Erasmus School of Economics

October 2018

Price Points over the Business Cycle

An Investigation of the Demand for Durable and Non-Durable Goods During Economic Expansions and Contractions

Master Thesis Economics and Business

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Abstract

In this thesis, I study the demand effect of the business cycle. More specifically, I investigate whether the demand for high price point durable brands is more sensitive to shocks in the business cycle than the demand for high price point non-durable brands. I build on the importance of social status and propose that this can be obtained by purchasing goods from premium priced brands. Since durable goods are less essential in nature, I suppose that relative consumption is especially relevant for this type of goods. Albeit statistically insignificant, this thesis provides initial evidence for a larger demand effect of the business cycle for high price point durable brands than for high price point non-durable brands. However, more research is needed to strengthen the reliability of the results.

Keywords: business cycles, relative price points, relative consumption, product durability, demand effects

Acknowledgements

To start with, I am very grateful to my thesis supervisor dr. Y. Peers of the Erasmus School of Economics. Without his valuable input, the thesis would not have been on the same level. Although he advised me on how to proceed at the times I got lost, he also supported me to make the thesis my own.

I would also like to acknowledge the second reader of my thesis, prof. dr. A.C.D. Donkers of the Erasmus School of Economics, for being part of the final phase of my masters.

Finally, I would like to thank my parents for their optimism and supportive attitude during the thesis process. They did whatever they could to make sure that I was able to successfully finalize my masters.

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Chapter 1: Introduction

The economy of the United States has fully recovered from the recent financial crisis and the affiliated Great Recession that began in 2007 and ended 2009 (NBER, 2012). There is a positive inflation (Reuters, 2018), the unemployment rate is historically low (Kitroeff, 2018) and the consumer confidence is booming (Shiller, 2018). All's well that ends well? Not really, because it is not a question of if, but when a new economic recession will occur.

For that reason, it is important that we learn our lessons from previous crises and make sure that we do not make the same mistakes again (The Associated Press, 2018). This is exactly the purpose of my thesis. I study the demand effect of the business cycle for premium priced brands and investigate whether there are any differences between durable and non-durable goods.

1.1 Relevance

I expect dissimilarities in the demand effect of the business cycle for durable and non-durable goods, because both types of goods are completely different in nature. Non-durable goods, like soft drinks and chocolate bars, are short lifespan products and so consumers buy them frequently. In contrast, durable goods, like televisions and dishwashers, have a much longer lifespan and therefore consumers purchase them only occasionally (Cambridge Dictionary, 2018; Macmillan Dictionary, 2018).

To start with, I suppose that there are differences in the total demand for durable goods compared to non-durable goods over the business cycle. The acquisition of non-durable goods is considered to be a necessity; one has to feed himself properly to survive. On the other hand, the purchase of durable goods is rather a matter of choice; one could repair a broken dishwasher instead of replacing it or decide to clean the dishes by hand (Cook, 1999). For that reason, it is much easier to delay the acquisition of durable goods to save money in times of an economic contraction (Weder, 1998). This means that the sales of durable goods are more sensitive to shocks in the business cycle, which suggests that the demand effect of the business cycle is larger for durable goods than for non-durable goods. This is confirmed by many other researchers before (e.g. Cook, 1999; Dekimpe & Deleersnyder, 2018; Deleersnyder, Dekimpe, Savary & Parker, 2004; Van Den Bergh, 2013).

Besides, I presume that the demand effect of the business cycle is affected by the relative price level of a product or brand as well. Since the disposable income is lower during an economic contraction, consumers tend to save money by economizing on price (e.g. Lamey, Deleersnyder, Dekimpe & Steenkamp, 2007; Van Den Bergh, 2013; Wakefield & Inman, 1993). For that reason, I expect that the demand for high price point brands, relative to low price point brands, is lower in case the economy shrinks. The opposite holds in times of an economic expansion.

The main goal of this thesis is to combine product durability and price levels and determine whether differences over the business cycle occur. Since non-durable goods have a short lifespan, the acquisition affects the present only; soft drinks only quench the thirst once and the exact same bottle of soda cannot be consumed again. In contrast, the purchase decision of a durable good impacts the present and the future; buying a premium quality television would result in a satisfactory watching experience now and in the years to come, whereas acquiring a lower priced alternative may cause disappointment and annoyance for a long period of time.

So, the acquisition of durable goods affects the future directly, whereas that of non-durable goods does not. For that reason, I predict that the impact of the business cycle on the demand for premium priced brands differs for durable and non-durable goods. Since price is an important determinant of perceived quality (Rao & Monroe, 1989), the products of expensive brands are expected to be better than those of cheap brands. Because the harm of purchasing a pig in a poke is felt for a longer period of time in case the product is a durable good, I predict that consumers are more reluctant to buy products from low price point brands for this type of goods and so they would prefer premium priced brands.

In case there is an immediate urge to replace a durable good during a recession, like when a shower breaks down and cannot be fixed, I expect that consumers buy products from low price point brands more frequently, caused by stricter budget constraints (e.g. Wakefield & Inman, 1993). However, they rather want to postpone the purchase until the economy recovers and there is more money available to spend on high quality durable goods to avoid a bad bargain (e.g. Cook, 1999; Dekimpe & Deleersnyder, 2018). This would suggest that the demand effect of the business cycle is larger for high price point durable goods than for high price point non-durable goods.

More important, the former is strengthened by the importance of one's position in society (Ejrnaes & Greve, 2017). It has been shown before that social status can be obtained by relative consumption levels, suggesting that people want to consume more of a particular good in case their peers do so as well (e.g. Alpizar, Carlsson & Johansson-Stenman, 2005). Since the disposable income of others decreases during a recession, less consumption is needed to maintain the same social status (Kamakura & Du, 2012). I apply this theory to relative price levels and assume that social status can be obtained by consuming goods from high price point brands. Since there is less money available during an economic contraction, less consumption of high price point brands is needed to keep the same position in society.

Kamakura and Du (2012) argue that relative consumption is important for (visible) positional goods in particular. Those positional goods, like jewellery and cars, are less essential in nature and so they are more or less related to durable goods, that score low on necessity as well. For that reason, I presume that the role of relative consumption is more important for durable goods than for non-durable goods. This again suggests that the demand effect of the business cycle should be larger for high price point durable goods than for high price point non-durable goods.

1.2 Research Question

To sum up, I investigate the demand effect of the business cycle for products or brands in multiple price classes and test whether there are differences for durable and non-durable goods. Above all, I consider the cheapest and most expensive brands in a particular product industry. The research question of this thesis is stated formally as follows:

"Is the demand effect of the business cycle larger for premium priced durable goods than for premium priced non-durable goods?"

To test for the effect of relative price levels over the business cycle, I perform a Pooled OLS Regression analysis. I consider several product categories to make sure that the results are not (product) industry-specific. For the non-durable goods, I include the markets of carbonated soft drinks, juices and coffee. Regarding the durable goods, I look at the dishwashers, laundry appliances and vacuum cleaners industries. The data is obtained from Passport, which is a market research database by Euromonitor International that contains statistics about industries, economies and consumers on a national and global scale (Euromonitor International, 2018).

1.3 Contribution and Implications

The primary goal of this thesis is to acquire some knowledge from the recent financial crisis. Although the economic harm of recessions may be enormous for firms, households, investors and governments, the insights obtained should be used to determine the right strategy in case a new economic downfall takes place. By doing so, the damage could be limited as much as possible (The Associated Press, 2018).

I argue that marketing managers should take into account the durability of a product when determining the right strategy. Many other researchers found that the demand for non-durable goods is relatively stable over the business cycle, whereas the demand for durable goods is much more sensitive for shocks in the economic climate (e.g. Deleersnyder et al. 2004). For that reason, both product types require a different approach. In my thesis, I confirm this claim and underscore the importance of a (marketing) strategy that keeps in mind the durability of a product.

However, the main contribution of this thesis is the fact that I combine the concepts of product durability and relative price point. I add on the existing literature by investigating the differences in the effect of the business cycle on the demand for premium priced durable and non-durable goods. To the best of my knowledge, this has not been studied by other researchers in the exact same way before.

In case I do find evidence for the claim that the effect of the business cycle on the demand for expensive brands is larger for durable goods than for non-durable goods, this would be relevant for (marketing) managers. It would suggest that, in times of an economic downfall, more consumers switch away from high price point brands to low price point brands in the durable good markets than in the non-durable good markets. This would mean that price cuts during economic crises are more effective for durable goods than for non-durable goods. In their turn, marketing managers should incorporate this in their decision about the preferred strategy over the business cycle.

1.4 Background: The Great Recession

In this thesis, I use data from 2009 to 2017. In those years, the economy was recovering from the Great Recession (NBER, 2012), which was mainly the result of overconfidence in the housing market by the American banking sector (Mankiw, 2018). Before the financial crisis occurred, the economy in the U.S. and the rest of the world was flourishing. Consumers felt positive about the economic prospects and they were spending their money on all kind of goods.

