.500**	-	-	-	0.504**	-	-	-
Furniture	0.296	-	-	-	0.290	-	-	-
Home Furn	0.231	0.127	0.237	-	0.183	0.131	0.175	-
Gen Merch	0.700**	0.703**	0.694**	-	0.698**	0.703**	0.691***	-

Note. KPSS value, *** p<0.01, ** p<0.05. The significance levels are based on the following paper; Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1). Some values cannot be determined, because these time series do not exist.

The KPSS test tests for stationarity. Hence, if the KPSS is insignificant for a series, this series is stationary. Conversely, if the KPSS test is significant, this series is non-stationary. For the KPSS test, it is preferred to use the p<0.05 level for significance.

Table 10 gives a summary of the most important results. The structure indicates what type of months are included per season, where “P” and “T” represent a peak and trough selling month respectively.

Table 10 Summary Result

Season	Structure	Stationary intertemporal pattern	Stationary intertemporal effect
Electronics	P-P	No	No
Food	No season	-	-
Jewelry	P-P-T	No	No
Shoe	P-T-T	No	No
Clothing	P-P-T-T	No	No
Sports winter	P-T-T	Yes	No
Sports Summer	P-P-P-T-T	Yes	No
Toy	P-P-P-T-T	No	No
Book Winter	P-P	Yes	No
Book Summer	P-P	No	No
Car	No Season	-	-
Furniture	No Season	-	-
Home Furniture	P-P-T-T	Yes	Yes
General Merch.	P-P-T-T	No	No

The results in Table 10 show that four seasons have a stationary intertemporal pattern. This means that the relation between the seasonal months does not change over time. The sales trend (see appendix 9.4.) might affect the monthly sales, but this does not influence the relation of the seasonal months. Furthermore, only one season showed a stationary intertemporal effect. This means that the relative magnitude of the intertemporal shift is stable. As an example of a stationary series, Figure 2 shows the output of the neutral CV for home furniture sector. The within- and between seasonal series do not show large fluctuations and the series remains close to its mean. This is an example of a stationary series.

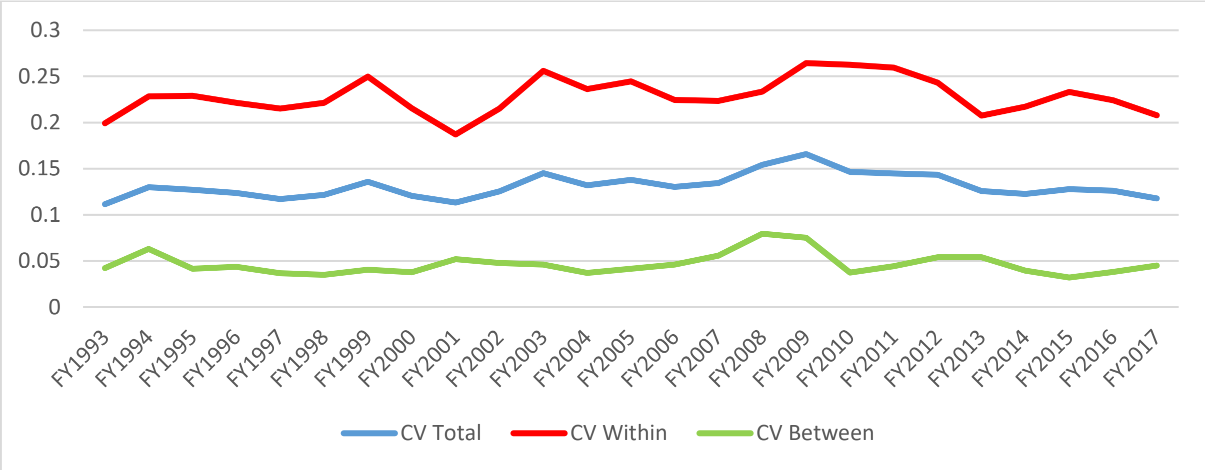

Figure 2 CV inequality series home furniture

In contrast Figure 3 shows the CV series of the electronics sector. This is an example of a non-stationary series.

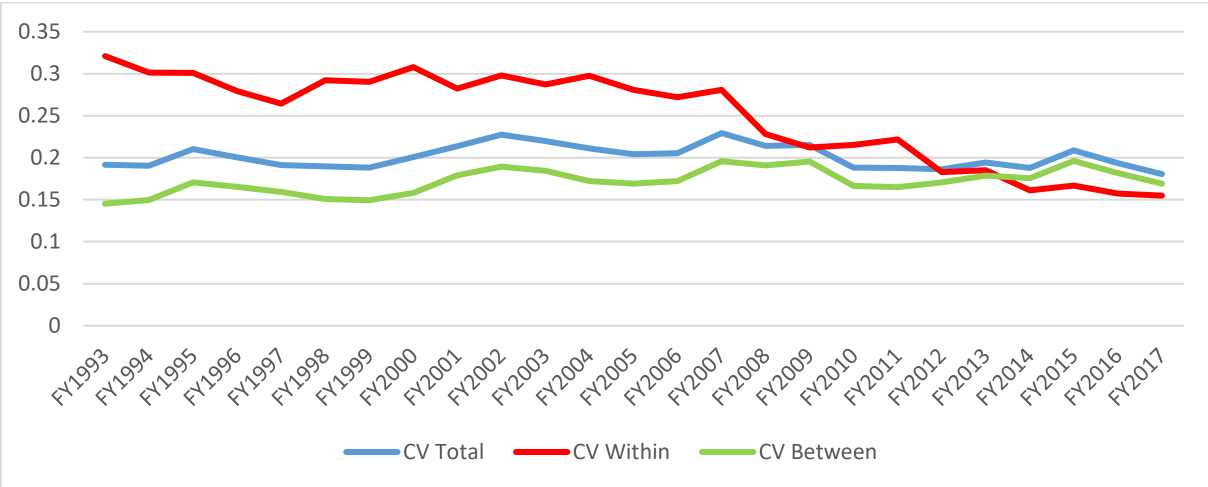

Figure 3 CV inequality series electronics

Hence hypothesis H2a “intertemporal patterns are stable over time”, is only accepted for both sports seasons, winter book season and the home furniture sector. Hypothesis H2b “Intertemporal effects are stable over time” is only accepted for the intertemporal sector. This means that the intertemporal shift is stable for the home furniture sector.

In the results, there are three aspects to discuss separately. First, both the electronics sector and shoe sector only the Gini between seasonal inequality series is stationary. This could be the result of that the largest changes occur in the extremes of the distribution. Since the Theil indices are most sensitive to these extremes, it could explain why they are not stationary. The Gini coefficient is more sensitive to changes in the middle of the distribution.

Since the Gini between seasonal coefficients is stationary, this indicates that the middle of the distribution does not show large fluctuations. The same conclusion can be drawn by looking at the total inequality series. The Theil indices have large fluctuations, whereas the Gini index does not fluctuate much. This means that the changes occur in the extreme months.

Second, the food, car and furniture sector do not have sales seasons. Therefore, the hypotheses are not applicable to this sector. It is only possible to look at the respective total inequality indices. The results show that the total inequality series are only stationary for the furniture sector. Nonetheless, the inequality values cannot be viewed in relation to a specific time period. Therefore, no conclusions can be drawn on how the months interrelate in these sectors.

Third, the non-stationary inequality series all show a downward trend. This means that monthly sales are becoming more egalitarian over time. Moreover, for the shoe sector, Table 9 shows that all within- and between seasonal inequality series are stationary. Meanwhile, both ADF and PP suggest that a unit-root is present in the series. This means that the within- and between inequality series are trend stationary. Hence, the intertemporal effect stably decreases over time in the shoe sector.

5.2. Linking Intertemporal Patterns.

In this section, the final hypotheses are answered. An intertemporal pattern can only be compared between seasons that have the same structure. This means that only seasons with the same number of months and structure in peaks and troughs are compared. This gives the following combinations where "P" and "T" represent a peak and trough selling month respectively:

No season	Food, car and furniture
P-P	Electronic, **book winter** and book summer season
P-P-T	Jewelry
P-T-T	Shoe and **sports winter season**
P-P-T-T	Clothing, **home furniture,** and general merchandise
P-P-P-T-T	**Sports summer season** and toys

The seasons indicated in bold represent stationary within seasonal seasons. There is no overlap of stable seasons within a seasonal pattern. It is not possible to compare unstable seasons, because these seasons cannot be compared within its own sector. Hence, there is no proof that there are similar intertemporal patterns across retail sectors. Therefore, H3a *the intertemporal pattern differs between sectors* is accepted.

The intertemporal effect cannot be compared between sectors. Only the between seasonal effect for the home furniture sector is stationary. This means that it is not possible to compare the intertemporal effect between retail sectors. As a result H3b: *The intertemporal effect differs between sectors* is accepted.

In the theoretical framework, Table 2 made predictions on whether the intertemporal shift is relatively large. Table 11 compares the predicted and actual intertemporal shift. This table shows that the predicted and actual intertemporal shift are mostly similar in the relative magnitude.

The magnitude of the actual intertemporal shift is determined by interpreting both the within- and between season inequality. The intertemporal shift is large in the case of a relatively high within season inequality and a relatively low between inequality. Thus, there are large differences between seasonal months, while the intertemporal shift controls for the spike in sales. Furthermore, the intertemporal shift is small in the case of either no seasonality, or when there is a relatively low within season inequality and a relatively high between season inequality. Thus, when the intertemporal shift does not control for a spike in sales.

Table 11 Comparison predicted and actual intertemporal shift

	Intertemporal shift predicted	Intertemporal shift actual
Electronic	-	-
Food	+	-
Jewelry	-	+/-
Shoe	+	+
Clothing	+	+
Sports	+/-	+
Toy	+	+/-
Book	-	-
Car	-	-
Furniture	-	-
Home Furn	+	+
Gen Merch	+	+

6. Discussion

This section discusses the results as found in the previous section by answering the main question. The main question of this thesis is:

How stable is the intertemporal shift of seasonal fluctuations in retail sales?

In order to understand the main research question, the intertemporal shift is divided into two aspects. First, the intertemporal pattern indicates how seasonal months interrelate. Second, the intertemporal effect, which represents the magnitude of the intertemporal shift relative to the yearly sales. Furthermore, the answer to the main question is the result of a joint interpretation of four sub-questions. First of all, some evidence is found for a stable intertemporal pattern. However, this effect is not found in all retail sectors. Secondly, only one retail sector, home furniture, showed a stable intertemporal effect. Finally, no evidence is found that retail sectors have the same intertemporal pattern, nor effect. This suggests that retail consists of seasons with a diverse range of product types and different contexts. The intertemporal aspects of seasonal fluctuations should, therefore, be considered per sector.

In this thesis, no strong evidence is found for stability in the intertemporal shift of seasonal fluctuations. Seasonality is an aspect of retail sales that is difficult to predict. This could mean that the intertemporal shift depends on specific circumstances. This thesis only used the price promotion strategy per sector to predict the intertemporal shift. The price promotion strategy and intertemporal shift seem to be correlated. However, no causal relation or other circumstances are explored in this thesis.

Nonetheless, treating sectors individually does give some stable results. Four of the eleven seasons showed a stable intertemporal pattern. Only the shoe sector showed a stationary decrease in the intertemporal pattern. The remaining six seasons did not show signs of a stable intertemporal pattern. Moreover, the intertemporal shift is stable for the home furniture sector.

In this thesis, four inequality measurements have been used. Two advantages of this specific approach are the robustness of the results and the ability to assess which type of months changed much over time. The latter advantage showed that for almost all non-stationary sectors the largest changes occurred in the more extreme, seasonal months. This is in line with the observation that the inequality within each sector has a downward trend.

Hence, the seasonal months are becoming more equal in their sales and the intertemporal effect is declining for these sectors. A proposed explanation for the declining inequality that could be studied in future research is that consumers increasingly buy goods online. Online shopping makes it accessible to always find the cheapest option. This could affect the sensitivity to the promotions of the physical shops, or the price competition throughout the year. The steepness of the trend is however not directly comparable between sectors.

Besides these differences, some similarities have been found between the seasons. First, both the car-and furniture sector do not show any seasonality and large inequalities. Both types of products are not only relatively large in size, but also in price. It seems that these sectors are not sensitive to seasonal influences. This could indicate that consumers are less affected by pricing strategies in a season for these goods. Consumers could be less moved by their impulses to buy these types of product.

Second, all other sectors, besides food, have at least one season. These types of products are less radical purchases. The winter is often the only season or has the largest seasonal effect. The Christmas period is, therefore, an important season for almost all retail sectors. Moreover, the results suggest that the intertemporal effect does exist in most seasons. Peak selling months are, in most cases, followed by trough sales months. This is important because in most sectors the intertemporal effect controls for a large part the increase in sales during the Christmas period. For example, in the clothing, sports, home furniture, and general merchandise sectors the peak in sales is almost completely diminished by the intertemporal effect. Moreover, for the jewelry and toy sector, around two-thirds of the increase in sales is controlled for by the intertemporal effect. This means that economic significance of peak selling seasons, especially the Christmas season is possibly overstated in the media. Where the media focuses on the sales peak, these results suggest that the intertemporal shift has to be taken into account in order to address the whole story of the seasonality.

Third, none of the seasons show signs of delaying purchases. This could be the result of monthly data. Both Christmas and Thanksgiving are at the end of the month. It could be the case that a delay of purchase occurs on a weekly time span, which is accounted for within the month. For example, people could delay their purchase one or two weeks before Black Friday, but this effect cannot be observed in monthly data.

7. Conclusion

This thesis used a combination of four inequality measurements in order to investigate the stability of the intertemporal shift of seasonal fluctuations in retail sales. The intertemporal shift in sales is caused by people speeding up or delaying their purchase at a certain point. In this thesis, the intertemporal shift is divided into two parts. First, the intertemporal pattern represents how seasonal months interrelate. Second, the intertemporal effect estimates to what extent the intertemporal shift controls for spikes in monthly sales. The four inequality measurements are the Gini coefficient, Theil T1, Theil T0 and Coefficient of Variation, each more sensitive to changes in different parts of the distribution. This approach adds robustness to the results. Moreover, describing the differences in the inequality series helps to better understand the season. The inequality measurements allowed to calculate a within- and between seasonal inequality value for each year of multiple sectors. Calculating these values for 24 years produced a series that can be tested for stationary.

Price promotion strategy is used to predict the intertemporal shift for each sector. This strategy depends on the price variation, price advertisement and average depth of discount. A combination of these aspects leads to a predicted intertemporal shift.

The within seasonal inequality series showed whether the relation between months within a season is stationary. This indicates a stable pattern of the intertemporal shift. The between inequality series represent the relative magnitude of the intertemporal effect. For a stationary intertemporal effect, the magnitude of the intertemporal shift remained equal relative to the total sales. The results showed that four of the eleven seasons had a stable intertemporal pattern. These include both sports seasons, winter book season and the home furniture season. However, only one retail sector, home furniture, showed a stable intertemporal effect. Hence, there is no significant proof for a stable intertemporal shift.

Comparing the inequality series gives more insight into how the intertemporal shift developed over time. Most non-stationary series showed a declining trend. This means that monthly sales are becoming more equal over time. Moreover, this declining trend is most drastic in the extreme months, which are part of a season. This means that seasonal months are becoming more equal over time and that the intertemporal effect is declining in most retail sectors.

Due to the intertemporal instability, linking the intertemporal shift was not possible for the studied sectors. The conclusion is, therefore, that the intertemporal shift is mostly unstable.

Nonetheless, the intertemporal shift has shown to play a large role for most seasons. The intertemporal shift is observable in monthly data and does controls for the increase in sales during the peak months. The magnitude of this effect depends on the sector.

7.1. Implications

In terms of managerial, policy and academic implications, these findings have some basic points. First, on a managerial level, information on the intertemporal sales pattern could be valuable. Information on how seasonal months interrelate could help to predict sales in the short-term. By using this information, inventory management could be improved. Even though most inequality series were not stable, the values did not fluctuate much. Furthermore, marketing strategies that are most aggressive could be implemented in the peak selling months, and proportionally less aggressive in the trough selling months, in order to mimic the intertemporal shift.

Second, on the policy level, this thesis provides some instruments to assess the effect of retail sales seasons on the economy. As retail sales is an important aspect of the economy, it is important to understand its characteristics, including seasonality. Where most of the attention goes to the peak selling months, the results in this thesis suggest to take the intertemporal effect into account. Without also discussing trough-selling months, policy might become biased towards the peak selling months.

Thirdly, for academic implications, analyzing the distribution of sales is important for a deeper understanding of retail sales. The method in this thesis was useful in observing an aspect of retail seasonality, the intertemporal shift. Future research could investigate whether the use of inequality measures would improve other approaches, like time series forecasting. Moreover, the intertemporal effect has not been studied thoroughly. There are still many aspects relating to this subject that could be investigated. For example, if there are differences across countries or between more specific product groups within a retail sector.

Finally, the results show that when one inequality measurement produces a stationary series, the series of the remaining inequality measurements are stationary as well. However, whenever a series is non-stationary, the inequality measurements show differences. These differences can be interpreted. This implies that drawing conclusions based on one inequality measurement might not be the best approach.

7.2. Limitations

The inequality measurements only provide a relative measure that cannot capture absolute differences in monthly sales. These measures could show a stable intertemporal effect, while the absolute magnitude of this effect can change. Moreover, a stable within seasonal inequality series cannot conclude with absolute certainty that the weights of the months do not change. For example, in the case of a season of December and January with 10 and 5 sales respectively, the inequality value is the same if the monthly sales interchange.

A second limitation is that the Gini coefficient is a downward-biased measure of inequality in small populations (Deltas, 2003). This would propose problems if the Gini coefficient was to be compared between seasons that have a different structure. However, no comparisons were made in this thesis.

The third limitation is that the intertemporal shift is only described. No causations can be assigned to why the intertemporal shift changes over time. There are many circumstances that could influence the seasonality. For example, sectors can be influenced by seasonal products as well as by varying prices (Einav, 2007). Without a good understanding of the seasonal characteristics, it is difficult to give direct implications. Price promotion strategy is used to predict the intertemporal shift. There seems to be a correlation. Therefore, studying the relation between price promotion strategy and the intertemporal shift could be a starting point. Future research should also study other characteristics per sector and how they influence the intertemporal shift.

The fourth limitation is that price promotion strategy is used to predict the intertemporal shift per sector. However, such a strategy also depends on firm characteristics (Voss & Seiders, 2003). This means that there can be large differences between firms within the same sector with regards to the intertemporal shift. These possible differences are not included in this thesis and can be subject to future research.

The fifth limitation is that retail is divided into different sectors. However, these sectors are still broad concepts. A conclusion was that the intertemporal shift could not be compared between sectors. It could be the case that within sectors there are large differences between products. Future research could investigate the intertemporal shift of specific products.

The final limitation is that of multiple testing. In this thesis, a lot of relations are tested. For a p-value of 0.05, this means that around 5% of the results are significant by chance. With an interpretation of a joint use in both the inequality measurement and stationary test, the negative effect of this limitation is restricted to some extent.

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9. Appendices

9.1. Results of ANOVA

9.1.1. Electronic Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.917	11	0.992	889.339	0.000
Within Groups	0.308	276	0.001		
Total	11.225	287			

9.1.2. Food Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.504	11	0.046	296.604	0.000
Within Groups	0.043	276	0.000		
Total	0.546	287			

9.1.3. Jewelry Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	68.576	11	6.234	962.803	0.000
Within Groups	1.787	276	0.006		
Total	70.363	287			

9.1.4. Shoe Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6.220	11	0.565	363.560	0.000
Within Groups	0.429	276	0.002		
Total	6.649	287			

9.1.5. Clothing Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11.453	11	1.041	722.947	0.000
Within Groups	0.397	276	0.001		
Total	11.850	287			

9.1.6. Sports Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	10.833	11	0.985	1158.632	0
Within Groups	0.235	276	0.001		
Total	11.068	287			

9.1.7. Toy Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	79.245	11	7.204	614.470	0.000
Within Groups	3.236	276	0.012		
Total	82.481	287			

9.1.8. Book Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	27.715	11	2.520	337.517	0.000
Within Groups	2.060	276	0.007		
Total	29.775	287			

9.1.9. Car Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.327	11	0.121	76.839	0.000
Within Groups	0.433	276	0.002		
Total	1.760	287			

9.1.10. Furniture Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.476	11	0.043	57.052	0.000
Within Groups	0.209	276	0.001		
Total	0.685	287			

9.1.11. Home Furniture Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.519	11	0.411	512.565	0.000
Within Groups	0.221	276	0.001		
Total	4.740	287			

9.1.12. General Merchandise Sector

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.222	11	0.747	375.164	0.000
Within Groups	0.550	276	0.002		
Total	8.772	287			

9.2. Bonferroni Post-Hoc Test Results

9.2.1. Electronics Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	0.140											
Mar	1.000	**0.006**										
Apr	**0.000**	**0.000**	**0.000**									
May	0.274	1.000	**0.013**	**0.000**								
Jun	1.000	1.000	1.000	**0.000**	1.000							
Jul	1.000	0.255	1.000	**0.000**	0.482	1.000						
Aug	**0.001**	**0.000**	**0.035**	**0.000**	**0.000**	**0.000**	**0.000**					
Sep	1.000	1.000	0.253	**0.000**	1.000	1.000	1.000	**0.000**				
Oct	1.000	1.000	0.077	**0.000**	1.000	1.000	1.000	**0.000**	1.000			
Nov	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.2. Food Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.000**											
Mar	**0.000**	**0.000**										
Apr	1.000	**0.000**	**0.000**									
May	**0.000**	**0.000**	**0.000**	**0.000**								
Jun	**0.000**	**0.000**	1.000	**0.000**	**0.000**							
Jul	**0.000**	**0.000**	**0.000**	**0.000**	1.000	**0.000**						
Aug	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.004**	**0.001**					
Sep	1.000	**0.000**	**0.000**	1.000	**0.000**	**0.000**	**0.000**	**0.000**				
Oct	**0.000**	**0.000**	1.000	**0.000**	**0.000**	1.000	**0.000**	**0.000**	**0.000**			
Nov	**0.000**	**0.000**	1.000	**0.000**	**0.000**	1.000	**0.000**	**0.000**	**0.000**	1.000		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.3. Jewelry Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.000**											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	1.000									
May	**0.000**	0.124	**0.000**	**0.000**								
Jun	**0.000**	**0.001**	0.110	1.000	**0.000**							
Jul	**0.000**	**0.000**	1.000	1.000	**0.000**	1.000						
Aug	**0.000**	**0.001**	0.118	1.000	**0.000**	1.000	1.000					
Sep	**0.000**	**0.000**	1.000	1.000	**0.000**	0.476	1.000	0.508				
Oct	**0.000**	**0.000**	1.000	1.000	**0.000**	1.000	1.000	1.000	1.000			
Nov	**0.000**	**0.002**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.4. Shoe Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.000**											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	1.000									
May	**0.000**	**0.000**	1.000	1.000								
Jun	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**							
Jul	**0.000**	**0.000**	0.096	0.059	0.052	0.635						
Aug	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**					
Sep	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.000	**0.002**	**0.000**				
Oct	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.000	**0.005**	**0.000**	1.000			
Nov	**0.000**	**0.000**	1.000	0.867	0.789	**0.040**	1.000	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.5. Clothing Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.002**											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	1.000									
May	**0.000**	**0.000**	1.000	1.000								
Jun	**0.000**	**0.000**	0.073	0.857	**0.000**							
Jul	**0.000**	**0.000**	0.211	1.000	**0.001**	1.000						
Aug	**0.000**	**0.000**	**0.000**	**0.000**	**0.012**	**0.000**	**0.000**					
Sep	**0.000**	**0.000**	**0.038**	0.503	**0.000**	1.000	1.000	**0.000**				
Oct	**0.000**	**0.000**	1.000	0.128	1.000	**0.000**	**0.000**	0.167	**0.000**			
Nov	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.6. Sports Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	1.000											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	1.000									
May	**0.000**	**0.000**	0.102	**0.002**								
Jun	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**							
Jul	**0.000**	**0.000**	**0.000**	**0.000**	**0.014**	**0.000**						
Aug	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.875	**0.000**					
Sep	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**				
Oct	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**			
Nov	**0.000**	**0.000**	**0.020**	0.734	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.7. Toy Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	1.000											
Mar	**0.001**	**0.021**										
Apr	0.100	1.000	1.000									
May	1.000	1.000	1.000	1.000								
Jun	1.000	1.000	1.000	1.000	1.000							
Jul	0.164	1.000	1.000	1.000	1.000	1.000						
Aug	0.556	1.000	1.000	1.000	1.000	1.000	1.000					
Sep	0.143	1.000	1.000	1.000	1.000	1.000	1.000	1.000				
Oct	**0.000**	**0.000**	0.631	**0.007**	**0.000**	**0.000**	**0.004**	**0.001**	**0.005**			
Nov	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.8. Book Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.000**											
Mar	**0.000**	1.000										
Apr	**0.000**	1.000	1.000									
May	**0.000**	1.000	0.434	**0.004**								
Jun	**0.000**	1.000	1.000	**0.018**	1.000							
Jul	**0.000**	1.000	1.000	0.381	1.000	1.000						
Aug	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**					
Sep	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**				
Oct	**0.000**	1.000	1.000	1.000	1.000	1.000	1.000	**0.000**	**0.000**			
Nov	**0.000**	1.000	1.000	**0.016**	1.000	1.000	1.000	**0.000**	**0.000**	1.000		
Dec	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.9. Car Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.011**											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	**0.000**									
May	**0.000**	**0.000**	1.000	**0.008**								
Jun	**0.000**	**0.000**	0.495	0.703	1.000							
Jul	**0.000**	**0.000**	1.000	0.220	1.000	1.000						
Aug	**0.000**	**0.000**	1.000	**0.000**	1.000	0.897	1.000					
Sep	**0.000**	**0.035**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**				
Oct	**0.000**	**0.024**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	1.000			
Nov	1.000	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	1.000	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.000	1.000	**0.004**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.10. Furniture Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	1.000											
Mar	**0.000**	**0.000**										
Apr	1.000	1.000	**0.000**									
May	**0.000**	**0.000**	0.075	**0.000**								
Jun	**0.007**	**0.036**	**0.000**	**0.006**	0.170							
Jul	**0.000**	**0.000**	**0.005**	**0.000**	1.000	1.000						
Aug	**0.000**	**0.000**	1.000	**0.000**	**0.005**	**0.000**	**0.000**					
Sep	**0.000**	**0.000**	**0.004**	**0.000**	1.000	1.000	1.000	**0.000**				
Oct	**0.000**	**0.002**	**0.000**	**0.000**	1.000	1.000	1.000	**0.000**	1.000			
Nov	**0.000**	**0.000**	0.089	**0.000**	**0.000**	**0.000**	**0.000**	0.868	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.242	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

9.2.11. Home Furniture Sector

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	**0.046**											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	0.342									
May	**0.000**	**0.000**	0.056	**0.000**								
Jun	**0.000**	**0.000**	0.133	**0.000**	1.000							
Jul	**0.000**	**0.000**	**0.000**	**0.000**	0.161	0.069						
Aug	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**					
Sep	**0.000**	**0.000**	0.077	**0.000**	1.000	1.000	0.119	**0.000**				
Oct	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	1.000	**0.020**	**0.000**			
Nov	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

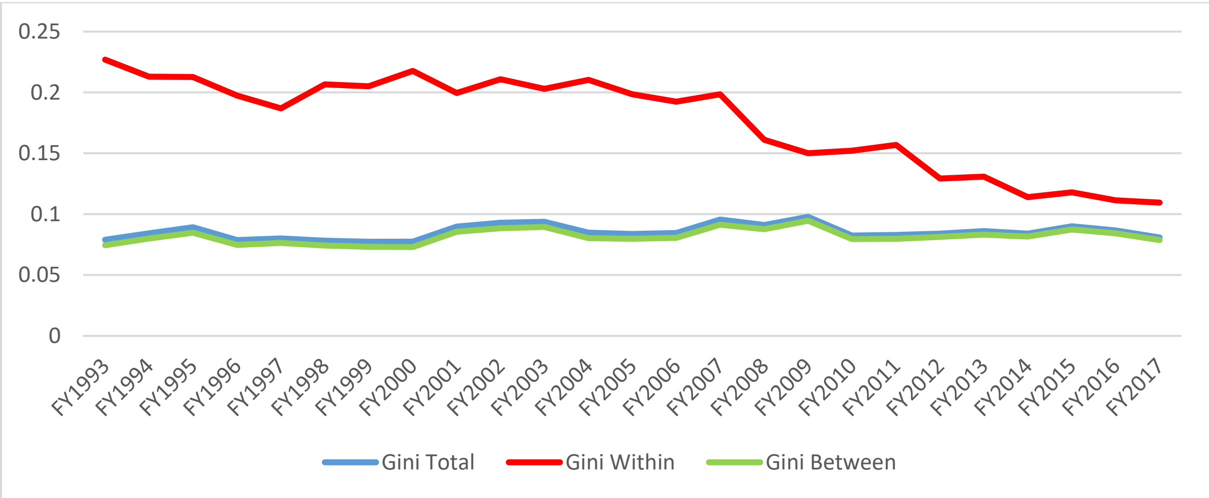
9.2.12. General Merchandise Sector

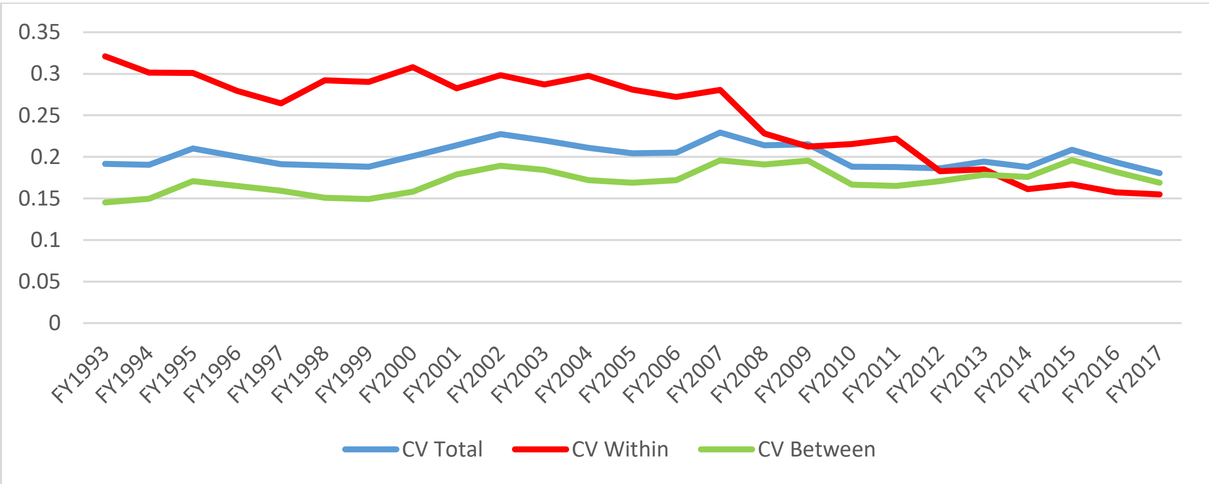
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan												
Feb	1.000											
Mar	**0.000**	**0.000**										
Apr	**0.000**	**0.000**	1.000									
May	**0.000**	**0.000**	**0.017**	**0.000**								
Jun	**0.000**	**0.000**	1.000	1.000	0.662							
Jul	**0.000**	**0.000**	1.000	1.000	**0.006**	1.000						
Aug	**0.000**	**0.000**	0.089	**0.002**	1.000	1.000	**0.037**					
Sep	**0.000**	**0.001**	**0.043**	0.994	**0.000**	**0.000**	0.102	**0.000**				
Oct	**0.000**	**0.000**	1.000	0.489	1.000	1.000	1.000	1.000	**0.000**			
Nov	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		
Dec	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

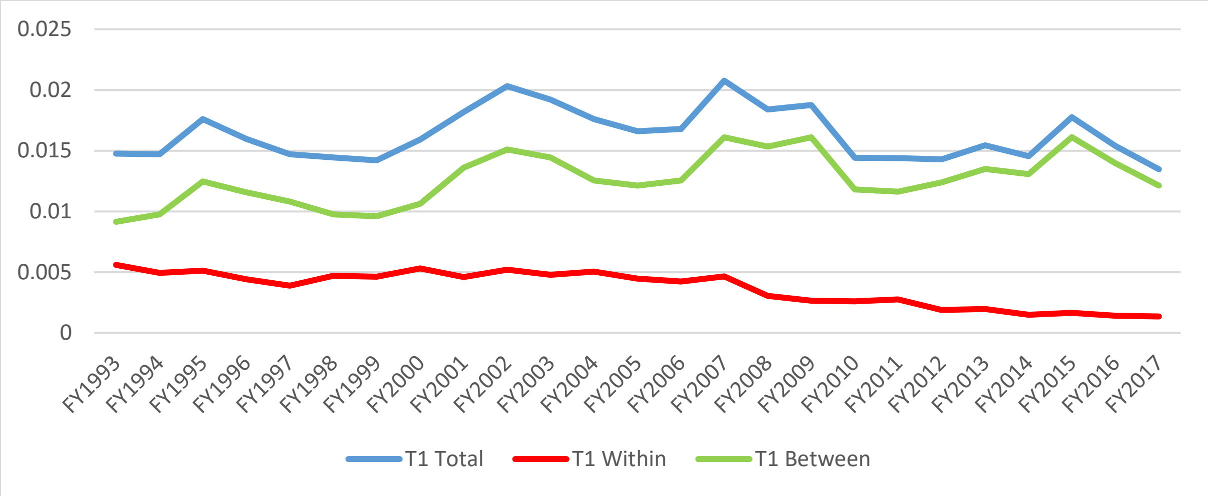
Note: table shows significance values. If significance level is < 0.05, it is indicated in bold.