At the same time, banks were accepting more and more mortgage applications from vulnerable consumers. These banks had two reasons to think that they were able to deal with these risks. To start with, banks take possession of the houses of money borrowers who go bankrupt. Since the economy was booming, banks thought it would not be difficult to sell these houses for a good price. Additionally, some risky and relatively save mortgages were pooled together and sold to third parties. In this way, the risk would come at the expense of private investors or hedge funds instead of the banks themselves (The Economist, 2013).

However, at the end of 2007, the American housing market collapsed. As a result of the increasing interest rates, many house owners could not afford their mortgage payments any longer. This means that the supply of houses increased, which made it more difficult to sell the houses and reduced the prices paid on the housing market. For that reason, house owners had to deal with residual debts, since the value of their mortgages was higher than that of the houses themselves. Besides, the value of the pooled mortgages decreased by a lot, and so the investors and hedge funds lost a substantial part of their money (The Economist, 2013).

In 2008, the whole U.S. economy experienced the consequences of the problems in the banking sector. The confidence in the economy was vanished and consumers, firms and investors tried to save money instead of spending it. Besides, in an attempt to survive the recession, companies fired more and more employees (Uchitelle, 2009). Additionally, the financial crisis in the U.S. expanded to other countries as well. The worldwide Great Recession began, and its effects were still notable for a long period of time (The Economist, 2013; 2014).

1.5 Structure of the Thesis

The remainder of this thesis is structured as follows. In the next chapter, I discuss some relevant theory about business cycles, relative consumption and price levels, and durable goods. Additionally, I introduce the hypotheses that are tested in this research. In Chapter 3, I describe the methods and models that are used to test for the differences in the demand effect of the business cycle for premium priced durable and non-durable goods. Besides, I present the descriptive statistics. Chapter 4 contains the main results and the robustness checks, whereas Chapter 5 concludes the research with some final remarks, limitations and directions for further research.

Chapter 2: Theoretical Framework

In this chapter, I consider some theoretical concepts that are relevant for this thesis. I start with a general introduction about business cycles and how they affect the (worldwide) economy to emphasize their relevance in the world around us. I put some extra focus on the price sensitivity over the business cycle, since it is strongly related to the impact of relative price levels. Additionally, I discuss some theory about relative consumption and price points. Thereafter, I define durable and non-durable goods, whereas I finalize the section with a justification of the hypotheses that are tested in this research.

2.1 Business Cycles

In brief, business cycles are often defined as '*alternate periods of economic growth and recession*' (Cross & Bergevin, 2012). In other words, they reflect the level of economic activity, commonly measured as real GDP. Zarnowitz (1985) argues that, although they may differ in amplitude (depth), scope (diffusion) and duration, fluctuations in the business cycle have many similarities as well. To start with, they take place on at least a national, but usually on an international scale and they appear in a broad spectrum of (economic) processes. Additionally, business cycles are ongoing and upward movements are preceded and succeeded by developments in downward direction.

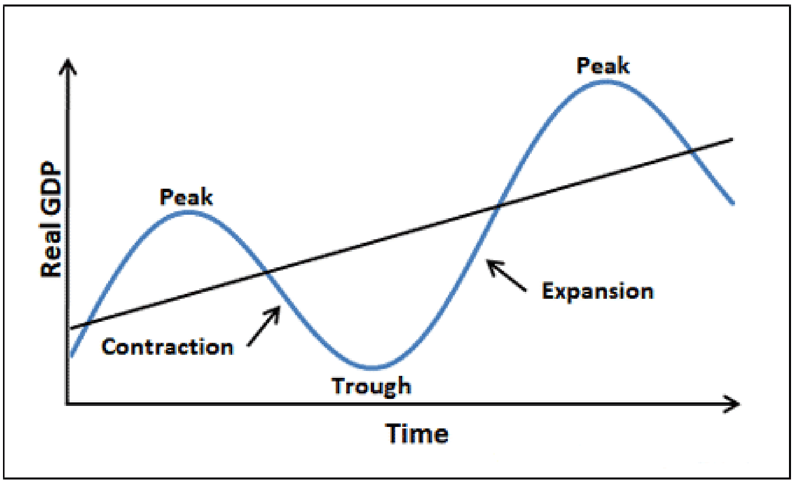

Figure 1: The Business Cycle (Source: Money-Zine)

Each business cycle consists of an expansion and a contraction period. In the expansion stage, the economy flourishes and the economic prospects are positive. However, during the contraction phase, the economy weakens and consumers feel less confident about the economic perspectives in the (near) future. However, a contraction does not necessarily mean that the economy shrinks in absolute terms. It can also be that the GDP growth rate reduces on a temporary basis, and so the state of the economy is worse than expected (Zarnowitz, 1985). A graphical representation of the business cycle can be found in Figure 1.

Based on the years after the World War II (1939-1946), a complete business cycle lasts for about six years on average. In five out of six years, the economy is in the expansion stage, whereas the contraction phase takes about one year (NBER, 2012; Stupak, 2017). However, keep in mind that these numbers are only averages. Individual business cycles may take much longer or shorter (Cross & Bergevin, 2012).

Although fluctuations in the business cycle may be caused by shocks in the supply side of the economy, they are most frequently the result of some distortions on the demand side. These shocks may result in a snowball-effect, which means that increases and declines in employment, income, sales and output strengthen each other. Imagine a situation in which people lose their jobs in a particular economic sector. This would result in a lower total income, which means that the total purchasing power drops. As a consequence, the sales in all economic sectors decreases and so firms would produce less goods. For that reason, less employees are needed and the whole process starts all over again (Achuthan & Banerji, 2004).

This example shows that developments in a single economic sector may evoke shocks that affect the economic environment of entire countries and ultimately the whole world (Christiano & Fitzgerald, 1998; Zarnowitz, 1985). Although some consequences of the shocks are experienced in the short term, disturbances in the business cycle may have long term effects as well. For instance, most firms cut their R&D expenditures during an economic contraction, whereas they (over)invest in research and development during economic expansions (Barlevy, 2007). Since the beneficial effects of R&D are often notable in long term, reducing the investments during economic contractions may harm the performance of a company in times of an economic expansion.

2.1.1 Price Sensitivity over the Business Cycle

The price sensitivity over the business cycle has been investigated by many other researchers before. For instance, Estelami, Lehmann and Holden (2001) found that consumers recall prices less accurate in case the GDP growth rates and inflation rates are higher. In other words, consumers are more aware of price levels during economic contractions, whereas they are less interested in prices when the economy is booming. This could be explained by the fact that, irrespective of the business cycle, lower income consumers are more aware of prices in general, since they have tighter budgets (Wakefield & Inman, 1993). As the household income is expected to be lower in case the economy shrinks, conducting a detailed price search would be more beneficial during economic contractions.

Additionally, Van Heerde, Gijsenberg, Dekimpe and Steenkamp (2013) add on these findings by investigating price elasticity over the business cycle for multiple consumer packaged goods categories and types of brands. On average, they argue that consumers are more price sensitive in case the economy is in the contraction phase, whereas the price sensitivity decreases in case the economy expands. However, the amplitude of the effect differs per brand type and product class. The latter is supported by Gordon, Goldfarb and Li (2013), which suggests that the impact of the business cycle on price sensitivity depends on the product (market) and brand characteristics.

2.2 Relative Consumption and Price Points

Consumers do not only care about absolute consumption, but they also attach value to relative consumption. In other words, they derive utility from consuming at least as much as their peers. This could be explained by the fact that social status may be determined by relative consumption levels (Fisher & Hof, 2000). Those who consume more of a particular good achieve a higher social position. A lot of research on the impact of relative consumption has been conducted before (e.g. Alpizar et al. 2005; Fafchamps & Shilpi, 2008).

One of the most prominent studies in this field is that of Kamakura and Du (2012). They argue that relative consumption is mainly important for less essential goods with a high (social-cultural) visibility. Such products are called positional goods and the utility derived from the consumption of these goods may differ over the business cycle. Since the disposable income shrinks in case the economy is in a recession, consumers have to lower their overall expenditures. This means that other consumers need to cut back their expenditures to save money. As a result, less consumption of positional goods is needed to maintain the same social hierarchy, which suggests that the derived utility differs over the business cycle for products of which relative consumption is important (Kamakura & Du, 2012).

In my thesis, I apply the importance of one's position in society to price levels instead of consumption levels. In case a brand is relatively expensive compared to its competitors, acquiring such a brand would contribute to a higher social standing. As is the case for relative consumption, one would want to confirm their peers by purchasing products from brands with a comparable price point to obtain an equal social status.

In line with Kamakura and Du (2012), I argue that the business cycle impacts the consumers' brand choice. During an expansion, households have more money to spend. For that reason, it is likely that other households switch away from lower price point brands to higher price point brands. This means that individual households should switch to more expensive brands to maintain the same social status and so the demand for premium priced brands increases.

2.3 Durable and Non-Durable Goods

Durable goods are defined as '*things you do not buy often because they are expected to last for a long time, for example cars, furniture, and appliances*' (Macmillan Dictionary, 2018). They are the exact opposite of non-durable goods, which are '*goods that do not last for a long time and that people buy often*' (Cambridge Dictionary, 2018).

The demand for durable and non-durable goods has been investigated in other studies before. For instance, Sethuraman, Tellis and Briesch (2011) argue that the advertising elasticity is larger for durable goods than for non-durable goods. More relevant for this thesis, it turns out that the demand for durable goods is more sensitive to the business cycle than the general economic activity. Consumers delay the replacement of durable goods during economic recessions, caused by the lower confidence in the economy. Consumers feel the urge to save their money to compensate for the higher risk of income loss or unemployment (Deleersnyder et al. 2004; Weder, 1998).

In contrast with the demand for durable goods, the demand for non-durable goods over the business cycle is relatively smooth. Although consumers may switch to cheaper brands (Lamey, Deleersnyder, Dekimpe & Steenkamp, 2007), the overall sales in a particular non-durable product industry are less sensitive to the business cycle (Weder, 1998). Consumers consider the purchase of non-durables as a necessity, whereas acquisition of durable goods is more like a choice. This suggests that, unlike non-durable goods, there is no pressing need to buy durable goods at a particular point in time. For that reason, it is easier to postpone the purchase of durable goods in case the economy is in a contraction phase (Cook, 1999; Deleersnyder et al. 2004). So, when the economy recovers, the demand for durable goods increases disproportionally more than the demand for non-durable goods (Van Den Bergh, 2013).

2.4 Hypotheses

To determine the impact of price points over the business cycle for durable and non-durable goods, I test three hypotheses. Figure 2 presents a schematic overview of the relevant research framework in this thesis.

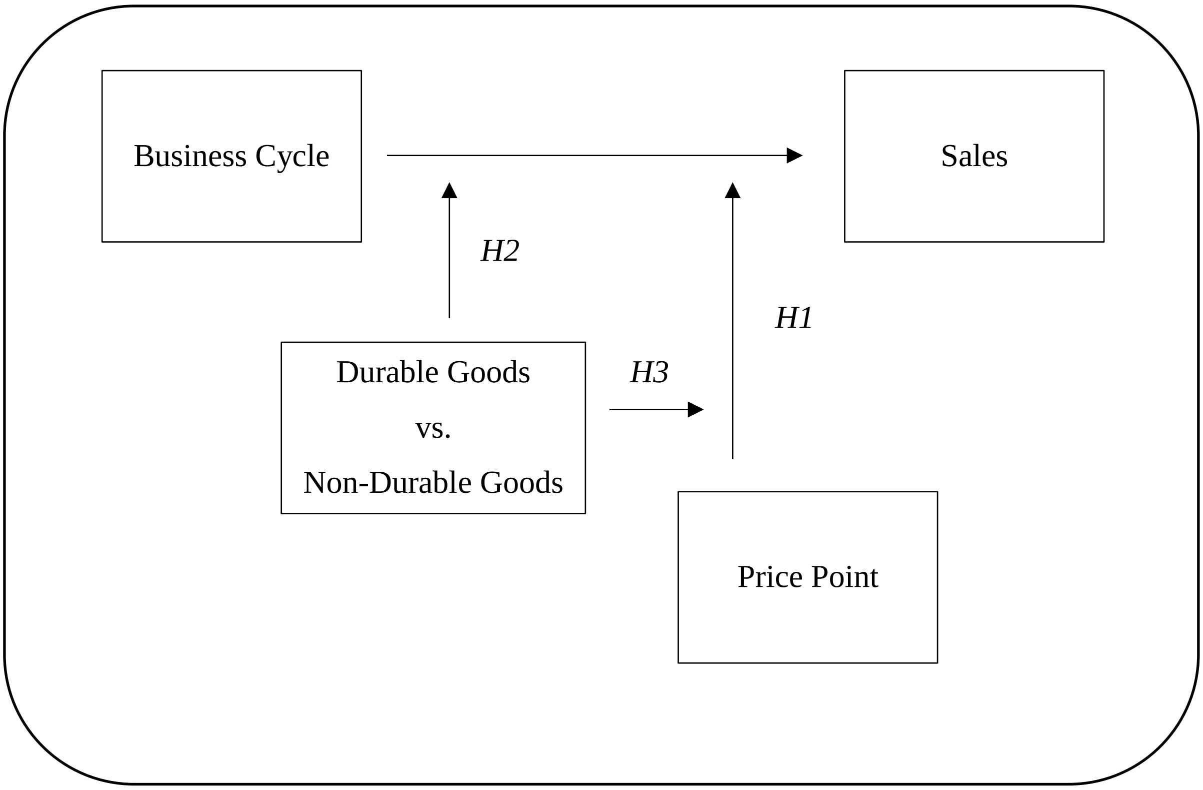

Figure 2: Research Framework

2.4.1 Price Points and the Business Cycle

Irrespective of the business cycle, there is a negative relationship between income and price knowledge (Wakefield & Inman, 1993). In other words, prosperity reduces the need to pay attention to price information. Since wages, and so the disposable income of households, increase during economic expansions, the benefits of an extensive search for price information are relatively limited (Estelami et al. 2001). On average, this means that consumers care less about price levels in case the economy is booming (Gordon et al. 2013). As a result, the demand for products from expensive brands increases.

In contrast, economic slowdowns harm the disposable income of households. This means that more consumers face a tight budget constraint (Estelami et al. 2001). Since low-income consumers care more about price levels than high-income consumers (Wakefield & Inman, 1993), the impact of relative price points is larger in case the economy is in the contraction phase (Gordon et al. 2013; Van Heerde et al. 2013). As a consequence, consumers switch to lower priced brands, like private labels, more frequently to cope with the reduced financial resources (Lamey et al. 2007; Van Den Bergh, 2013)

Overall, the above suggests that the demand for premium priced brands is countercyclical, which means that it rises when the economy weakens (Gordon et al. 2013). Next to the disposable income argument, there is the effect of social status. People care about their position in society, which can be strengthened by relative consumption (Fisher & Hof, 2000). In comparison to others, consuming more of particular goods results in a higher social standing. This is mainly the case for positional goods, which are products that are less essential and highly visible. Since others reduce their expenditures on this kind of goods during a recession, less consumption is needed to maintain the same social standing. So, the demand for positional goods is lower during economic contractions (Kamakura & Du, 2012).

In this thesis, I use brand identity instead of product positionality to determine the importance of relative consumption. I suppose that consumers derive utility from consuming at least as much premium priced brands as their peers. So, in case associates purchase more high price point brands in a particular product industry, one wants to acquire more premium priced brands himself as well to signal an equal social status. Since there is more money available during economic expansions, it is likely that other consumers buy more products from high price point brands. So, to maintain the same position in society, one should purchase more premium priced brands himself as well. This means that the demand for high price point brands increases more than that of low price point brands. The opposite holds in case of a recession. Formally, this results in the following hypothesis:

<u>Hypothesis 1</u>*: In case the economy expands, the demand for high price point brands compared to the demand for low price point brands increases. In case the economy shrinks, the opposite happens.*

2.4.2 Product Durability and the Business Cycle

In general, the quantity of goods demanded decreases during economic downturns, caused by the lower disposable income (Van Den Bergh, 2013). However, other researchers argued that the durability of a product moderates the effect of the business cycle on the market size. During economic contractions, consumers want to save money by reducing the quantity bought or by postponing the purchase until the economic environment has recovered (Katona, 1975). Since non-durable goods, like food and beverages, are more necessarily in nature and buying them have become habitual, economizing on quantity is not very likely (Deleersnyder et al. 2004). In fact, consumers rather save on non-durable goods by switching to lower priced brands (Shama, 1981; Lamey et al. 2007).

On the contrary, the acquisition of durable goods is much easier to postpone. It is considered as a choice, because there is no urgent need to purchase them. For instance, the replacement of durable goods can be easily delayed by repairing those that do not function well (Clark, Freemand & Hanssens, 1984). Besides, the purchase of durable goods can be postponed by choosing alternative options; one could decide to travel by public transport instead of buying a car. For those reasons, the overall quantity of durable goods demanded is lower in case the economy is in the contraction phase.

Overall, this suggests that the demand effect of the business cycle is larger for durable goods than for non-durable goods. The market size of durable goods is expected to be more sensitive to the business cycle than that of non-durable goods. This results in the following hypothesis:

<u>Hypothesis 2</u>*: In case the economy expands, the demand for durable goods compared to the demand for non-durable goods increases. In case the economy shrinks, the opposite happens.*

2.4.3 Price Points, Product Durability and the Business Cycle

Although the first two hypotheses are a good starting point, the ultimate goal of this thesis is to determine whether the impact of the business cycle on the demand for premium priced brands differs for durable and non-durable goods. As mentioned before, non-durable goods are consumed in the short term, whereas durable goods have a longer life span (Cambridge Dictionary, 2018; Macmillan Dictionary, 2018). For that reason, purchasing a bad quality durable good harms the utility of consumption in the present and in the future. On the other hand, a bad purchase of a non-durable good affects the short-term consumption experience only.