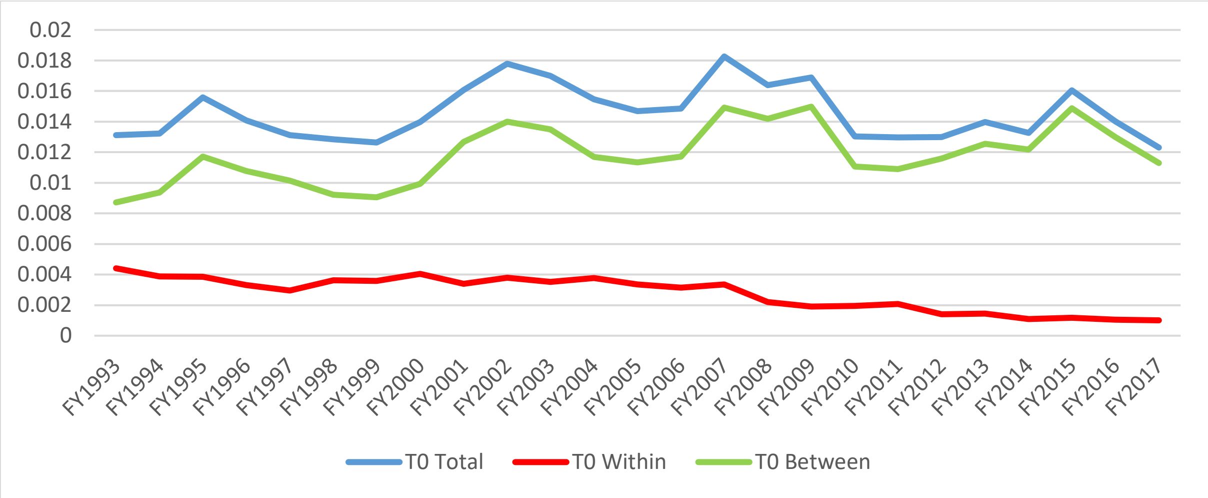
9.3. Inequality Values

9.3.1. Electronics Sector

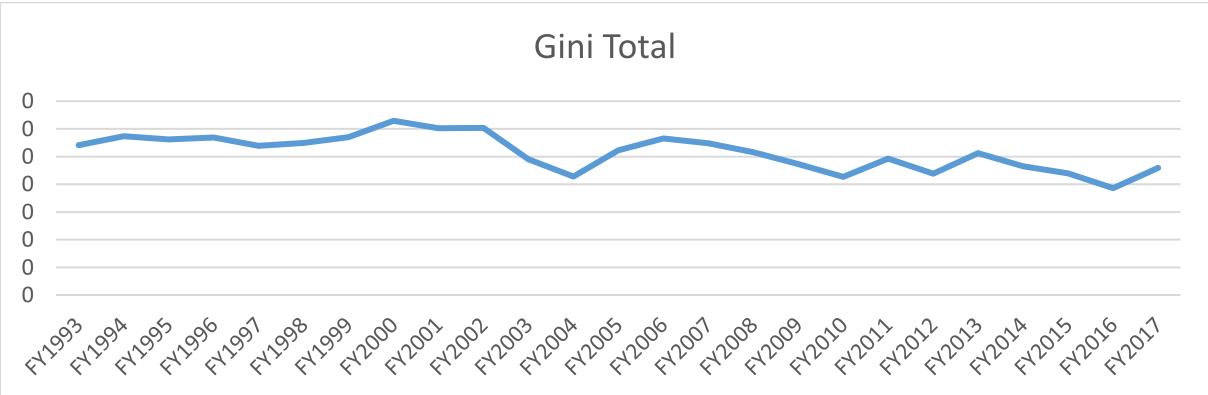


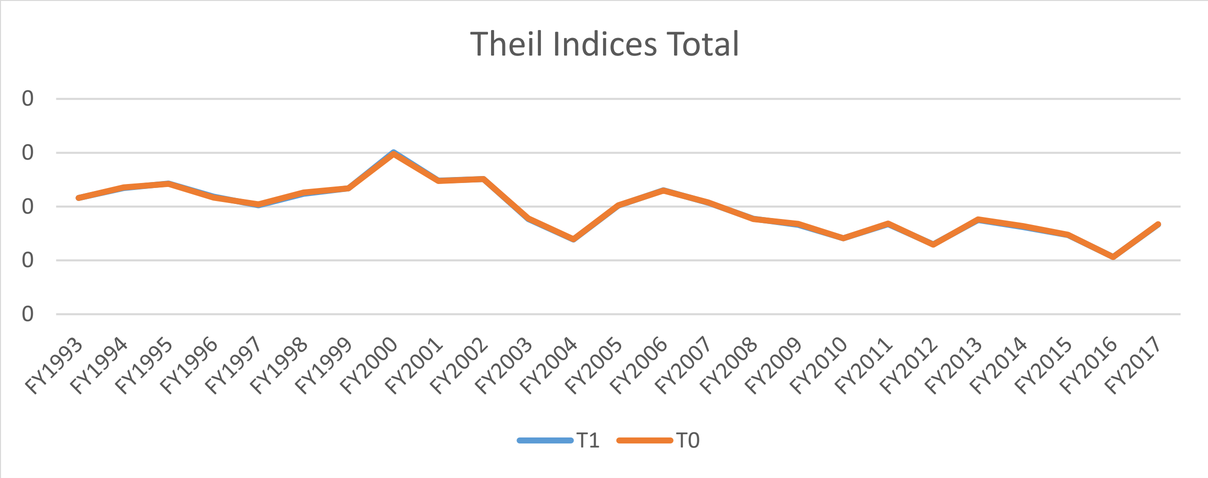


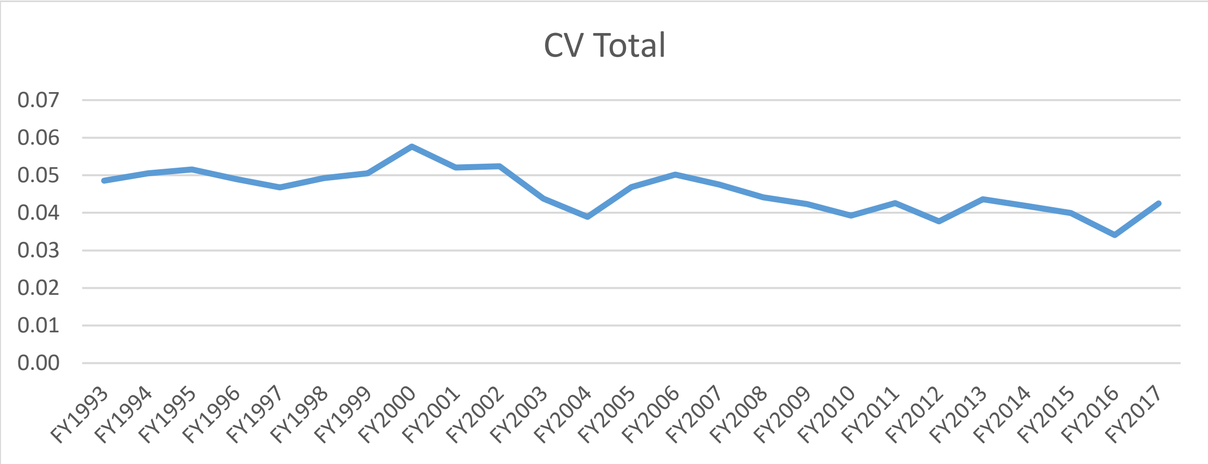




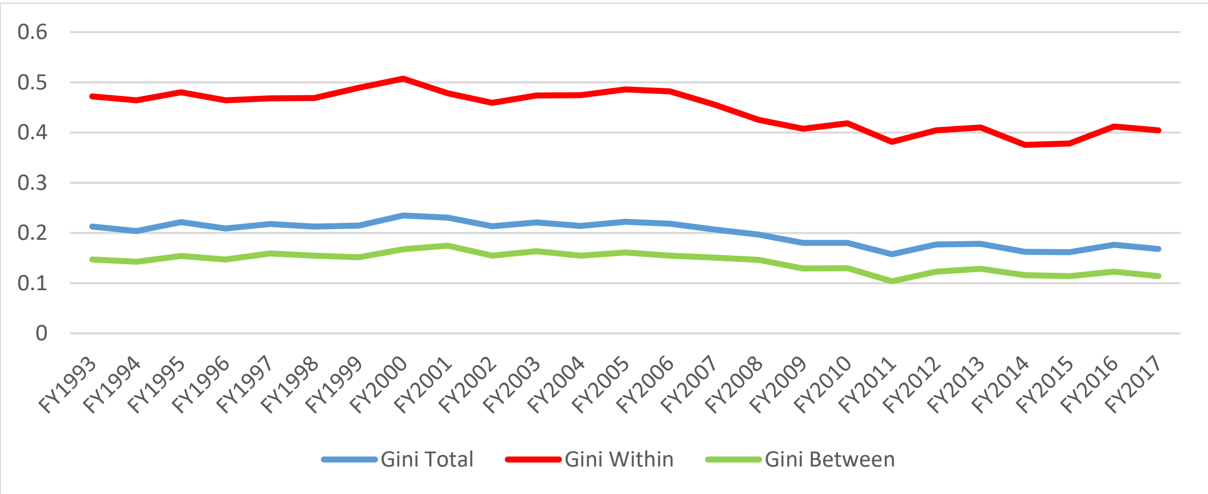
9.3.2. Food Sector

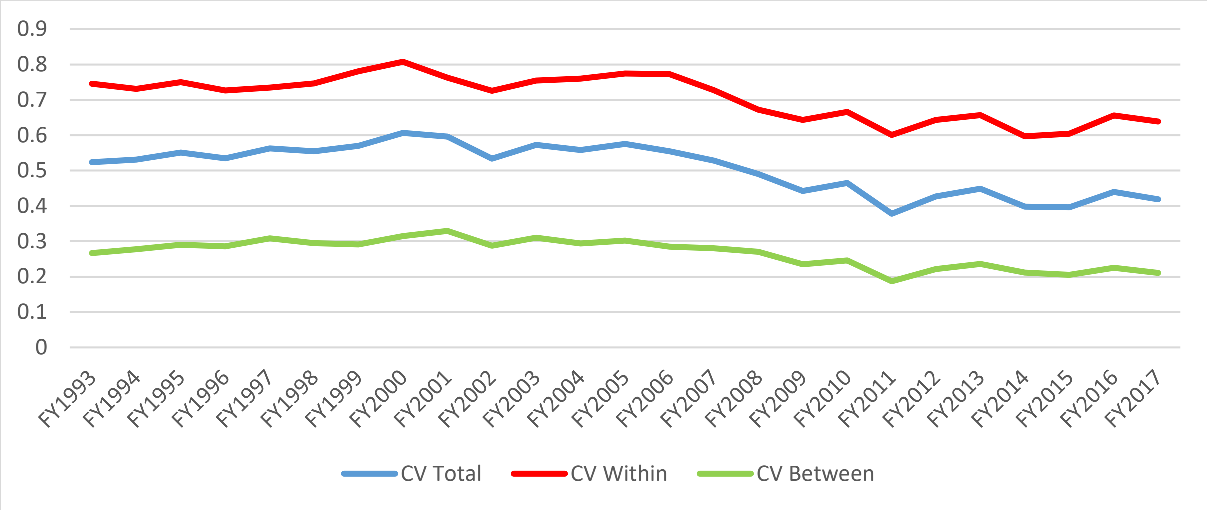




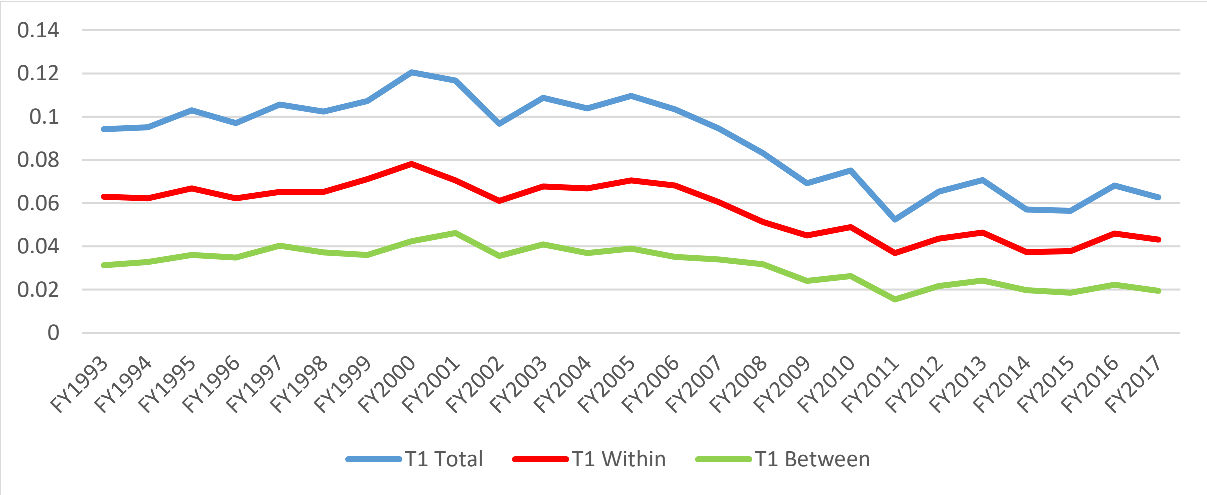


9.3.3. Jewelry Sector





0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
CV Total
CV Within
CV Between



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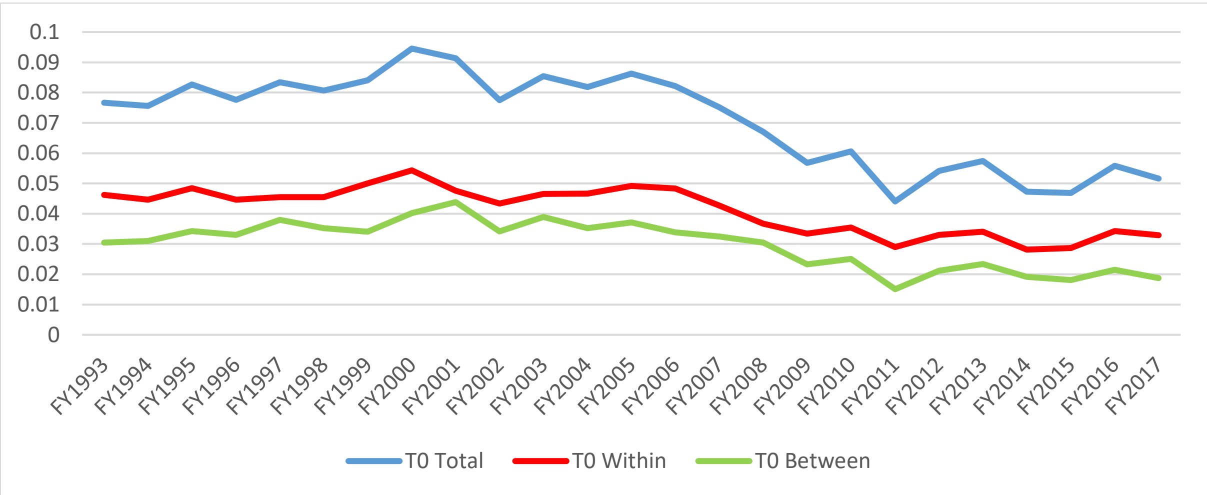
0.04
0.02
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
T1 Total
T1 Within
T1 Between



0.1
0.09
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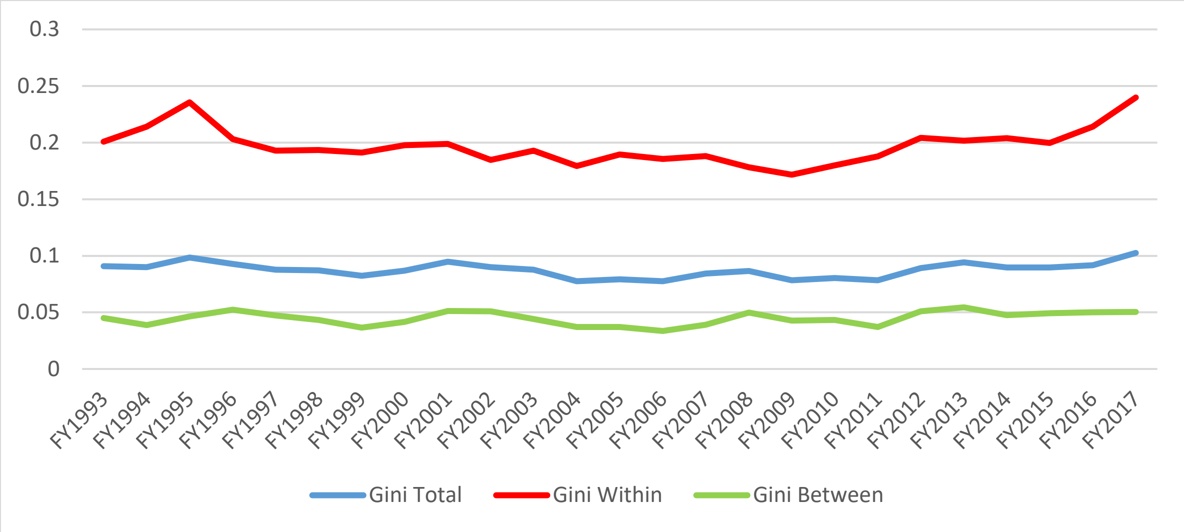
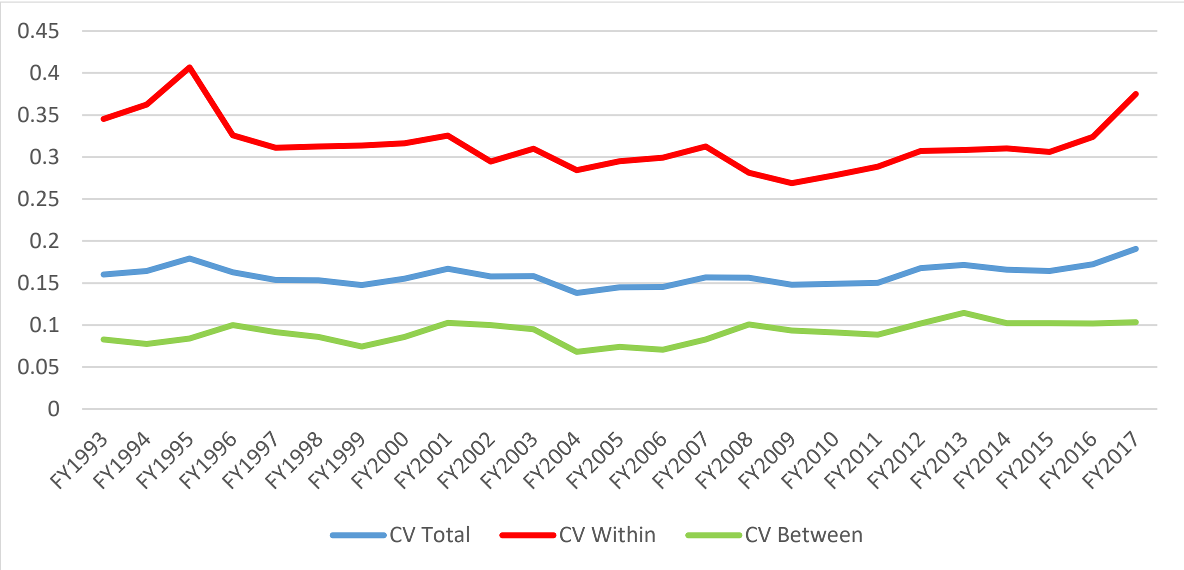
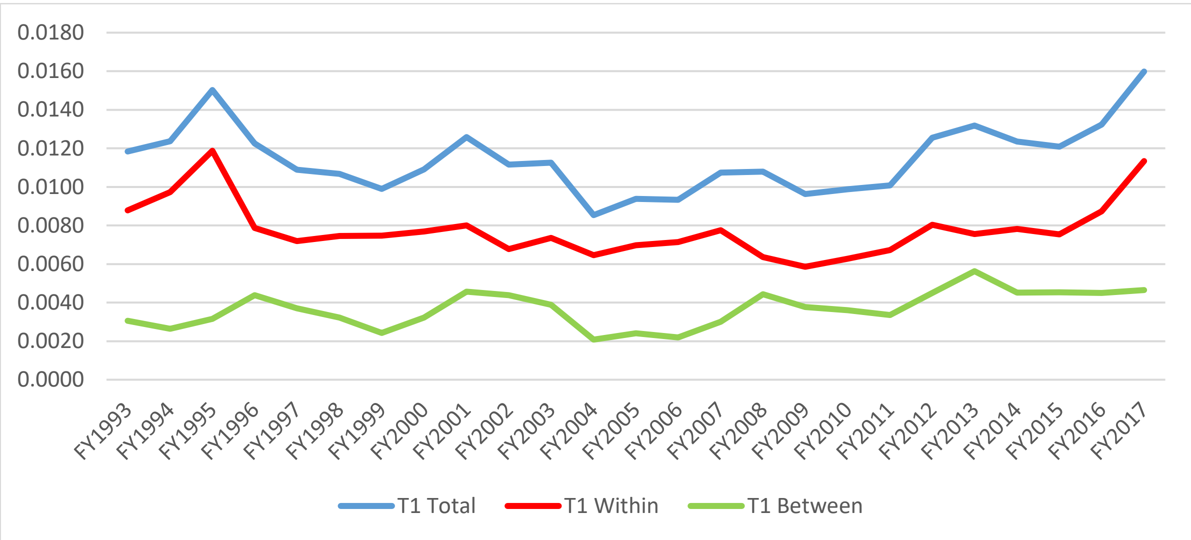
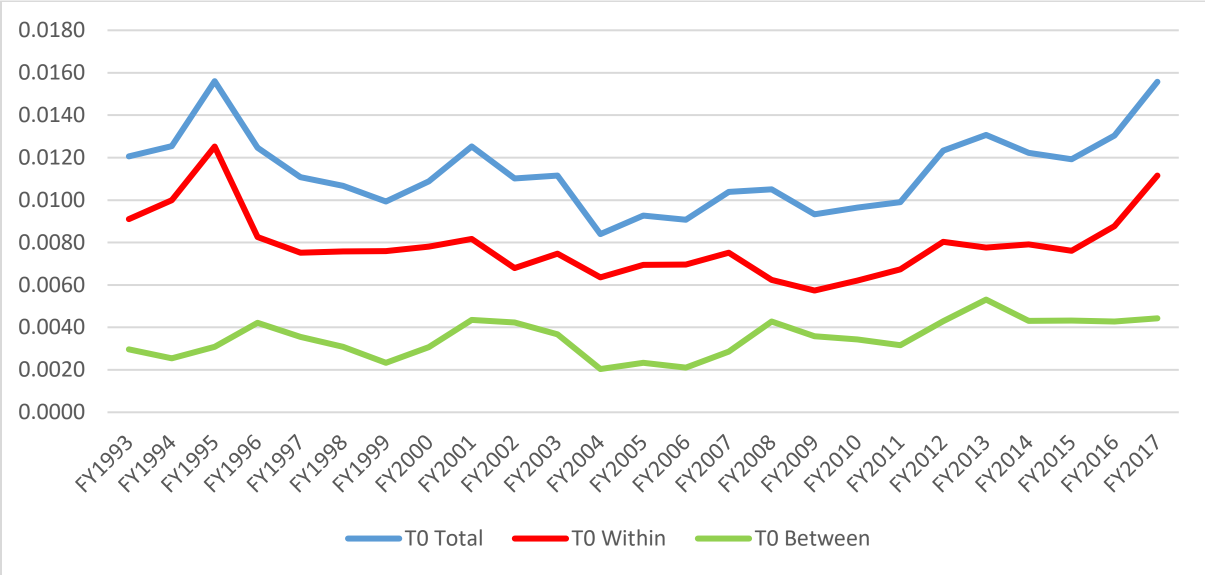
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
T0 Total
T0 Within
T0 Between