This suggests that consumers want to avoid a bad bargain for durable goods especially. Since the price of a product is a predictor of its quality (Rao & Monroe, 1989), goods from high price point brands are expected to be better than goods from low price point brands. So, to avoid a bad purchase, consumers prefer to buy durable goods from premium priced brands.

However, as mentioned before, the disposable income of households is lower during economic contractions (Estelami et al. 2001; Van Den Bergh, 2013). For that reason, it is harder to afford durable goods from premium priced brands. So, in case it is impossible to postpone the purchase of durable goods, consumers buy products from low price point brands as they lack the financial resources to afford premium priced brands.

Again, this argument is reinforced by the importance of relative consumption. Remind that the desire to confirm the consumption level of associates is especially relevant for goods that score low on essentiality (Kamakura & Du, 2012). Since durable goods are less essential in nature than non-durable goods, I propose that the role of relative consumption is larger for the former type of goods. This implies that the demand effect of the business cycle would be larger for high price point durable goods than for high price point non-durable goods. The hypothesis is stated formally as follows:

<u>Hypothesis 3</u>*: In case the economy expands, the demand for high price point brands compared to the demand for low price point brands increases more for durable goods than for non-durable goods.*

Chapter 3: Methods and Models

In this chapter I describe the methods and models that are used in this thesis. Additionally, I discuss the consulted data sources, whereas I finalize the section with an overview of the relevant descriptive statistics.

3.1 Methods

To study the demand effect of the business cycle, I perform some multiple regression analyses. This is a very appropriate technique to determine the relationship between one interval- or ratio-scaled dependent variable and one or more interval- or ratio-scaled independent variables. The coefficients are estimated by the Ordinary Least Squares (OLS) method, in which the difference between the actual and the predicted value of the dependent variable is as small as possible (Field, 2009; Janssens, Wijnen, De Pelsmacker & Van Kenhove, 2008). OLS regression requires several assumptions (Brooks, 2008):

1. The average value of the error term is zero
2. Homoscedastic residuals
3. No autocorrelation
4. No correlation between the independent variables and the residuals
5. Normally distributed residuals
6. At least interval scaled variables or dummy variables
7. No Multicollinearity
8. Linear relationship

3.1.1 Panel Data

The database that is used consists of panel data, which is also called longitudinal data. An important characteristic of panel data is that it contains some time series and cross-sectional components. More specifically, the observations in a longitudinal database are from the same set of individuals or objects (often called entities) at multiple points in time (Brooks, 2008; Janssens et al. 2008).

Broadly speaking, there are three types of (regression) models that can be used to investigate panel data; pooled OLS regression models, fixed effects models and random effects models. A pooled OLS regression model is the most basic technique to investigate panel data.

It estimates a single equation on all the data together by using the usual OLS method. This means that the intercept is equal for all entities and constant over time (Brooks, 2008).

A fixed effect model allows the intercepts to differ for each entity. In other words, the intercepts have to be time consistent, but may vary cross-sectionally. The effects of the other (slope) variables are fixed from a cross-sectional perspective and over time. It is also possible that the intercept is constant cross-sectionally, but varies over time. In this case, it is called a time-fixed effects model (Brooks, 2008).

The final option is the random effects model, which again suggests different intercepts for each entity that are stable over time. However, in this case the intercept is based on a unit- and time-consistent constant term and a 'variable' part that is time consistent, but varies cross-sectionally (Brooks, 2008).

Since I am not interested in brand-specific effects, I do not want a model that includes dummy variables for each brand individually. I want to test for the effect of price points over the business cycle for durable and non-durable goods, irrespective of the effects for individual brands. This would suggest that the pooled OLS regression method is appropriate.

However, in line with Gordon, Goldfarb and Li (2013), I have to include product-specific dummy variables. I do so to capture the different output levels (see Chapter 3.3.1.3) and the variation in market size per product category (see Chapter 3.3.1.2). For that reason, I use a pooled OLS regression model with a category fixed effect intercept. Mathematically, this pooled regression model is expressed as follows:

$$y_{it} = \alpha + \beta x_{it} + \beta D_i + u_{it}$$

In this model, y_{it} represents the dependent variable and x_{it} displays the independent variables that explain the variation in the dependent variable. D_i is a dummy variable that captures the product category-specific effects. Additionally, α is the estimated intercept, whereas β_i displays the estimated effect of the independent variables on the dependent variable. The disturbance term, u_{it}, represents the deviation in the dependent variable that is not captured by the independent variables (Brooks, 2008).

3.2 Models

For all three hypotheses in this thesis, I use a separate model. Although each of the models has its own components, there are some similarities as well. In fact, the models are built upon a certain '*base model*', which is expressed as follows:

$$LN(SALES_t) = \alpha + \beta_1 LN(SALES_{t-1}) + \beta_2 BC_t + \beta_3 CAR + \beta_4 JCE + \beta_5 COF + \beta_6 LAU + \beta_7 VAC + u_{it}$$

The exact definitions of the variables can be found in Table 1. In general, the base model states that the actual sales of a brand can be predicted by the sales in the previous year, the general state of the economy and the product industry in which a brand operates. All these factors have its own effect on the sales in period *t*.

To test the hypotheses, I add some variables and interaction effects to this base model. The exact definitions of these (interaction) variables are presented in Table 1 as well. In the following subsections, I discuss the extended models and how they can be used judge the validity of the hypotheses.

3.2.1. Model Hypothesis 1

In the first model, I investigate the impact of the business cycle on the demand for high price point brands compared to that of low price point brands. In formula form, the model is displayed as follows:

$$LN(SALES_t) = \alpha + \beta_1 LN(SALES_{t-1}) + \beta_2 BC_t + \beta_3 CAR + \beta_4 JCE + \beta_5 COF + \beta_6 LAU + \beta_7 VAC + \beta_8 PRICE_H + \beta_9 (BC_t * PRICE_H) + u_{it}$$

The interaction effect between the business cycle variable and the high price point dummy (BC_t*$PRICE_H$) can be used to test the first hypothesis. In case the interaction effect is positive, it means that the sales of high price point brands increase more than that of low price point brands in case the business cycle variable improves. The would suggest that the demand effect of the business cycle is larger for high price point brands than for low price point brands.

3.2.2 Model Hypothesis 2

In the second model, I test whether the impact of the business cycle differs for durable and non-durable goods. The model is expressed follows[1]:

$$LN(SALES_t) = \alpha + \beta_1 LN(SALES_{t-1}) + \beta_2 BC_t + \beta_3 CAR + \beta_4 JCE + \beta_5 LAU + \beta_6 VAC + \beta_7 DUR + \beta_8 (BC_t * DUR) + u_{it}$$

[1] Including five product category dummy variables in the model, would result in a linear pattern in the data. *CAR*, *JCE* and *COF* would capture observations in the non-durable goods markets (*DUR* = 0), whereas *LAU*, *VAC* and *DIS* (default option) would include data points in the durable goods markets (*DUR* = 1). This would make it impossible to estimate the regression coefficients. For that reason, I removed *COF* from the model.

Variable	Description
$SALES_t$	the quantity of goods sold during the current year.
$SALES_{t-1}$	the quantity of goods sold during the previous year.
BC_t	the business cycle variable that compares the (logged) actual state of the economy with the calculated trend. I will elaborate on this variable in Chapter 3.3.1.1.
CAR, JCE, COF, LAU, VAC	dummy variables that capture the product industry. They represent the carbonates, juices, coffee, laundry appliances and vacuum cleaners industries respectively. The dishwashers industry is selected as the default option. The dummy variables are added to account for the different measurement levels of sales and markets sizes per product category.
$PRICE_H$	a dummy variable that takes the value 1 in case the brand is in the high price point category and 0 otherwise. The reference group consists of the low price point brands.
DUR	a dummy variable that captures the durability of a product. The variable takes the value 1 in case the brand operates in a durable goods market and 0 otherwise.
$BC_t*PRICE_H$	the interaction effect between the business cycle variable and the high price point dummy variable. In case the effect is positive, I conclude that the proportion of high price point brands sold (compared to low price point brands sold) increases in case the actual economic environment is above the calculated trend.
BC_t*DUR	the interaction effect between the business cycle variable and the durable goods dummy variable. In case the effect is positive, I conclude that the proportion of durable goods sold (compared to non-durable goods sold) increases in case the actual GDP is above the calculated trend.
$PRICE_H*DUR$	the interaction effect between the high price point dummy variable and the durable goods dummy variable. The interaction variable is added for completeness considerations, but is irrelevant for this research.
$BC_t*DUR*PRICE_H$	the interaction effect between the business cycle variable, the high price point dummy variable and the durable goods dummy variable. In case the effect of this variable is positive, I conclude that the increase in the proportion of high price point durable brands sold (compared to low price point durable brands sold) is larger than the increase in the proportion of high price point non-durable brands sold (compared to low price point non-durable brands sold) in case the actual economic environment is above the calculated trend.