9.3.4. Shoe Sector

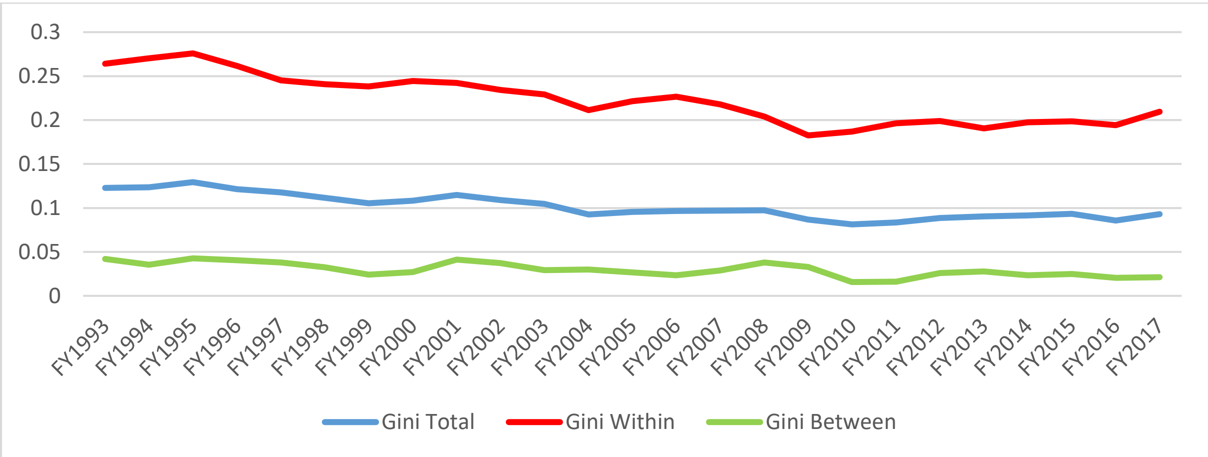


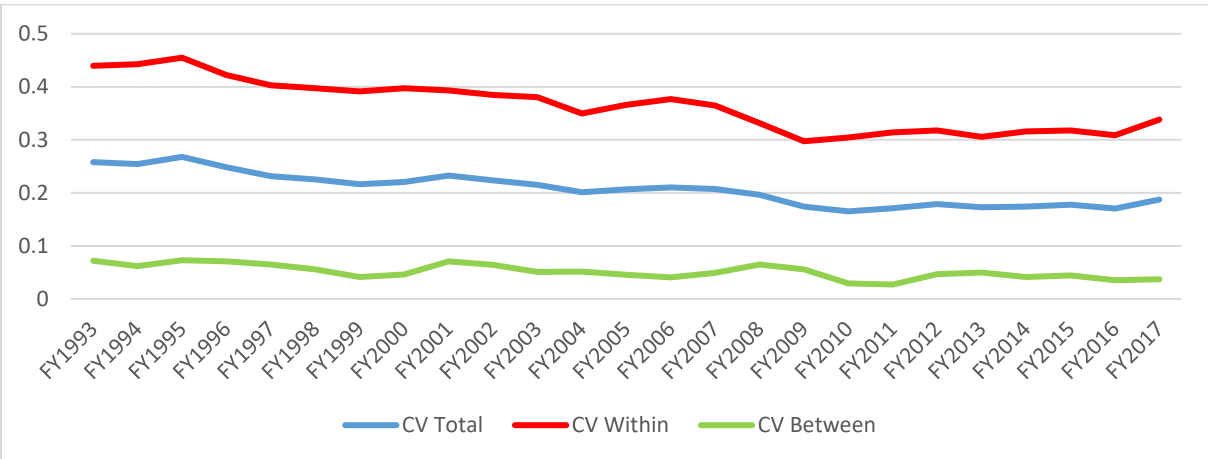


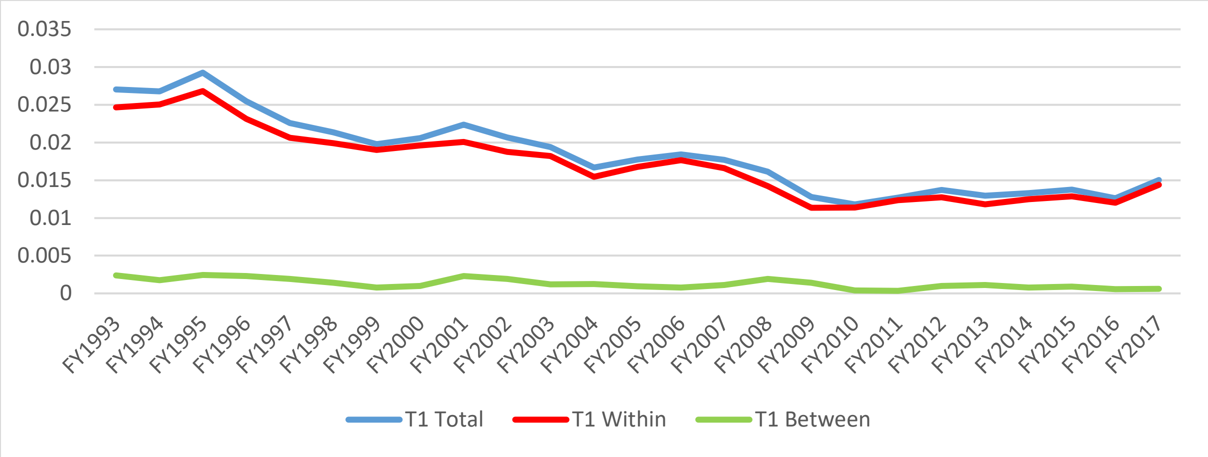


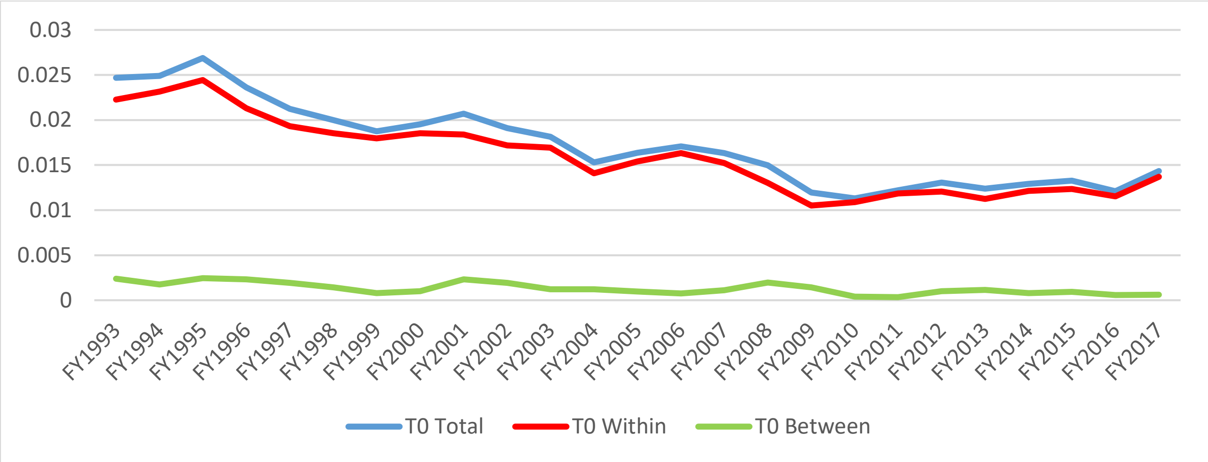


9.3.5. Clothing Sector

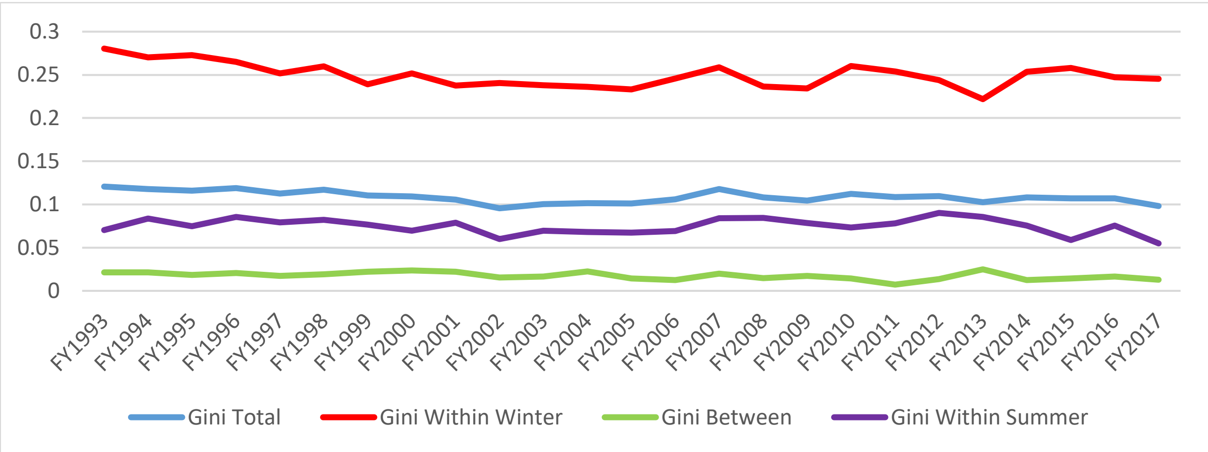


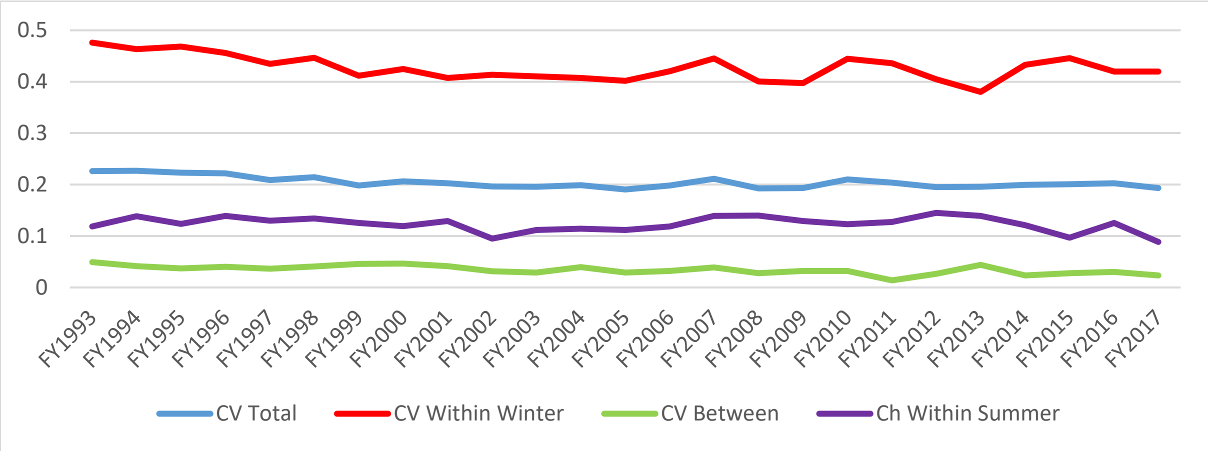






9.3.6. Sports Sector

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0.3
0.2
0.1
0
FY1993
FY1994
FY1995
FY1996
FY1997
FY1998
FY1999
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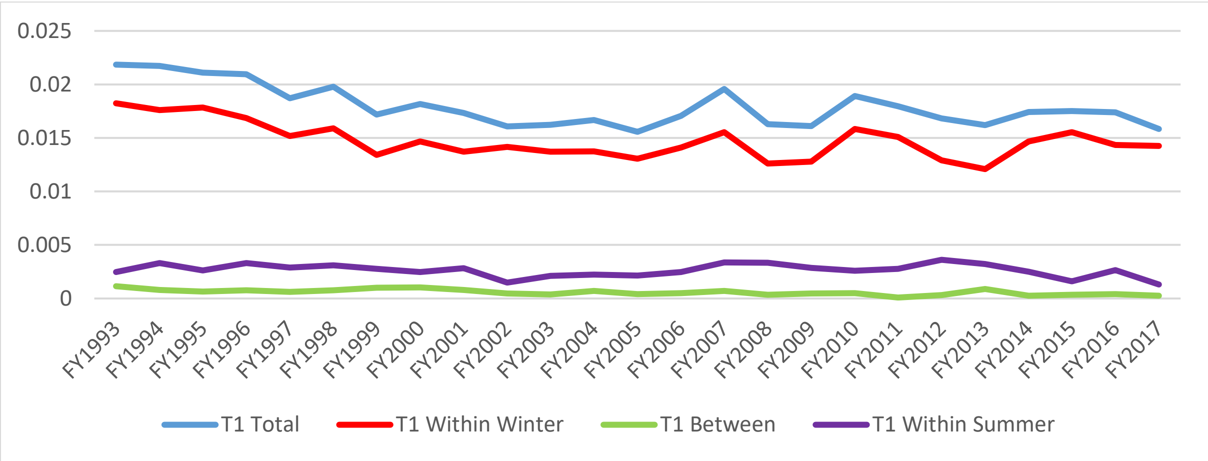
FY2002
FY2003
FY2004
FY2005
FY2006
FY2007
FY2008
FY2009
FY2010
FY2011
FY2012
FY2013
FY2014
FY2015
FY2016
FY2017
CV Total
CV Within Winter
CV Between
Ch Within Summer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0.015
0.01
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FY1993
FY1994
FY1995
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FY1998
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FY2003
FY2004
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FY2006
FY2007
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FY2011
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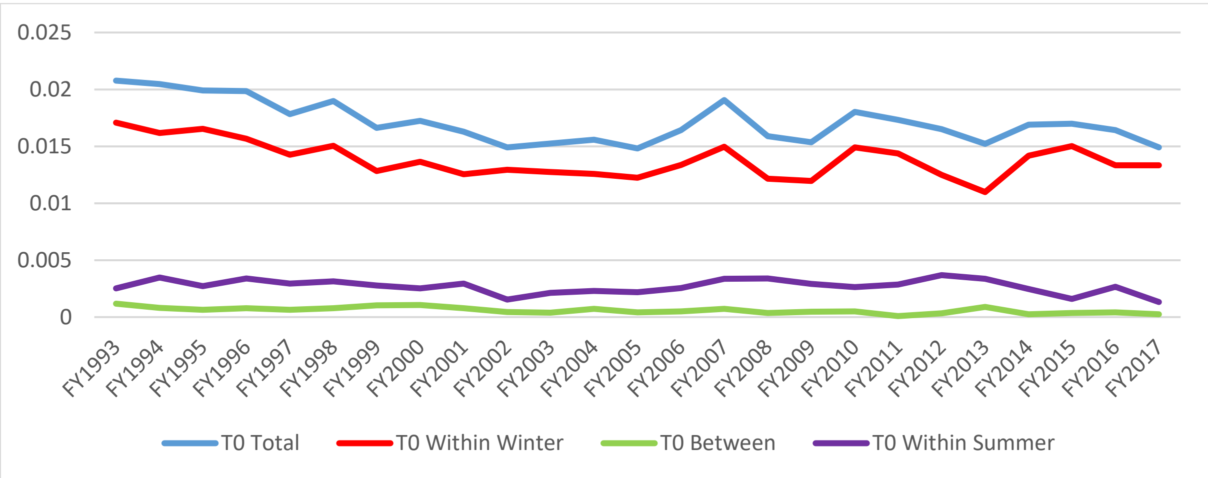
FY2013
FY2014
FY2015
FY2016
FY2017
T1 Total
T1 Within Winter
T1 Between
T1 Within Summer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0.02
0.015
0.01
0.005
0
FY1993
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FY1995
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FY1998
FY1999
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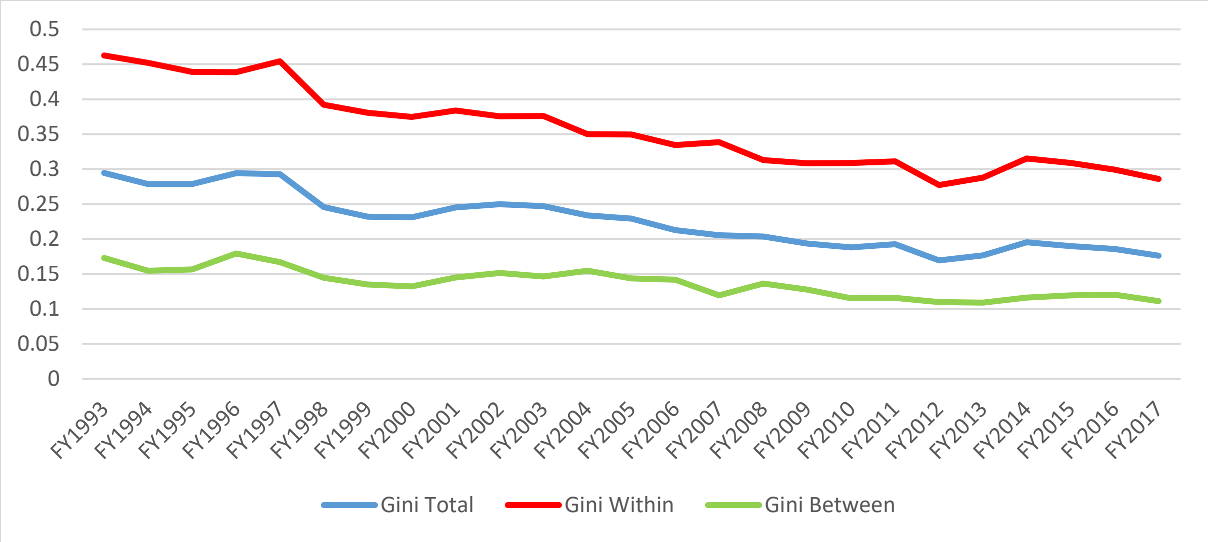
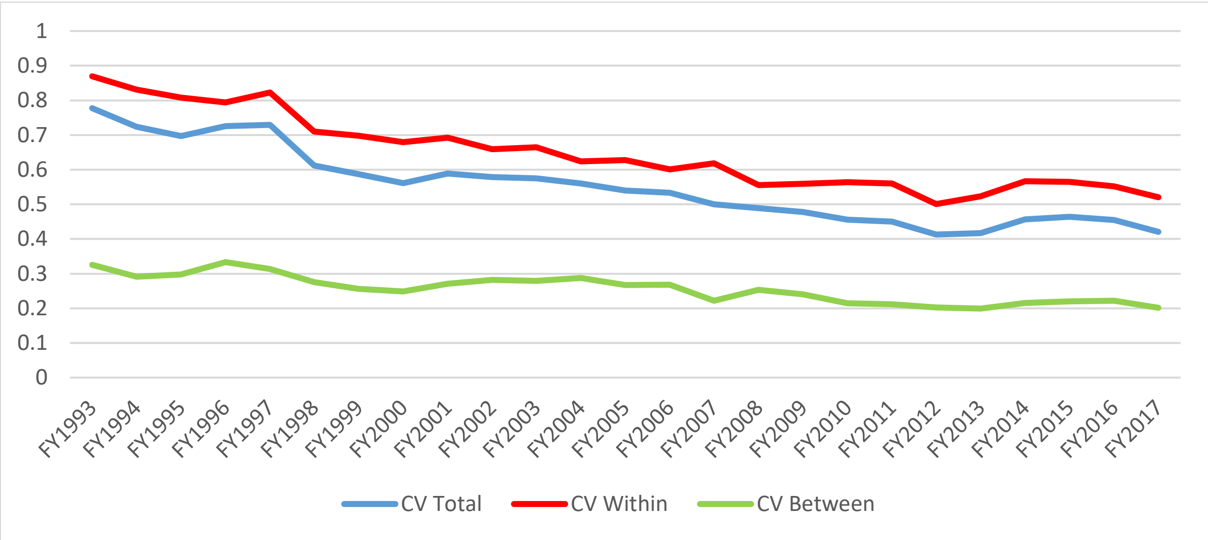
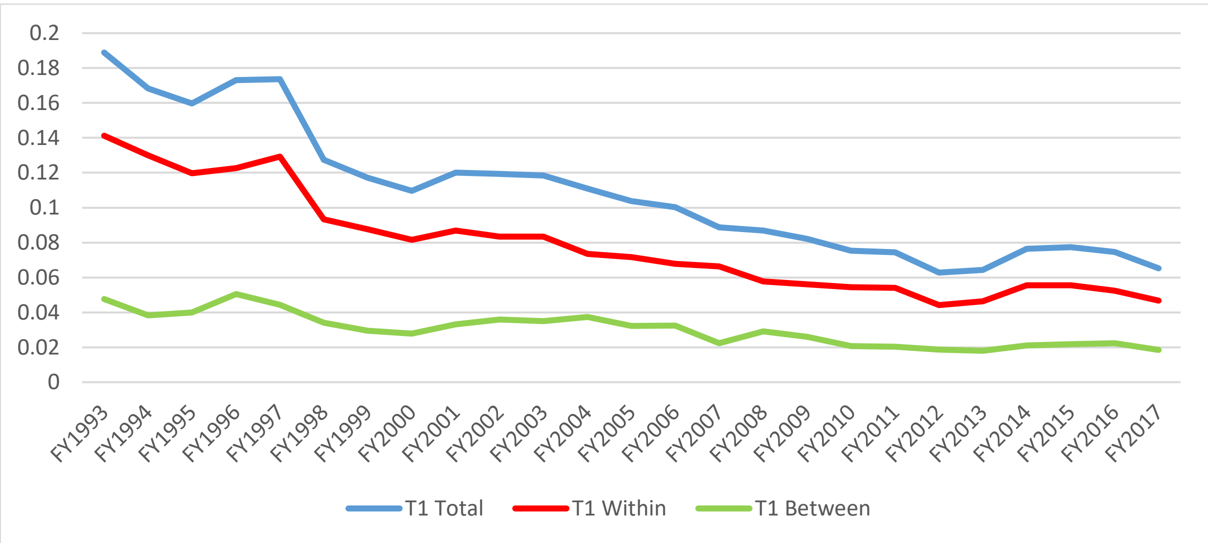
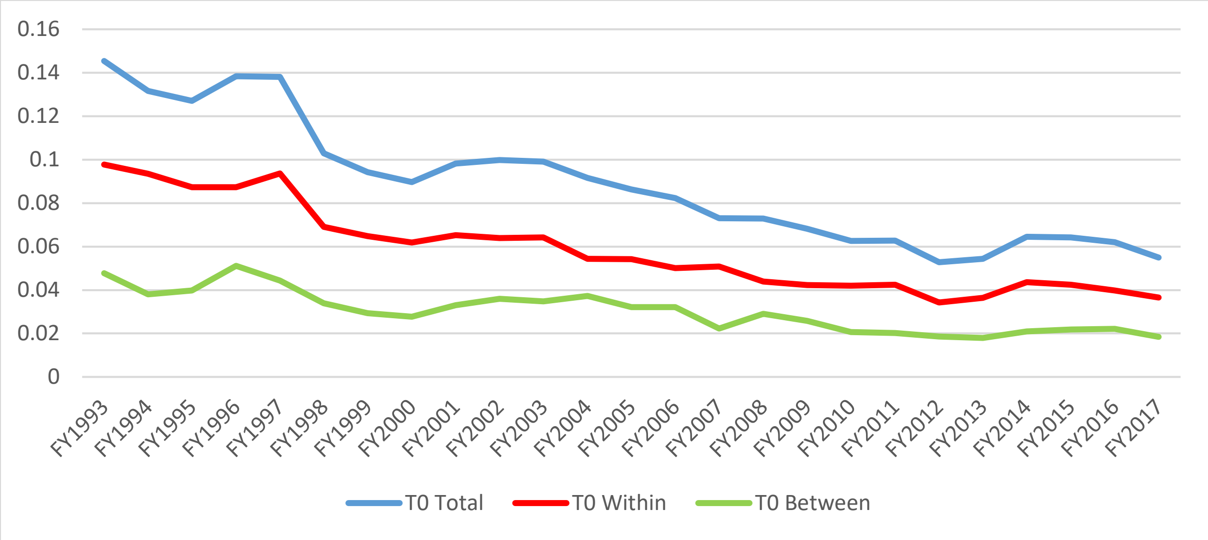
FY2002
FY2003
FY2004
FY2005
FY2006
FY2007
FY2008
FY2009
FY2010
FY2011
FY2012
FY2013
FY2014
FY2015
FY2016
FY2017
T0 Total
T0 Within Winter
T0 Between
T0 Within Summer

9.3.7. Toy Sector

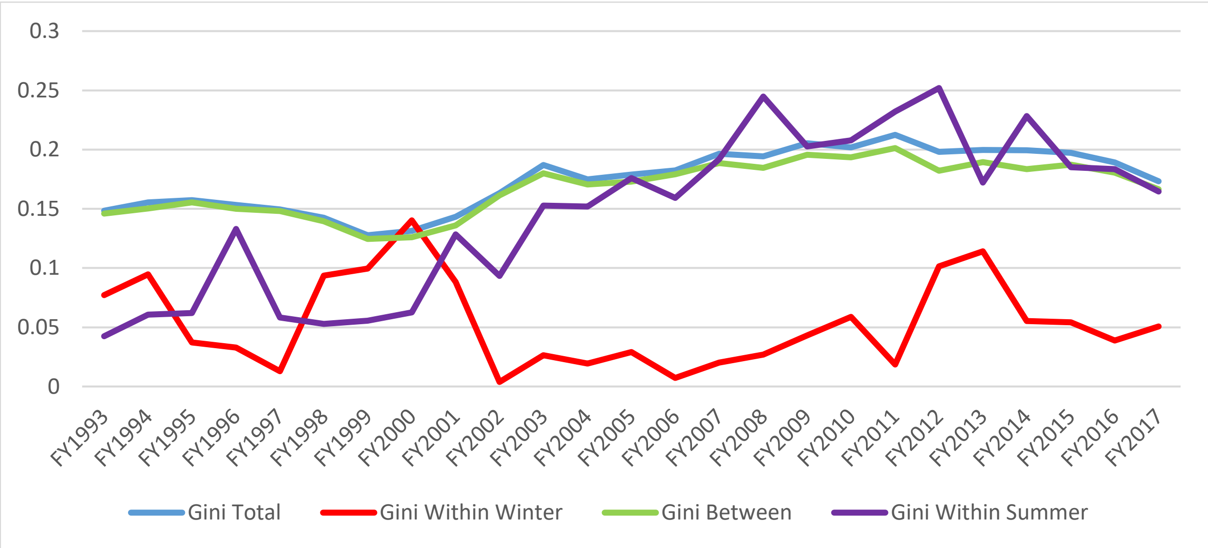


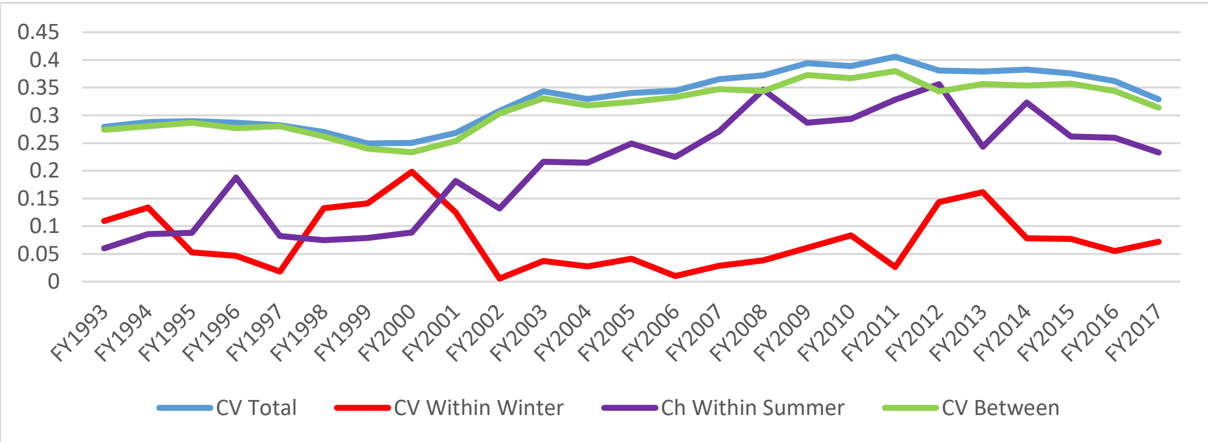


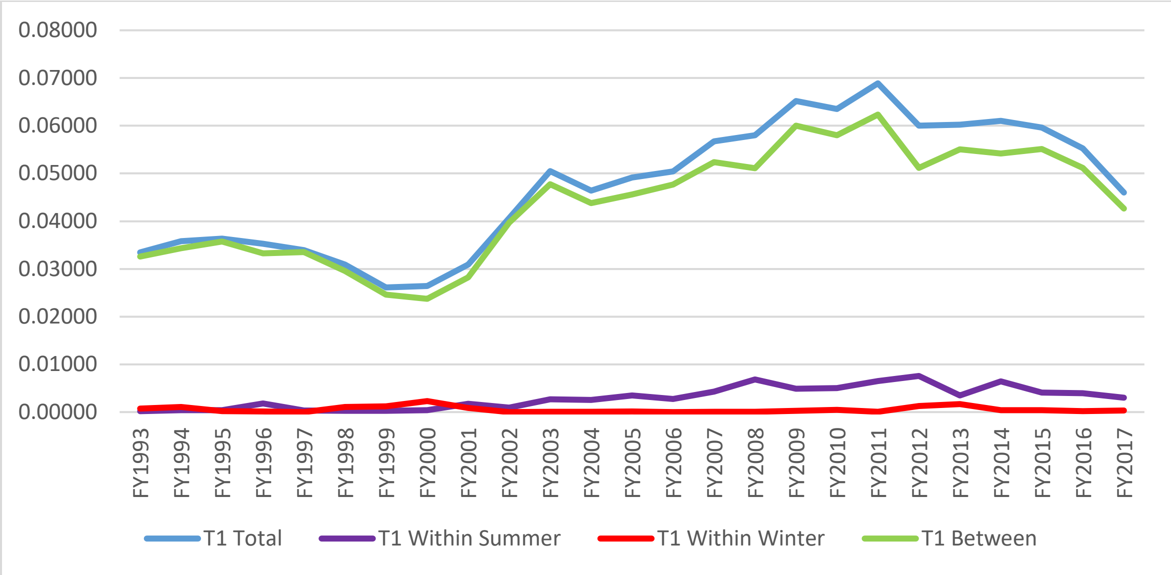




9.3.8. Book Sector



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0.02000
0.01000
0.00000
FY1993
FY1994
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FY1996
FY1997
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FY1999
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FY2001
FY2002
FY2003
FY2004
FY2005
FY2006
FY2007
FY2008
FY2009
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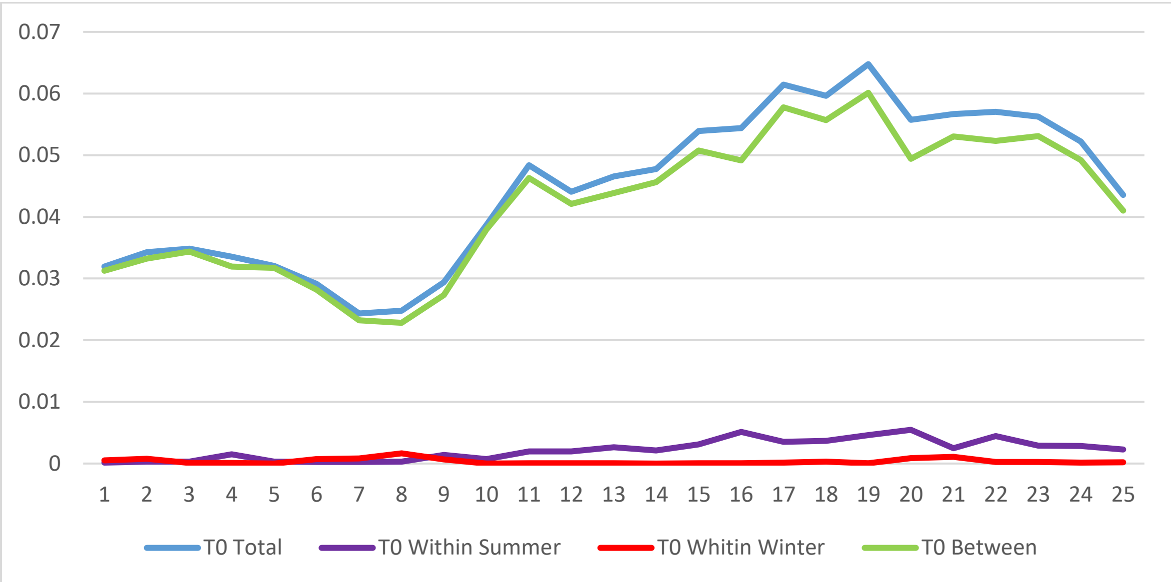
FY2011
FY2012
FY2013
FY2014
FY2015
FY2016
FY2017
T1 Total
T1 Within Summer
T1 Within Winter
T1 Between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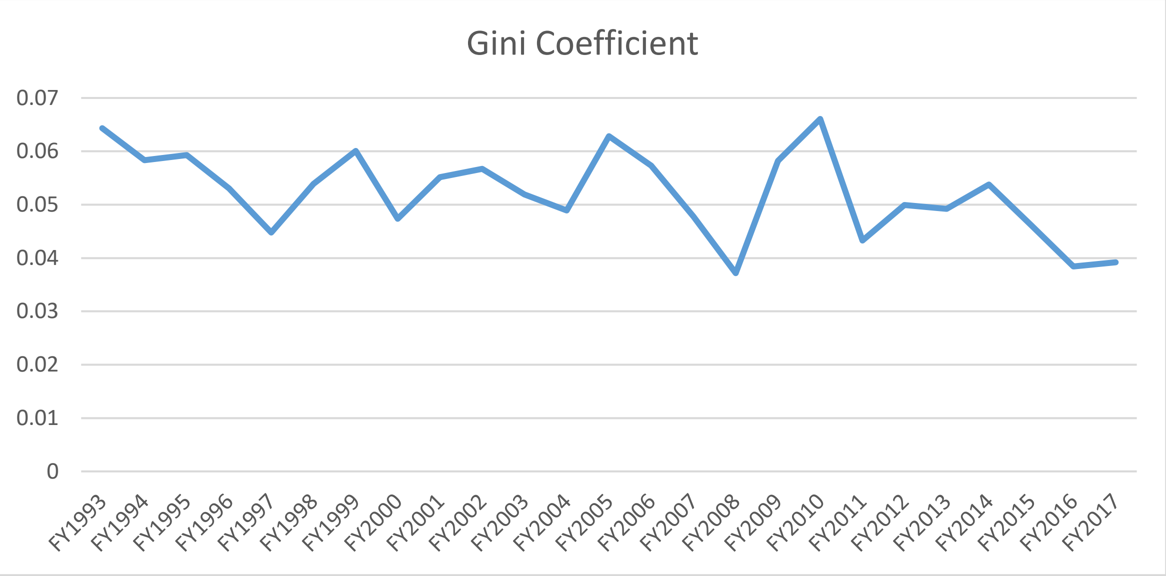
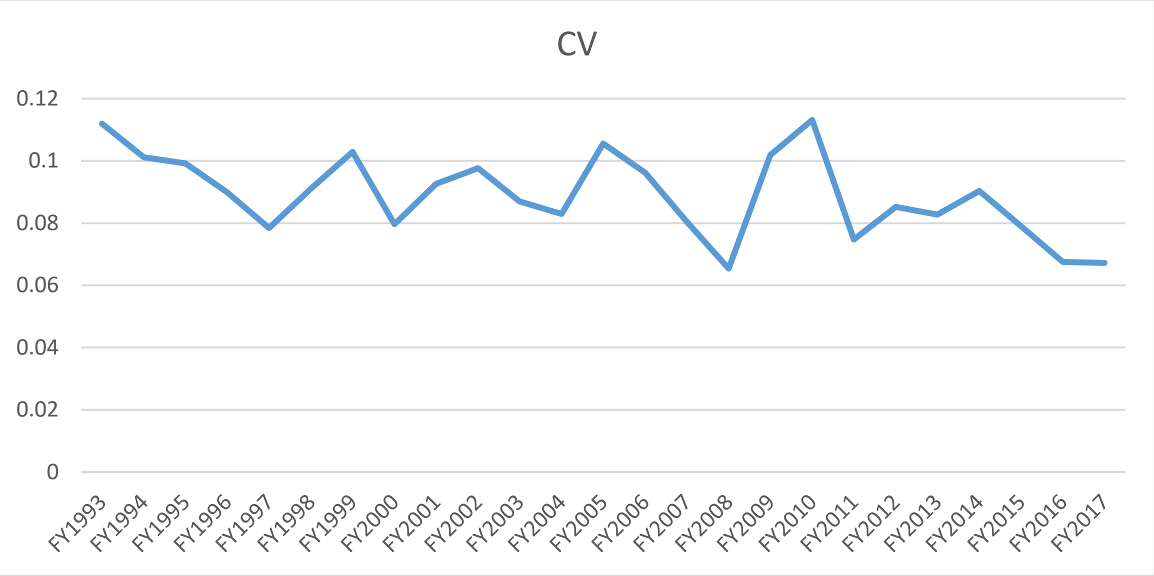
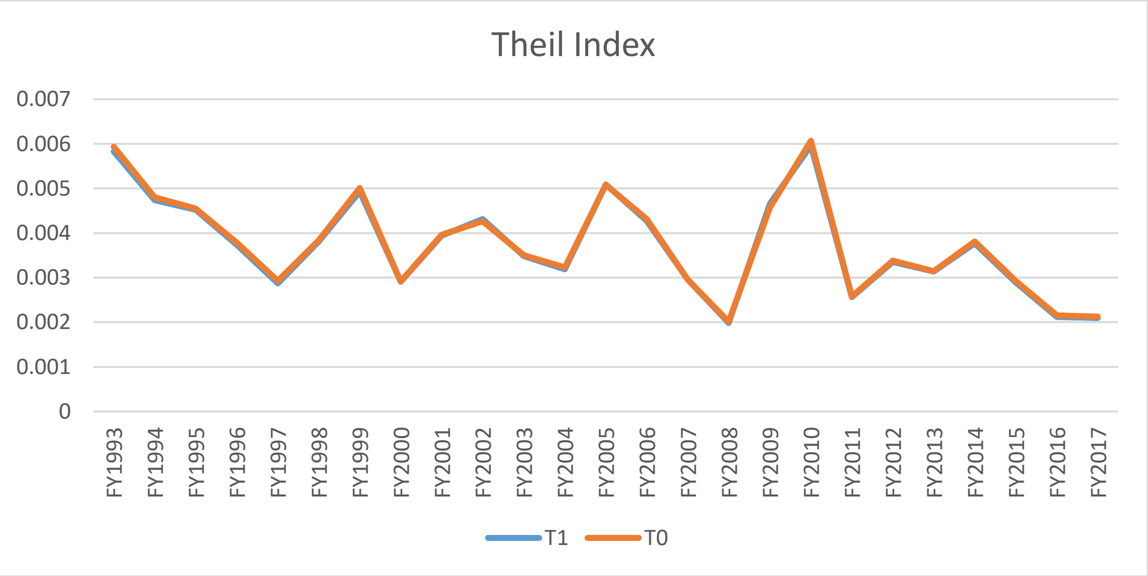
0.06
0.05
0.04
0.03
0.02
0.01
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
T0 Total
T0 Within Summer
T0 Whitin Winter
T0 Between