Table 1: Description of the Variables in the Models

The interaction effect between the business cycle variable and the durable goods dummy variable (BC_t*DUR) is used to judge the second hypothesis. In case the interaction term is positive, it suggests that the sales of durable goods increase more than the sales of non-durable goods in case actual state of the economy exceeds the calculated trend. This would mean that the demand effect of the business cycle is larger for durable goods than for non-durable goods.

3.2.3 Model Hypothesis 3

The final model is used to test whether the sales of premium priced durable goods are more sensitive to the business cycle than the sales of premium priced non-durable goods. The model is specified as follows:

$$
\begin{aligned}
LN(SALES_t) = \alpha + \beta_1 LN(SALES_{t-1}) + \beta_2 BC_t + \beta_3 CAR + \beta_4 JCE + \beta_5 LAU \\
+ \beta_6 VAC + \beta_7 PRICE_H + \beta_8 DUR + \beta_9 (BC_t * PRICE_H) + \beta_{10}(BC_t * DUR) \\
+ \beta_{11}(PRICE_H * DUR) + \beta_{12}(BC_t * DUR * PRICE_H) + u_{it}
\end{aligned}
$$

The interaction effect between the business cycle variable, the durable goods dummy variable and the high price point dummy variable (BC_t*DUR*$PRICE_H$) can be used to test the third hypothesis. In case the impact is positive, it suggests that the increase in the proportion of high price point durable goods sold is larger than the increase in the proportion of high price point non-durable goods sold. In other words, the demand effect of the business cycle would be larger for premium priced durable goods than for premium priced non-durable goods.

3.3 Data

The main data source that I use in this thesis is called Passport by Euromonitor International. This is a global market research database that contains statistics about industries, economies and consumers. Although the database provides a wide variety of raw data, an extensive number of reports are available as well. Some of these reports contain global developments and trends, whereas others provide detailed brand-specific analyses (Euromonitor International, 2018).

I employ Passport to obtain brand-specific sales data over time. Since the U.S. economy is the largest economy in the world (The World Bank Group, 2018), I focus on the economic developments in that country. For most product industries in the U.S., the brand shares (in unit sales) are available from 2008 up till 2017. Since the models contain a lagged variable of sales, this means that I am able to include observations from 2009 to 2017. So, the sample period is determined based on the data available.

Next to the sales data, I also consult Passport for some brand-specific price information. Although the database contains the actual prices per brand, there is no information available about historical prices. For that reason, I assume that the relative price levels are the same over the sample period. In other words, I assume that if '*Brand A*' is more expensive than '*Brand B*' these days, then this also were the case in the past. This suggests that brands that are in the high price point category today were so in previous years as well.

Even though Passport provides the prices of many brands in the non-durable goods industries, there is not much price information available for the juices market. For that reason, I use the average price of a brand on Walmart.com, which is the leading grocery retailer in the U.S. (Statista, 2018). The same problem occurs for the brand in the durable goods markets. Passport offers the prices of a few brands per product category only. To cope with this issue, I consider the average price of a brand within a particular product market on Amazon.com. Since this is the biggest online retailer in the U.S. (Tyler, 2018), I expect that the prices on this website are accurate.

Finally, I consult The World Bank Group to obtain information about the state of the economy in the U.S. over time. This databank offers a variety of economic data on a national and global scale (The World Bank Group, 2018).

3.3.1 Descriptive Statistics

The descriptive statistics section is divided into three parts. In the first part, I explain the creation of the business cycle variable. Next, I discuss some descriptive statistics per product category. Thereafter, I focus on the price point classification and the development of sales over the sample period for low and high price point brands.

3.3.1.1 The Business Cycle

I use the Gross Domestic Product in the U.S. to capture the effect of the business cycle. First, I take the natural logarithm and calculate a trend GDP. Thereafter, I compare the actual GDP with the calculated trend. In case the actual GDP is above the trend, I conclude that the economy expands. If the opposite occurs, I suppose that the economic conditions are disappointing. As the business cycle variable and the dependent variable in the regression models ($SALES_t$) are both log-transformed, BC_t and the related interaction effects should be interpreted as demand elasticities.

Although most researchers use a more advanced application, comparing the logged actual state of the economy with some trend value is a commonly used method to capture the effect of the business cycle (e.g. Lamey, Deleersnyder, Steenkamp & Dekimpe, 2012; Peers, Van Heerde & Dekimpe, 2017). For simplicity reasons, I calculate a linear trend, in which I capture the Gross Domestic Product in the U.S. from 2002 to 2017. I use 2002 as a starting point, because of the introduction of euro. This event caused a shock in the economic environment on a global scale (e.g. Bartram & Karolyi, 2006; Galati & Wooldridge, 2009).

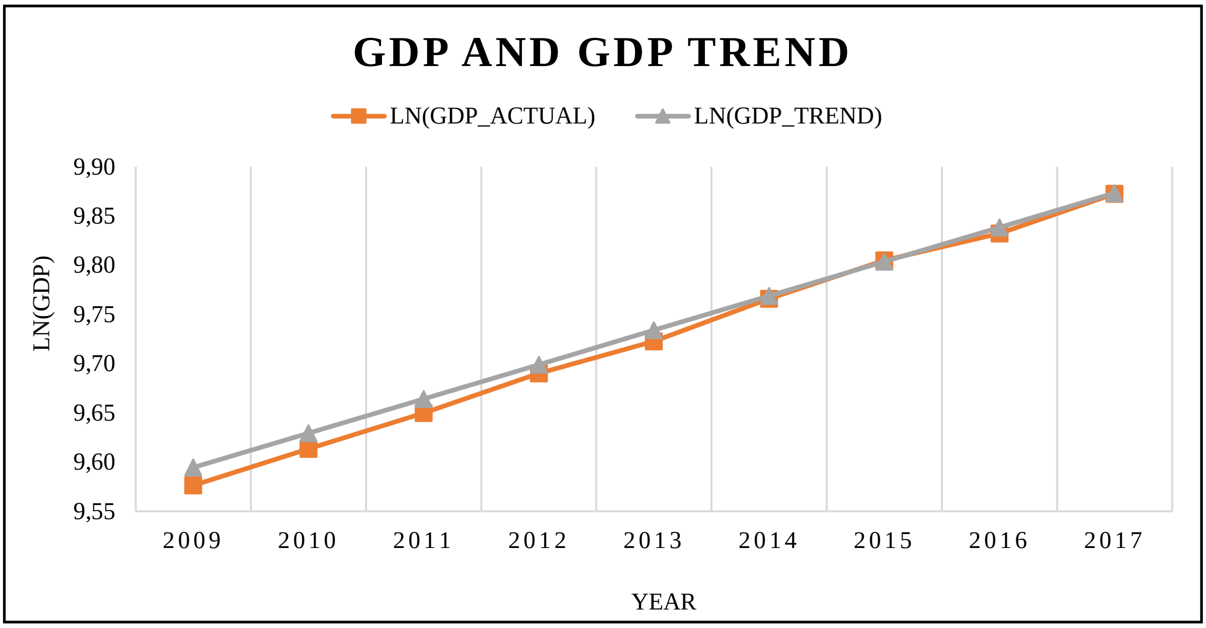

Figure 3: Actual GDP and the GDP Trend

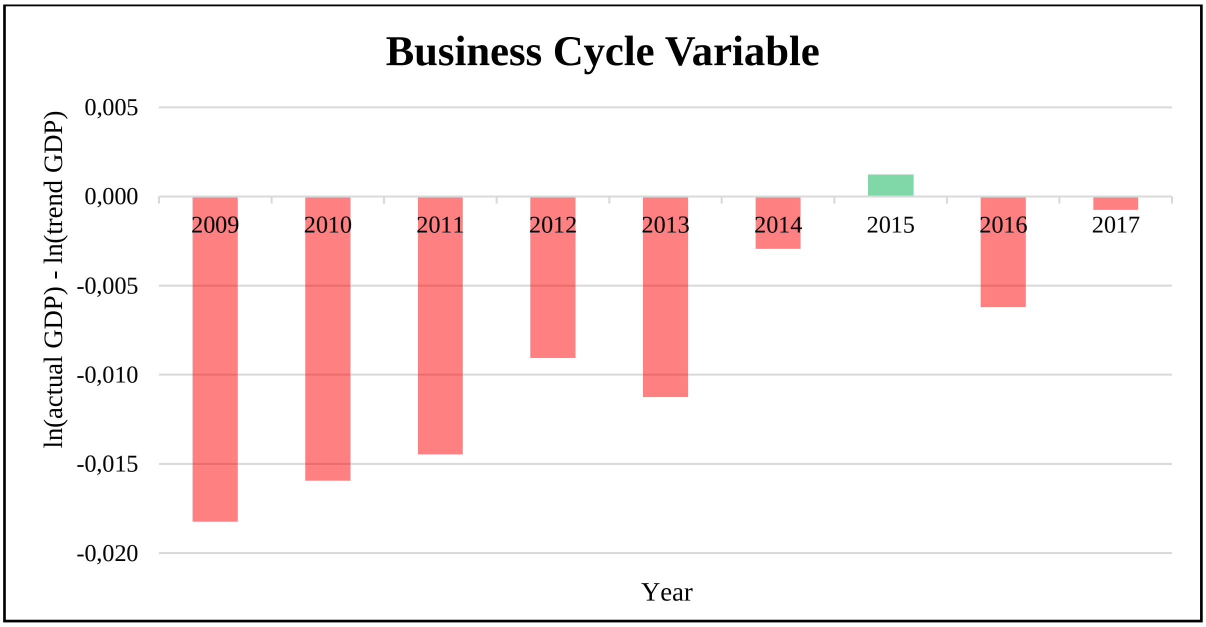

Figure 4: The Business Cycle Variable

As can be found in Figure 3 and 4, the (logged) actual GDP is below the calculated trend in the whole sample period, except for 2015. Rather than a dichotomous variable, the business cycle is included in the model as a continuous variable. In other words, the deepness of the economic 'downfalls' are taken into consideration. For that reason, there is still some variation in the business cycle variable, and so the limited number of years in which the economy expands is not that problematic.

3.3.1.2 Product Categories

To investigate the impact of price points over the business cycle, I select six product categories; carbonates, juices, coffee, dishwashers, laundry appliances and vacuum cleaners. The first three product types represent the non-durable goods, whereas the final three categories capture the durable goods. Based on the relative price points, I select eight brands per product category. For more information about the sample selection process, I refer to Chapter 3.3.1.3.

In Table 2, I present the aggregated market shares of the selected brands in 2017. It turns out that the coverage of the sample is the largest for the laundry appliances industry, whereas it is the smallest for the coffee sector. More information about the product markets and the brands within a particular industry can be found in Appendix 1.

Product Category	Market Size (2009)	Market Size (2017)	Sample Coverage
Carbonates	36,251.4	31,816.4	32.89%
Juices	13,736.7	11,042.4	38.38%
Coffee	732,401.5	766,297.6	26.00%
Dishwashers	5,511.6	7,888.2	42.07%
Laundry Appliances	14,447.3	17,675.2	68.92%
Vacuum Cleaners	30,033.6	34,345.8	64.23%

Table 2: Market Size and Sample Coverage Per Product Category

3.3.1.3 Price Points

The distribution of the brands over the price point classes is crucial for this thesis. Per product industry, I select the fifteen[2] biggest brands and rank them based on the average price of their products. I define the four most expensive brands as the high price point brands and the four cheapest brands as the low price point brands. Those eight brands are included in the sample of this study.

In Table 3, I present the average prices per price point class for all six product categories. It turns out that there is a considerable difference in the average prices; the middle price points are remarkably larger than the low price points and the high price points are substantially larger

[2] For some product categories, Passport provides data on less than fifteen brands. For instance, in the dishwasher industry there are only fourteen brand shares available. For that reason, I can only select fourteen brands in that particular industry. However, for most product industries, Passport distinguishes fifteen or more brands.

than the middle price points. However, next to the average prices per price point class, it is important to look at the prices of individual brands as well. The difference in price between the most expensive low price point brand and the cheapest middle price point brand must be notable. The same applies to the disparity in price between the most expensive middle price point brand compared to the cheapest high price point brand. In case the differences are negligible, consumers would hardly experience any price difference between the price point classes and so the distinction would be rather vague.

	Low	Middle	High
Carbonates	$ 1.14	$ 1.28	$ 1.41
Juices	$ 0.73	$ 1.46	$ 2.75
Coffee	$ 9.60	$ 21.12	$ 60.06
Dishwashers	$ 381	$ 785	$ 1,014
Laundry Appliances	$ 715	$ 1,088	$ 1,259
Vacuum Cleaners	$ 159	$ 258	$ 400

Table 3: Average Price Per Price Point Class

It appears that the smallest price difference is between the most expensive low price point brand and het cheapest middle price point brand in the carbonates industry (4.2%). In most of the other product classes, the asymmetry in price is considerably larger. For that reason, I conclude that the differences in price between the price point classes are large enough, irrespective of whether I look at the average prices or the prices of individual brands.

3.3.1.3.1 Sales Per Price Point Class

To determine the development of sales per price point class, I add up the sales of the brands in a particular price class while ignoring the different measurement levels. As can be found in Figure 5, the difference in sales between high and low price point brands remains relatively stable over time in the non-durable goods industry. During the first years of the sample period, in which the difference between the actual and the trend GDP is relatively large, the sales of both high and low price point brands grows. However, in the second half of the sample period, the sales are relatively constant; there is a small increase in high price point brands sold and a small decrease in the market for low price point brands. Since the economy was relatively strong in the final years of the sample period, this could indicate a minor increase in the proportion of high price point brands sold (compared to low price point brands sold) in case the economic environment more or less meets the expectations.