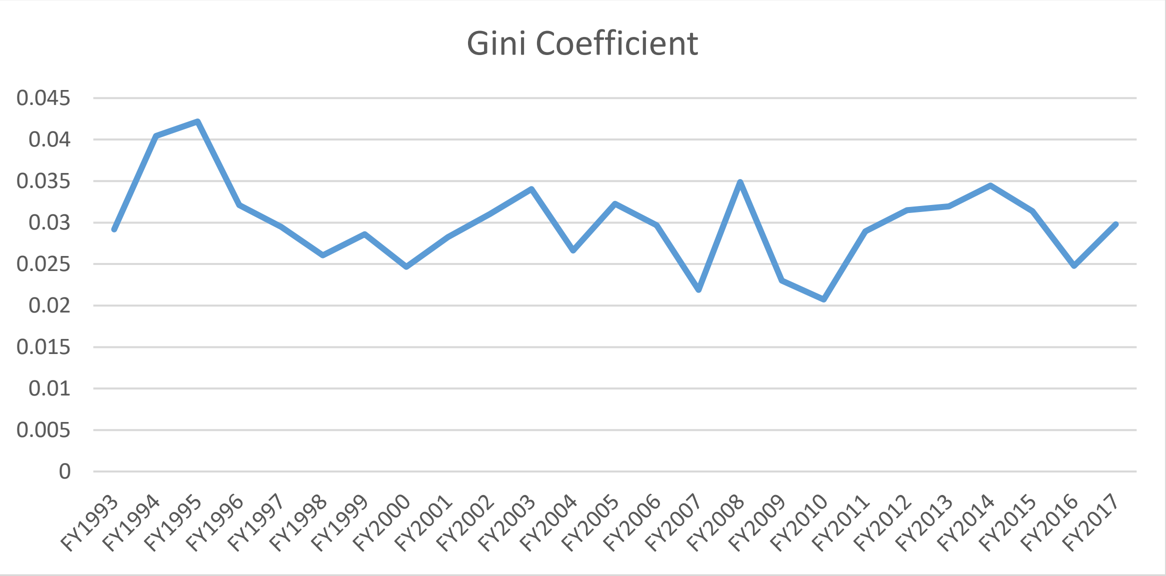
9.3.9. Car Sector

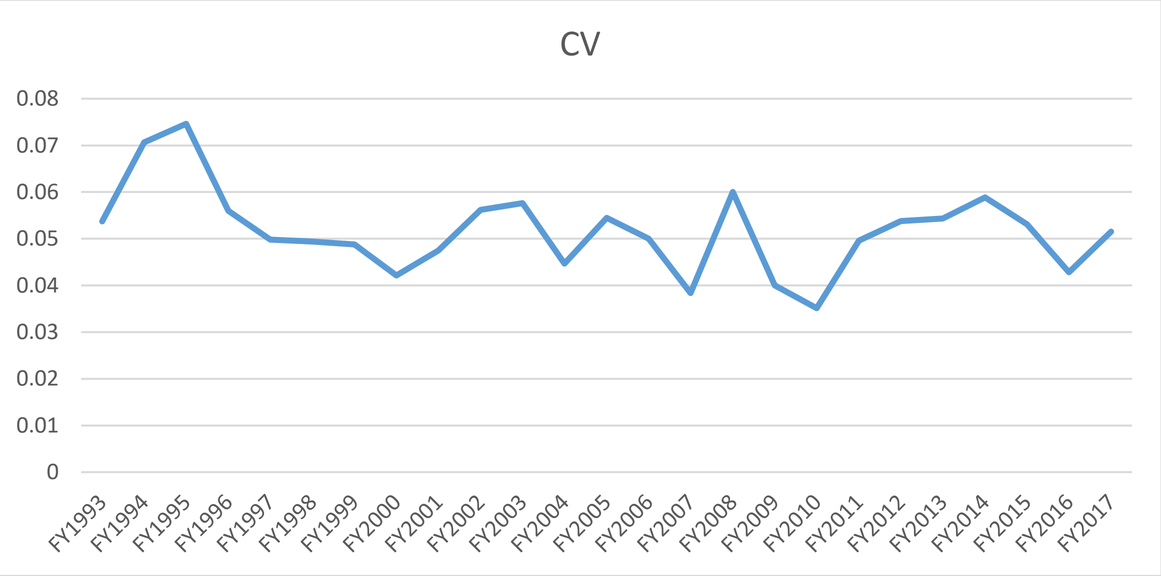


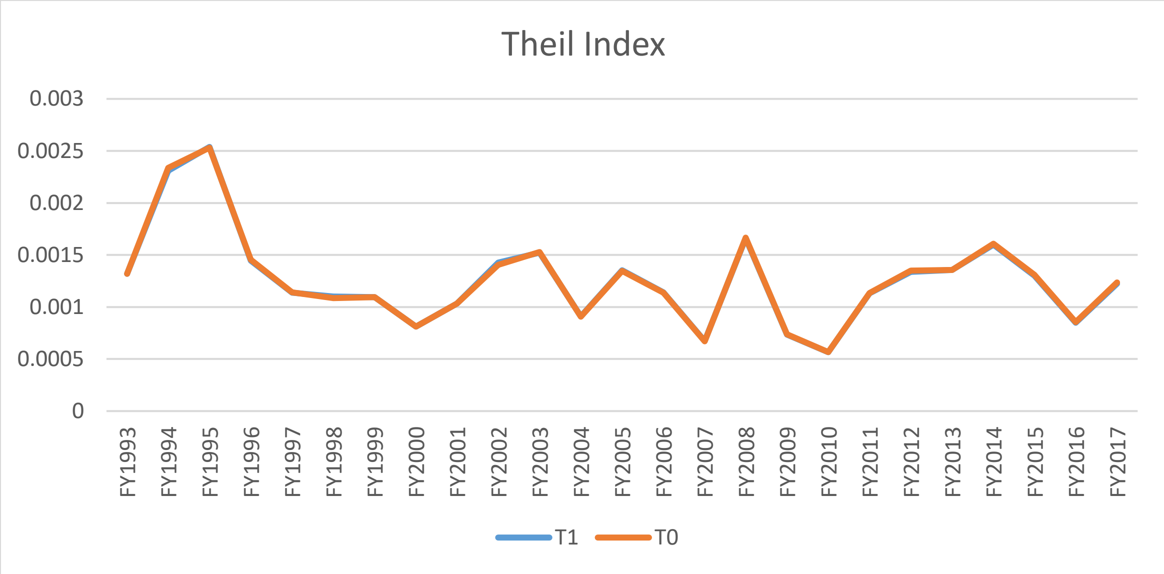




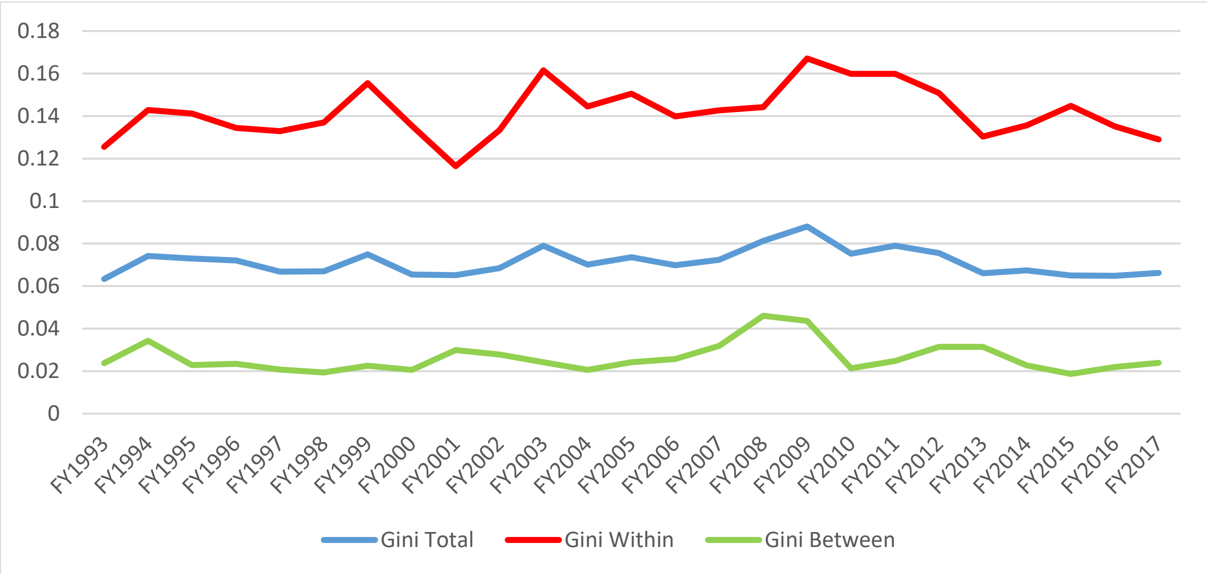
9.3.10. Furniture Sector

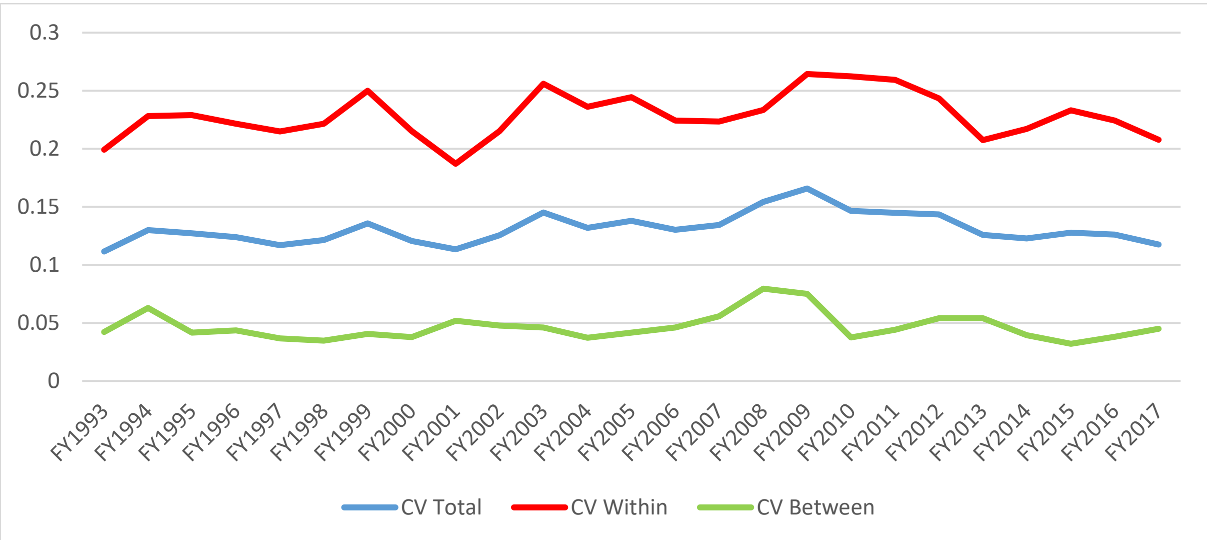


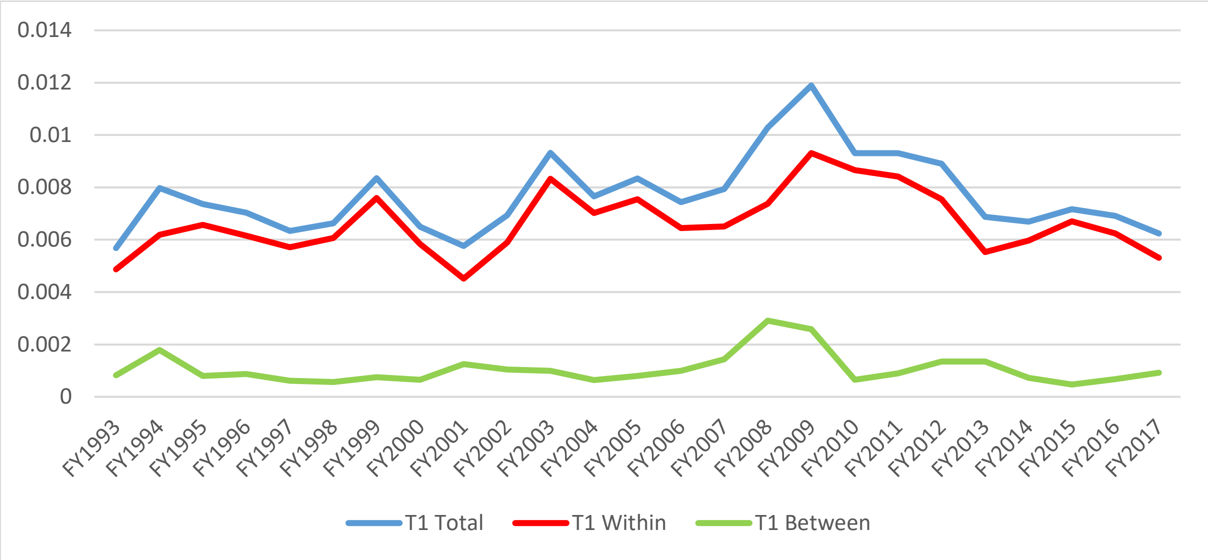


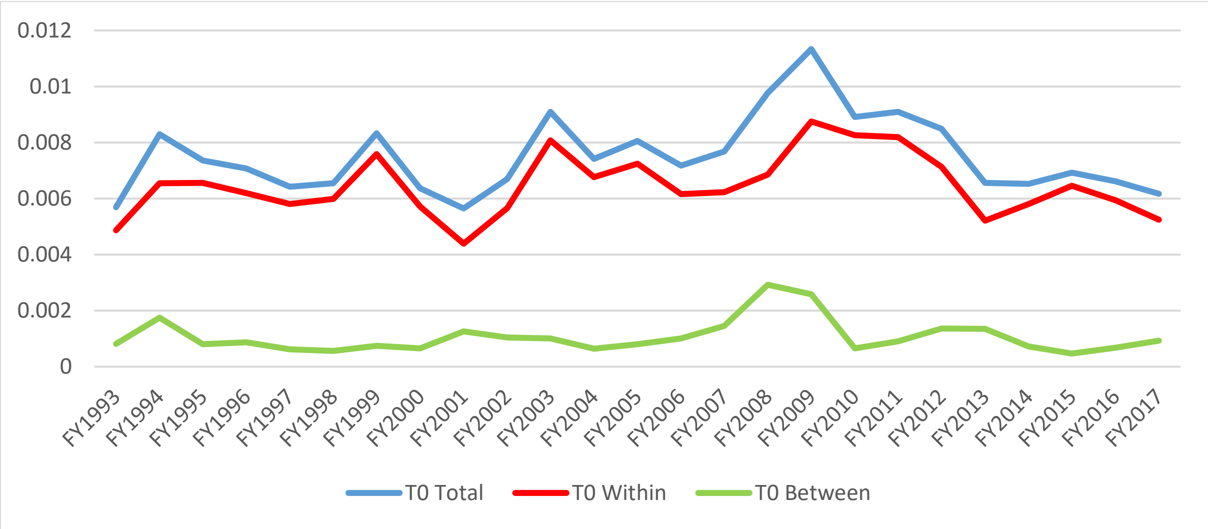


9.3.11. Home Furniture Sector

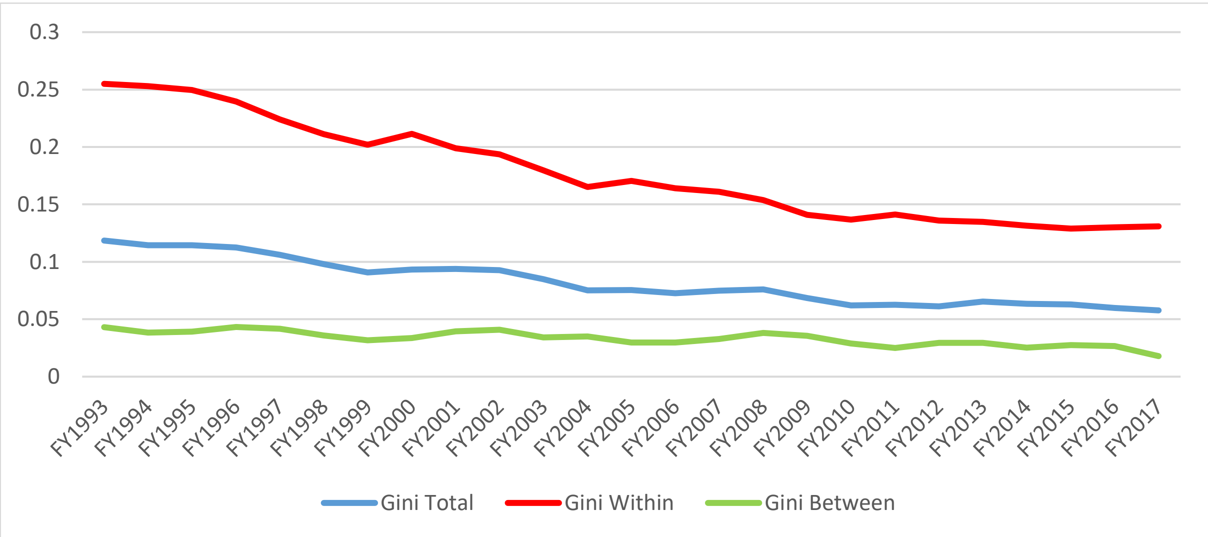


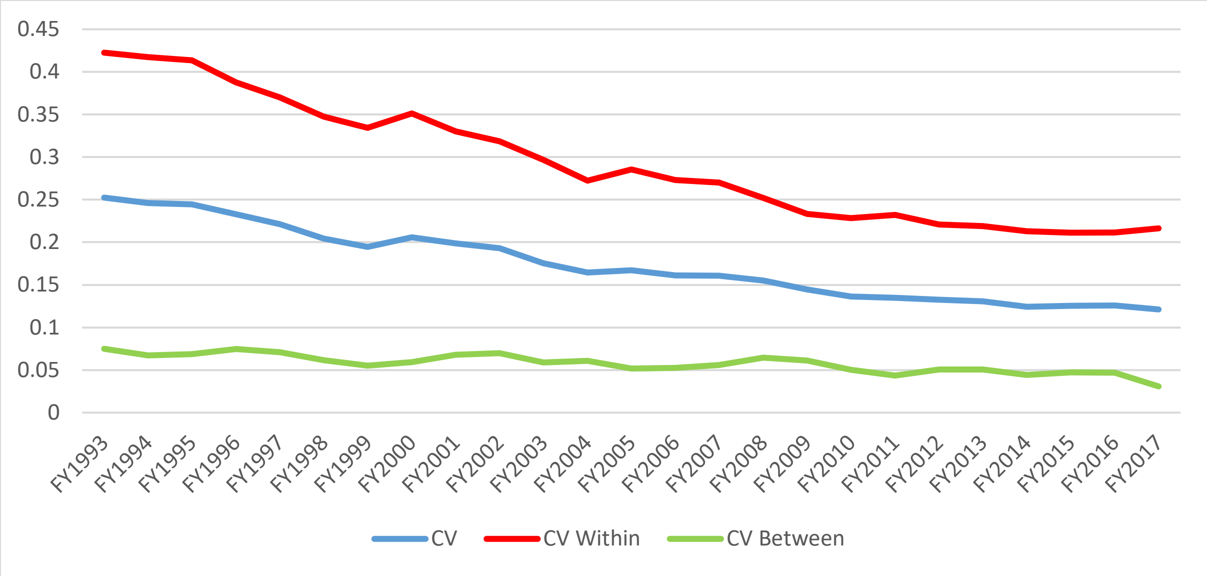




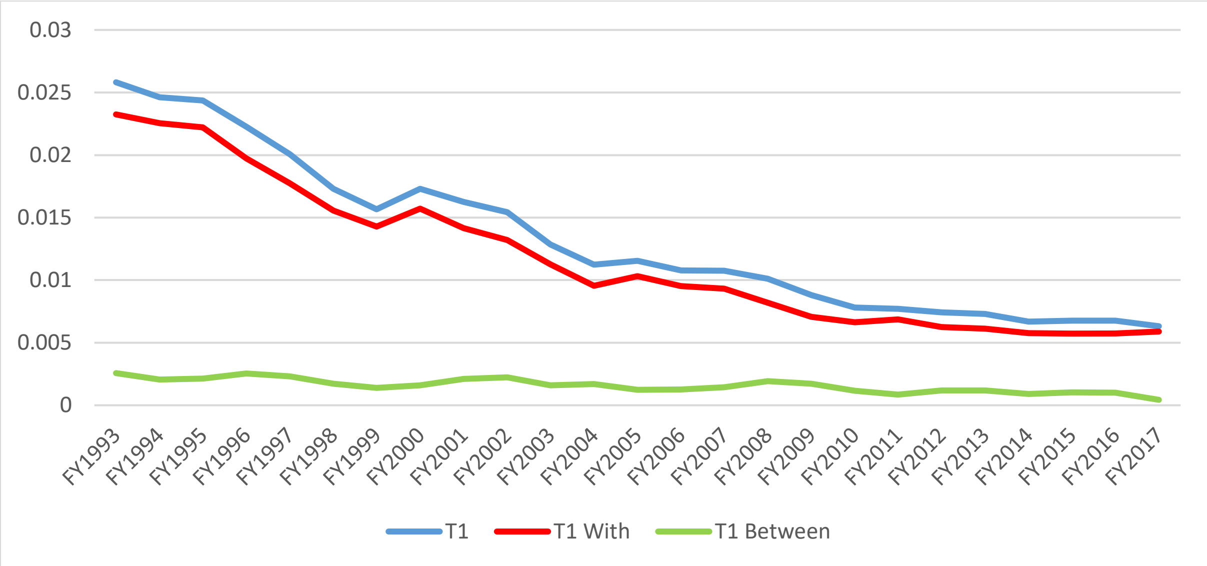


9.3.12. General Merchandise Sector

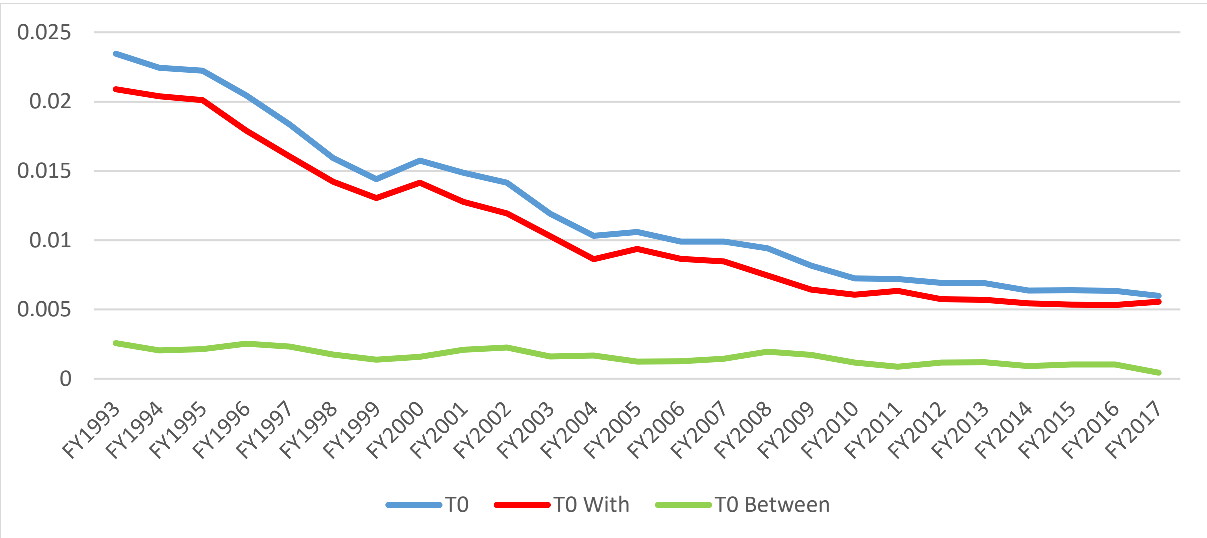




0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
CV
CV Within
CV Between



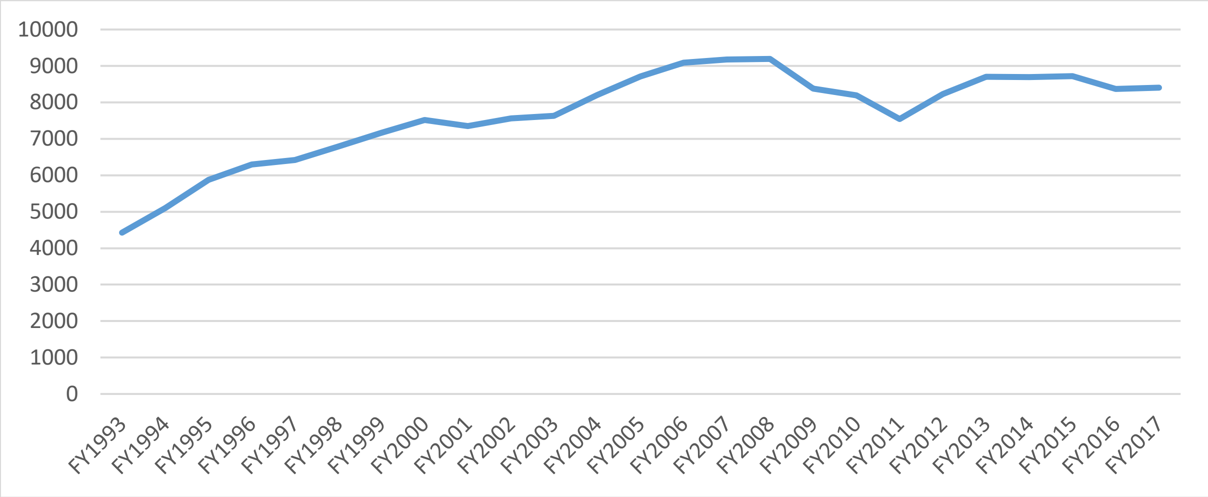
0.03
0.025
0.02
0.015
0.01
0.005
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
T1
T1 With
T1 Between



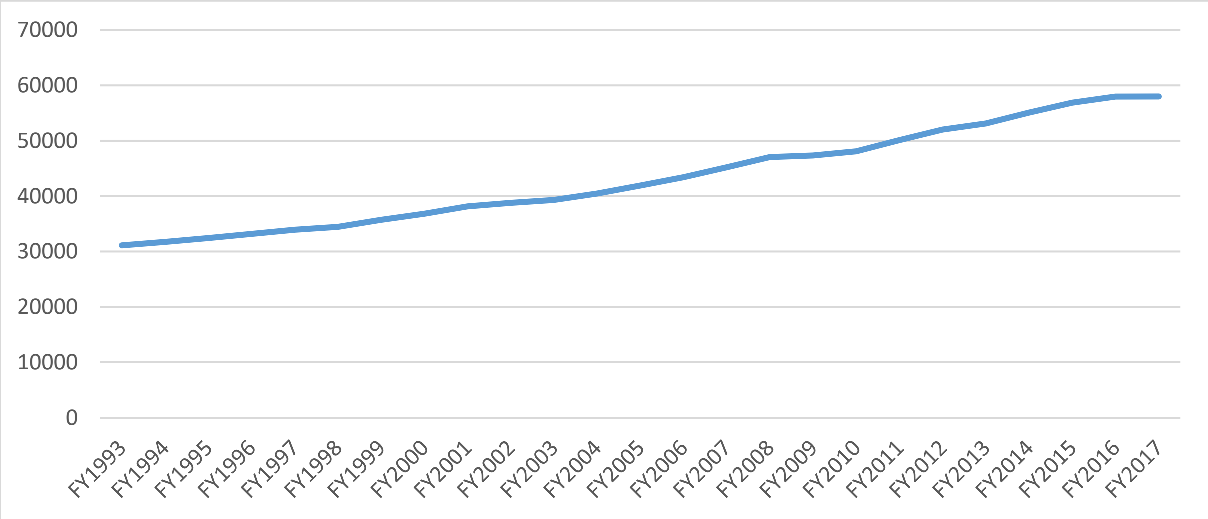
0.025
0.02
0.015
0.01
0.005
0
FY1993 FY1994 FY1995 FY1996 FY1997 FY1998 FY1999 FY2000 FY2001 FY2002 FY2003 FY2004 FY2005 FY2006 FY2007 FY2008 FY2009 FY2010 FY2011 FY2012 FY2013 FY2014 FY2015 FY2016 FY2017
T0
T0 With
T0 Between