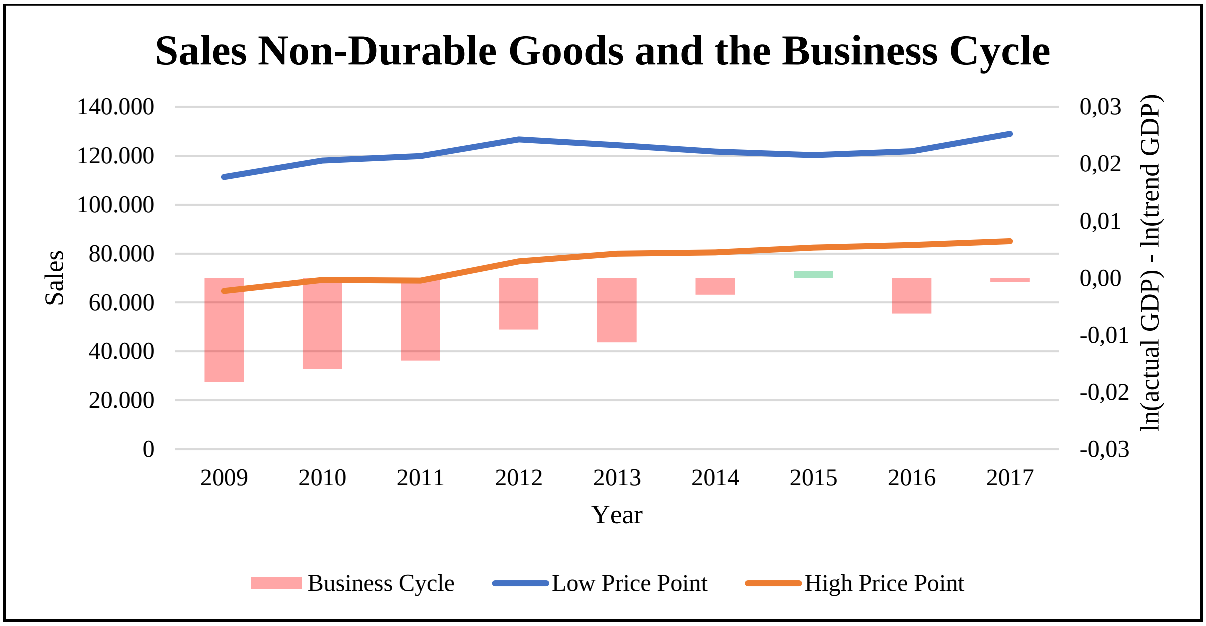

Figure 5: Sales Per Price Point over the Business Cycle for Non-Durable Goods

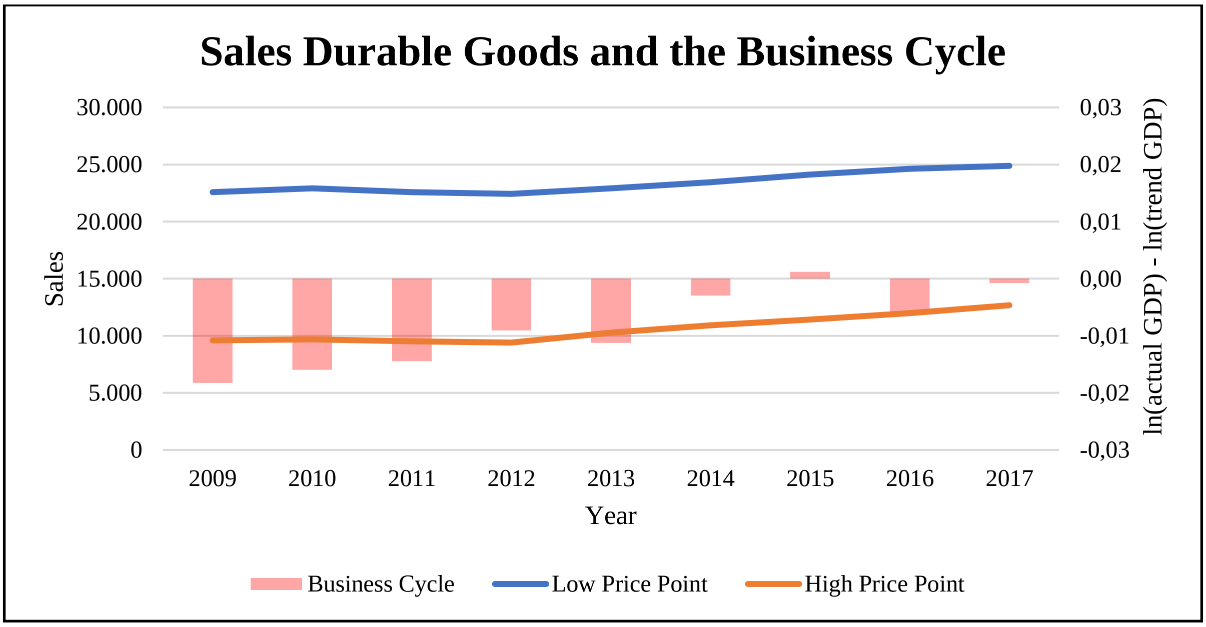

Figure 6: Sales Per Price Point over the Business Cycle for Durable Goods

If I look at the sales of durable goods in Figure 6, it turns out that the overall market for low and high price point brands increases over time. This is especially the case when the business cycle variable is close to zero. This would suggest that the demand for durable goods sold increases in case the economic environment is relatively strong, which confirms the expectations.

However, visually, I do not observe any differences in the sales per price point. The proportion of high price point brands sold (compared to low price point brands sold) remains relatively stable over time. Still, statistical analysis is needed to formally test the hypotheses of this thesis.

Chapter 4: Results

In this chapter, I discuss the main findings of this research. I start the section with a short overview of the results that are obtained in case I investigate the demand effect of the business cycle for each product category individually. Thereafter, I perform the OLS regression analyses by using the models as discussed in Chapter 3.2. I finalize the chapter with some robustness checks, in which I ignore the impact of the product-specific dummy variables.

4.1 Preliminary Analysis Per Product Category

Before I conduct the analysis for the sample as a whole, I first perform some category-specific analyses. More specifically, I look at the correlation between the dependent and the independent variables and run the regression models for each product category individually. As mentioned earlier, I select eight brands per product industry and the sample period runs from 2009 to 2017. This means that there are 72 (eight brands times nine years) data points per product category.

Table 4 contains the correlations between sales in each product industry and the business cycle variable. In the first hypothesis, I test whether the demand effect of the business cycle is larger for high price point brands than for low price point brands. This suggests that the proportion of high price point brands sold (relative to low price point brands sold) should increase in case the business cycle variable improves, whereas the proportion should decrease in case the actual state of the economy moves further away from the calculated trend in negative direction. It turns out that the correlation between $Ln(SALES_t)$ and $BC_t(PRICE_H)$ is positive in four out of six product categories. The exceptions are the carbonates industry and the juices sector. However, the correlation is significant for the dishwashers industry only.

Prod. Cat.	Ln(SALES)					
Variable	CAR	JUI	COF	DIS	LAU	VAC
$BC_t(PRICE_H)$	-0.007	-0.103	0.175	0.397**	0.046	0.020
BC_t	-0.046	-0.007	0.056	0.137	0.025	0.039

*Table 4: Correlation Ln(Sales) and the Independent Variables. ** $p < 0.05$*

Overall, the correlation in most product industries suggests that the proportion of high price point brands sold increases in case the economy expands. This means that the demand effect of the business cycle is larger for high price point brands than for low price point brands in case I investigate each product industry separately. However, the correlation is significant in only one product market. So, the correlation analysis provides (mainly statistically insignificant) initial evidence for the validity of Hypothesis 1.

In Hypothesis 2, I suppose that the demand effect of the business cycle is larger for durable goods than for non-durable goods. If this would be true, the proportion of durable goods sold (relative to non-durable goods sold) increases in case the economy expands, whereas it decreases in case the business cycle variable is negative. As presented in the final row of Table 4, the correlation between BC_t and $Ln(SALES_t)$ is negative for the carbonates and juices industries, whereas it is positive for the coffee, dishwashers, laundry appliances and vacuum cleaners markets.

The former suggests that, in case the business cycle variable improves, the sales volume increases in all three the durable goods industries. In the non-durable goods markets, this is the case for the coffee industry only. So, the correlation analysis mainly confirms the expectations in Hypothesis 2. However, since the impact of BC_t is insignificant in all product categories, it only provides statistically insignificant initial evidence.

Hypothesis 3 states that the demand effect of the business cycle is larger for high price point durable goods than for high price point non-durable goods. This means that, during economic expansions, the increase in the proportion of high price point brands sold (compared to low price point brands sold) is larger for durable goods than for non-durable goods. It turns out that the correlation between $BC_t(PRICE_H)$ and $Ln(SALES_t)$ is higher in the durable goods industries than in the non-durable goods markets. The only exception is the coffee sector, for which the correlation is larger than for the laundry appliances and vacuum cleaners industries. However, the correlation is significant for the dishwashers industry only. So, although the coffee industry causes some disruptions, the initial support for Hypothesis 3 is present, yet statistically insignificant.

An important drawback of correlations is that one cannot control for omitted variables (Field, 2009; Janssens et al. 2008). This means that a high correlation may be caused by some unknown variable and so the presumed relationship between the variables of interest may still be weaker or even missing. To deal with this limitation, I perform some regression analyses for each individual product category. The relevant regression coefficients are presented in Table 5. For an overview of the effects of all variables in the models, I refer to Appendix 2.

Variable	CAR	JUI	COF	DIS	LAU	VAC
BC_t*$PRICE_H$	-0.905	3.306	-3.524	-3.645	9.119*	2.654
(Hypothesis 1 & 3)	(1.563)	(2.920)	(3.858)	5.687	(5.009)	(2.987)
BC_t	-1.014	-0.803	-5.683***	2.446	1.326	2.261
(Hypothesis 2)	(0.812)	(1.486)	(1.992)	(3.186)	(2.535)	(1.493)

*Table 5: Impact of the Business Cycle on Sales Per Product Category. *** $p < 0.01$, * $p < 0.10$*

Since I cannot statistically test whether the estimated regression coefficients differ significantly per product category, it is impossible to formally test the hypotheses. For that reason, I only look at the effects of the relevant variables per product category. I do not compare the size of the effects in Industry A with that in Industry B.

To start with, it appears that the interaction effect between the business cycle variable and the high price point dummy variable ($BC_t*PRICE_H$) is positive in only half of the product categories; juices, laundry appliances and vacuum cleaners. This means that Hypothesis 1 would be supported by only three product industries. Besides, the impact would be significant in the laundry appliances industry solely. For that reason, I conclude that the initial evidence for Hypothesis 1 is mixed and mainly statistically insignificant in the preliminary analysis.

Additionally, the impact of BC_t is negative in the carbonates, juices and coffee industries, whereas it is positive in the dishwashers, laundry appliances and vacuum cleaners sectors. This suggests that consumers purchase more durable goods in case the economy expands, whereas they do not so for non-durable goods. Although this confirms Hypothesis 2, the effect of the business cycle variable is significant in the coffee industry only. Consumers drink more coffee in case the actual state of the economy is below the expectations. A possible explanation may be that economic contractions cause stress, which results in a higher consumption of unhealthy foods (Dave & Kelly, 2012; Goldman-Mellor, Saxton & Catalano, 2010). Although drinking coffee may not necessarily be unhealthy, higher stress levels are associated with a higher consumption of coffee in other studies before (Conway, Vickers, Ward & Rahe, 1981). So, overall, the initial evidence for Hypothesis 2 is present, but mostly insignificant again.

Finally, the effect of $BC_t*PRICE_H$ is positive in two durable goods categories (laundry appliances and vacuum cleaners) and one non-durable goods industry (juices). This means that I do not find a clear pattern when it comes to the sign of the effect. Since it is impossible to statistically test whether the size of the effect differs per product category, I cannot judge the support for Hypothesis 3 by the preliminary analysis.

4.2 Main Findings

Although the preliminary analysis provides some useful insights, it ignores the common structure in the overall dataset. Besides, it is impossible to formally test the hypotheses, since I do not know whether the dissimilarities in the estimated coefficients are statistically significant. For that reason, I consider the data of the individual product industries jointly and run the regression models as described in Chapter 3. The results can be found in Table 6.