9.4. Total Sales Trend

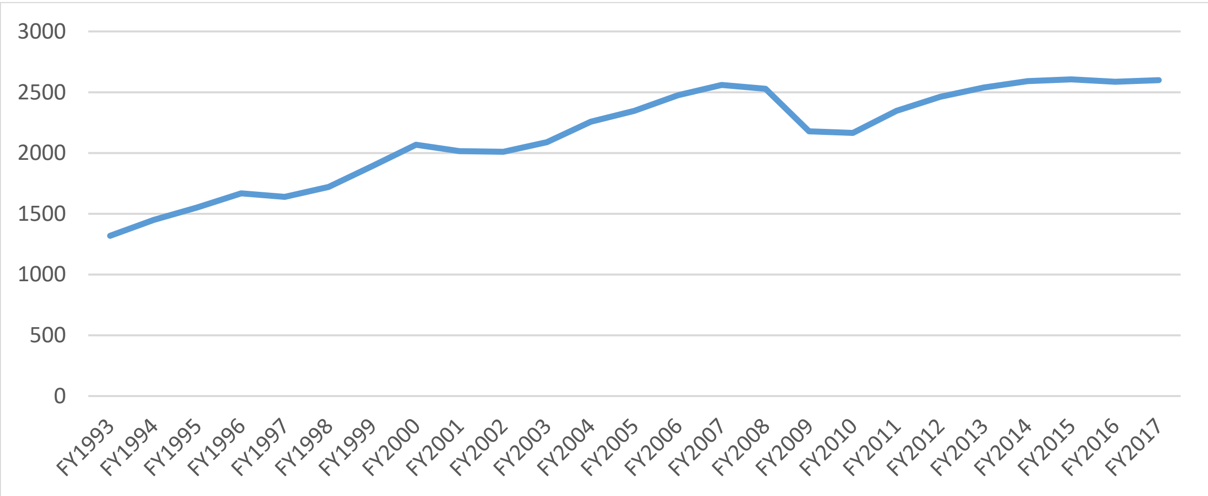
9.4.1. Electronics Sector



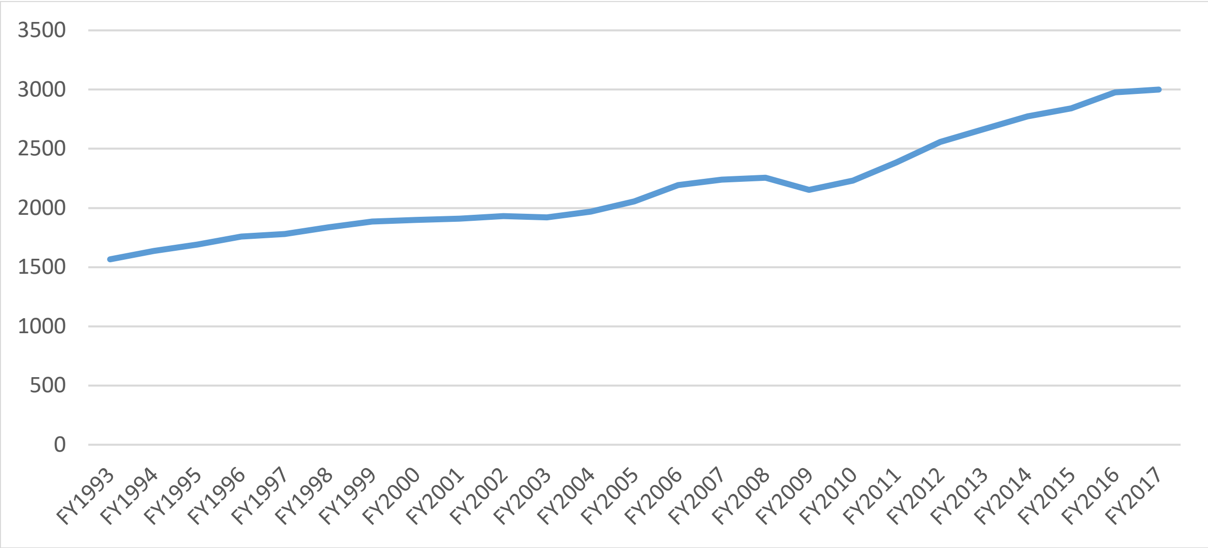
9.4.2. Food Sector



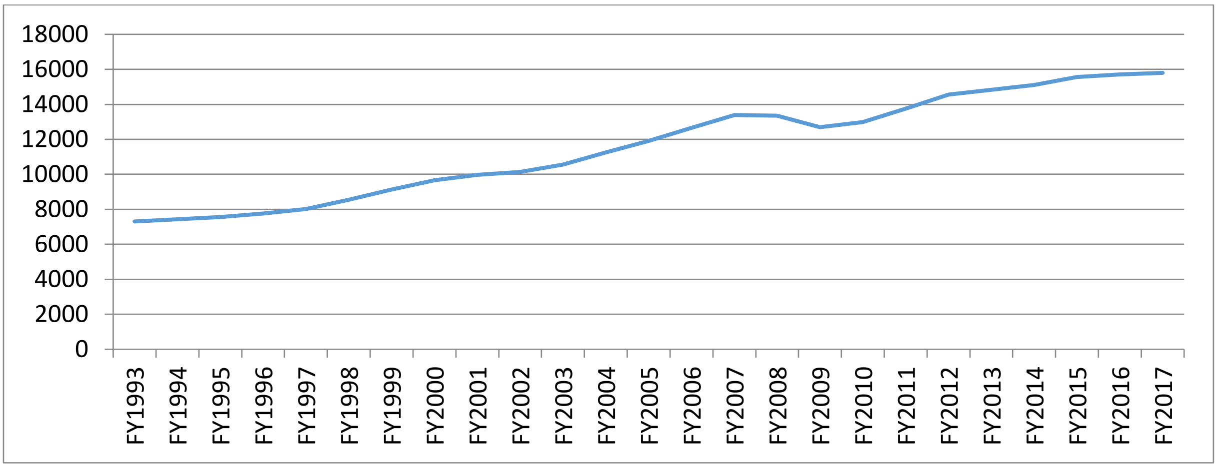
9.4.3. Jewelry Sector



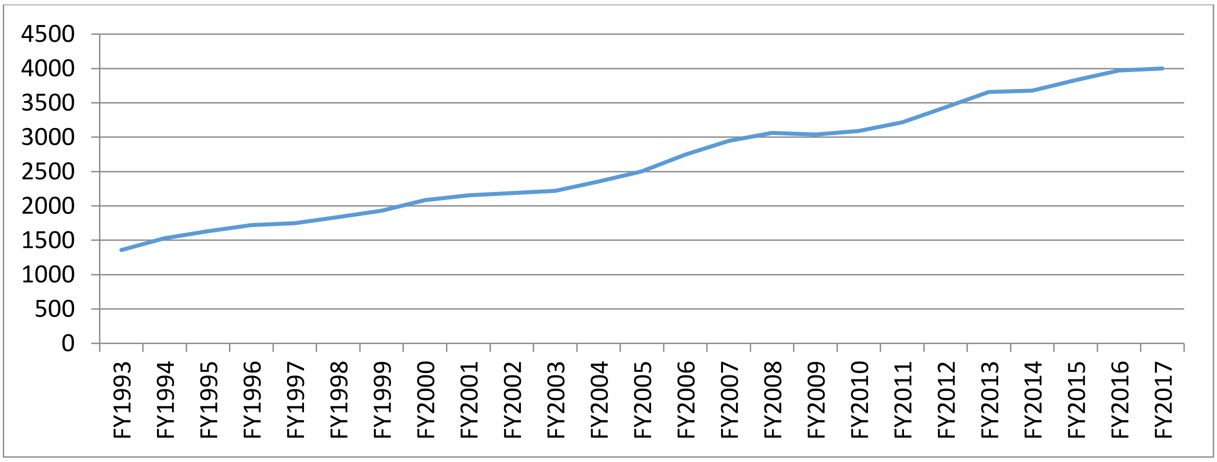
9.4.4. Shoe Sector



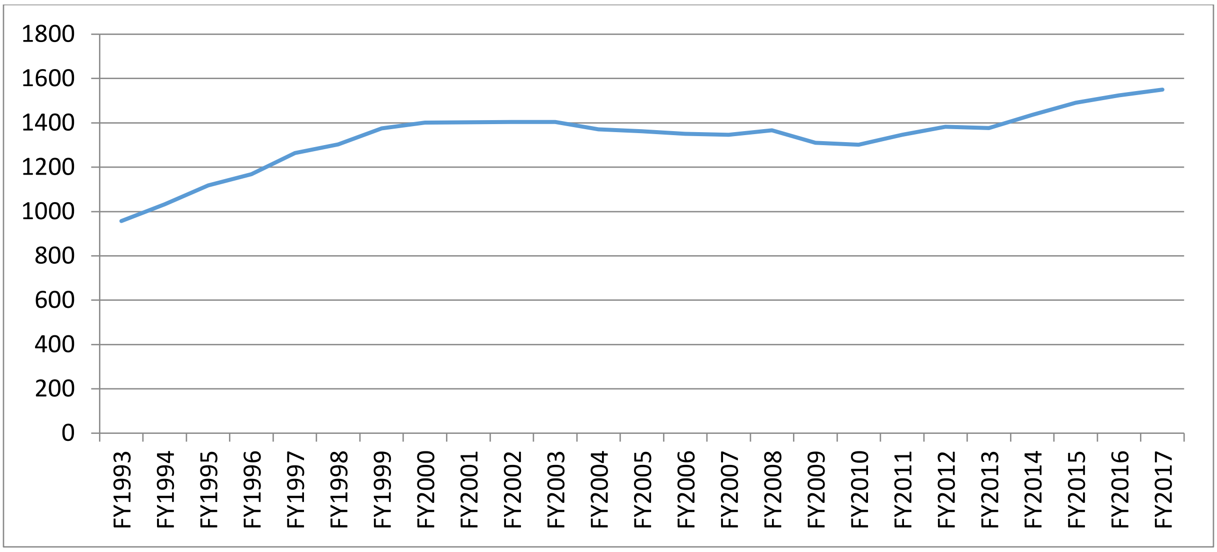
9.4.5. Clothing Sector



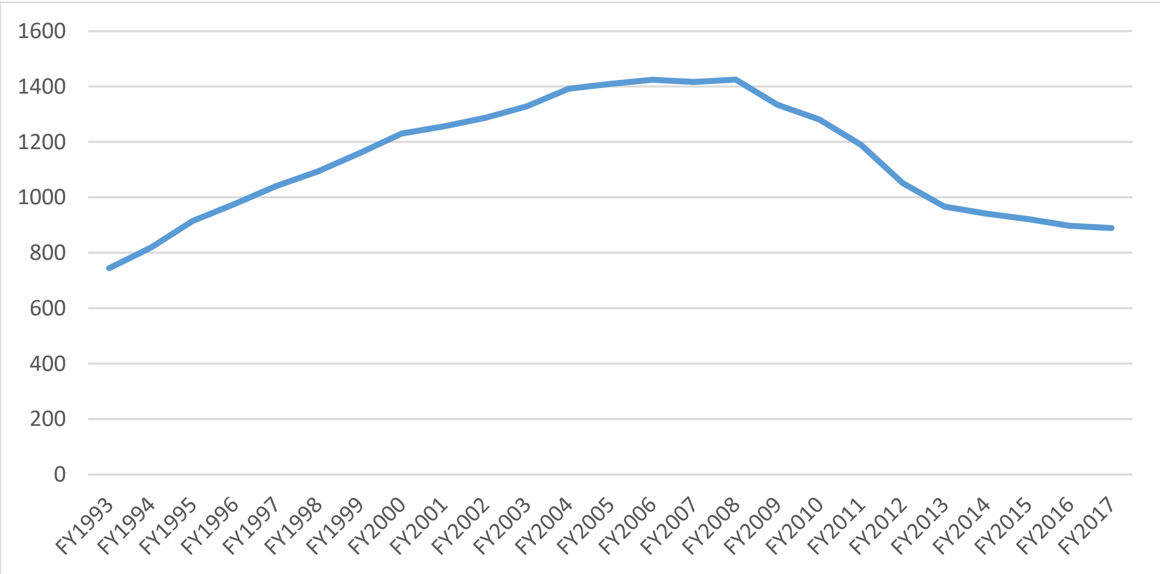
9.4.6. Sports Sector



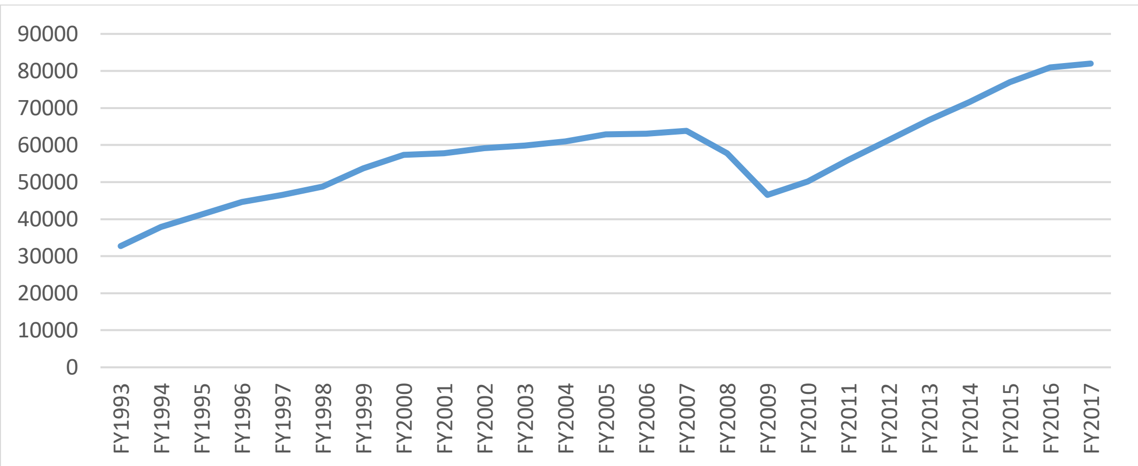
9.4.7. Toy Sector



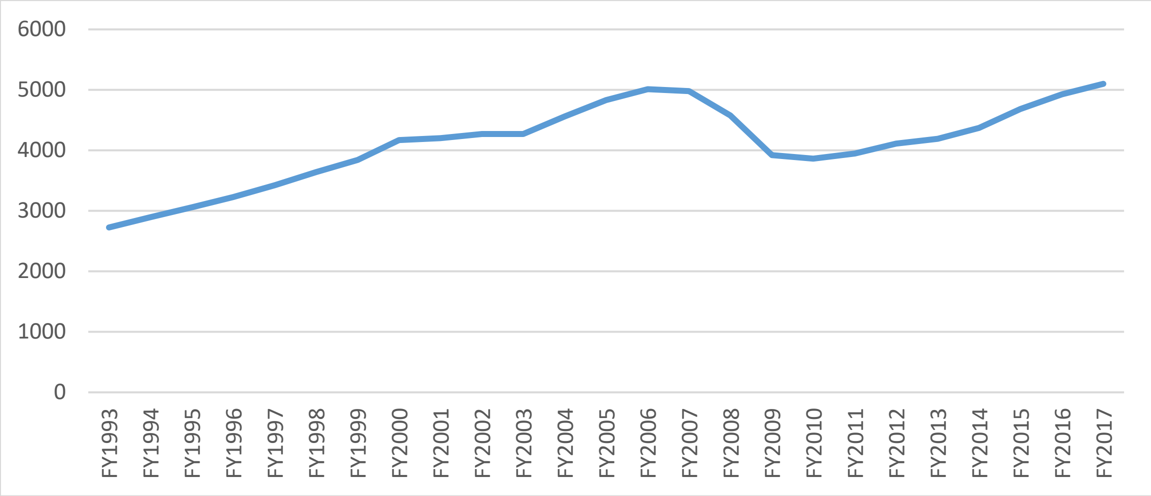
9.4.8. Book Sector



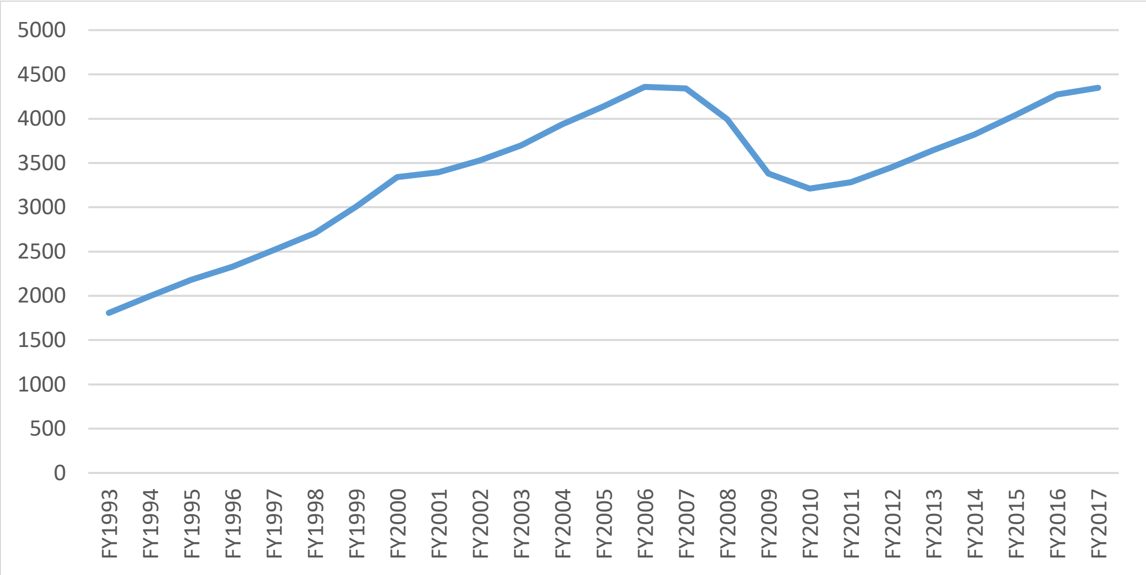
9.4.9. Car Sector



9.4.10. Furniture Sector



9.4.11. Home Furniture Sector



9.4.12. General Merchandise Sector