Since I use a log-log model to correct for the different measures of sales volume, the interpretation of the results is slightly more complicated. In case the model would not be transformed, it would provide information about the impact of the independent variables on the dependent variable in absolute terms. However, the log-log model captures the effects in relative terms and elasticities. Consider the following model:

$$ln(y) = b_0 + ln(b_i x_i) + b_j x_j + \varepsilon$$

In the model above, y and x_i are both log-transformed. This means that the effect of x_i on y is expressed as an elasticity. The interpretation is quite straightforward; In case x_i increases by one percent, y grows by b_i percent. To determine the impact x_j on y, one should use the inverse of the natural logarithm. This inverse is called the exponential function e (Benoit, 2011; Halvorsen & Palmquist, 1980). In formula, the effect of a one unit change in x_j on y (in %) should be calculated as follows:

$$y = (e^{b_n} - 1) \times 100\%$$

4.2.1 Findings Model 1

In Model 1, I test whether the sales of high price point brands compared to that of low price point brands is positively affected by the business cycle. By doing so, I can determine whether the demand effect of the business cycle is larger for high price point brands than for low price point brands. The explanatory power of Model 1 is 0.996, which means that the independent variables explain 99.6% of the variation in *Ln(SALES$_t$)*. Additionally, the F-test reject the null hypothesis of $\beta_0 + \beta_1 + \ldots + \beta_n = 0$, suggesting that the model is meaningful. For that reason, further interpretation of the results is allowed (Brooks, 2008; Janssens et al. 2008).

It appears that the logged sales in the previous year have a significant impact on the logged sales in the current year. In case *Ln(SALES$_{t-1}$)* increases by one percent, *Ln(SALES$_t$)* grows by 0.987%. This suggests that sales levels in the past can be used to explain sales levels in the present. However, the impact of the business cycle variable (*BC$_t$*) is insignificant, suggesting that there is no direct effect of the strength of the economy (compared to the calculated trend) on the sales in a particular product industry.

Variable	Model 1	Model 2	Model 3
Constant	0.108^{***} (0.032)	0.142^{***} (0.052)	0.131^{**} (0.054)
$Ln(SALES_{t-1})$	0.987^{***} (0.005)	0.986^{***} (0.005)	0.986^{***} (0.005)
BC_t	-0.673 (1.205)	-2.546^{**} (1.200)	-2.390 (1.695)
CAR	-0.053^{**} (0.022)	-0.083^{***} (0.024)	-0.082^{***} (0.024)
JUI	-0.054^{***} (0.020)	-0.085^{***} (0.027)	-0.084^{***} (0.027)
COF	0.027 (0.031)		
LAU	-0.036^{*} (0.021)	-0.035^{*} (0.021)	-0.035^{*} (0.021)
VAC	-0.023 (0.023)	-0.021 (0.023)	-0.022 (0.023)
$PRICE_H$	0.030^{*} (0.018)		0.014 (0.0260)
DUR		0.007 (0.033)	-0.008 (0.039)
BC_t*$PRICE_H$	0.799 (1.705)		-0.315 (2.397)
BC_t*DUR		4.559^{***} (1.698)	3.436 (2.397)
$PRICE_H$*DUR			0.034 (0.037)
BC_t*$PRICE_H$*DUR			2.238 (3.389)

*Table 6: Regression Coefficients Model 1, 2 and 3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

The effect of the product category dummy variables is significant for three product markets; carbonates (-5.2%), juices (-5.3%) and laundry appliances (-3.5%). This suggests that the development of sales in those product industries behaved significantly different than in the other product categories, irrespective of the business cycle and the price points. Besides, the direct effect of the high price point dummy variable is significant as well (3.0%), implying that the demand for high price point brands increased over the sample period, independent of the state of the economy.

More important, the impact of $BC_t*PRICE_H$ is insignificant. This indicates that the demand effect of the business cycle is equal for high and low price point brands. In case I ignore the fact that the influence of the interaction variable is statistically insignificant, the proportion of high price point brands sold (relative to low price point brands sold) would be larger in case BC_t increases. More specifically, an improvement of the business cycle variable by one percent would result in an increase in sales that is 0.779% larger for high price point brands than for low price point brands. So, the support for Hypothesis 1 is merely statistically insignificant.

4.2.2 Findings Model 2

Model 2 is used to test whether the sales of durable goods are more sensitive to shocks in the business cycle than the sales of non-durable goods. If this would be the case, it suggests that the demand effect of the business cycle is larger for durable goods than for non-durable goods. In accordance with Model 1, the Adjusted R-squared of Model 2 is 0.996. Additionally, the F-test is insignificant, which indicates that the model is meaningful (Brooks, 2008; Janssens et al. 2008).

The effect of the $Ln(SALES_{t-1})$ is positive and very large again. In case the logged sales during the previous year increase by one percent, the logged sales in the current year grow by 0.986%. Also, unlike Model 1, the impact of the business cycle variable is statistically significant. In case BC_t grows by one percent, the logged sales would drop by 2.546%, irrespective of the product market and the product durability.

Additionally, the impact of the product category dummy variables is significant in two product industries. Compared to the other product sectors, the logged sales of brands that operate in the carbonates, juices or laundry appliances markets are 8.0%, 8.1% and 3.4% lower respectively (all else being equal). Besides, the direct effect of the durable goods dummy variable (*DUR*) turns out to be insignificant, which suggests that the increase in the demand for a particular product is not affected by its durability directly.

More important, the effect of BC_t*DUR is positive and significant. An improvement of the business cycle variable by one percent would result in an increase in sales that is 4.559% larger for durable goods than for non-durable goods. This implies that the demand effect of the business cycle is indeed larger for durable goods than for non-durable goods, which confirms Hypothesis 2.

4.2.3 Findings Model 3

In Model 3, I test whether the demand for high price point durable brands is more affected by shocks in the business cycle than the demand for high price point non-durable brands. It turns out that the independent variables explain 99.6% of the variance in (the logged) sales in Model 3. Also, the F-test rejects the null hypothesis of a simultaneous effect of the regression slope parameters that is equal to zero. For that reason, further interpretation is allowed (Brooks, 2008; Janssens et al. 2008).

In line with Model 1 and 2, the logged sales in the previous year significantly affect the logged sales in the current year. In case the former increases by one percent, the latter grows by 0.986%. Besides, the direct impact of the business cycle variable is negative, yet insignificant. This suggests that the state of the economy (compared to the calculated trend) does not affect (the logged) sales directly.

In accordance with the findings in the previous models, the impact of the product category dummy variables is significant in three industries. All else being equal, $SALES_t$ is 7.9%, 8.1% and 3.4% lower for brands that are in the carbonates, juices or laundry appliances market respectively.

Additionally, the effect of the high price point dummy variable and the durable goods dummy variable turns out to be insignificant. The same applies to the four interaction effects in the model. Since the influence of $BC_t*PRICE_H*DUR$ is insignificant, I conclude that I do not find any statistically significant evidence that supports Hypothesis 3.

However, in case I ignore the insignificance of the effect, $BC_t*PRICE_H*DUR$ would be positive. This suggests that the increase in sales of high price point durable brands is larger than that of high price point non-durable brands in case the business cycle variable improves. More specifically, if BC_t grows by one percent, the increase in the demand for high price point durable brands would be 2.238% larger than the increase in the demand for high price point non-durable brands. So, even though it is statistically insignificant, the positive effect would be in line with the expectations in Hypothesis 3. For that reason, I conclude that this thesis provides statistically insignificant initial evidence for the claim that the demand effect of the business cycle is larger for premium priced durable brands than for premium priced non-durable brands.

To sum up, the support for the hypotheses is mixed. Although statistically insignificant, the impact of the business cycle on the sales of premium brands is positive, suggesting that the demand effect of the business cycle is larger for high price point brands than for low price point brands (Hypothesis 1). Additionally, I find statistically significant evidence that supports Hypothesis 2. The demand effect of the business cycle is larger for durable brands than for non-durable brands. Finally, Model 3 provides statically insignificant evidence for the claim that the demand effect of the business cycle is larger for high price point durable brands than for high price point non-durable brands (Hypothesis 3).

However, as can be found in Appendix 3, some of the OLS regression assumptions are being violated in all three models. I will explain how this affects the reliability of the results and how to correct for this is the *Limitations* and *Recommendations* sections.

4.3 Robustness Checks

To judge the generalizability of the findings, I test whether comparable results are obtained in case I ignore the product category-specific effects. I do so by removing the product industry dummy variables. Apart from this, the analyses and the models are exactly the same. The regression coefficients can be found in Table 7.

As is the case for the original analysis, the explanatory power of the models is very large; the independent variables explain 99.6% of the variation in (the logged) sales in Model 1, 2 and 3. Besides, the F-test rejects the null hypothesis of $\beta_0 + \beta_1 + \ldots + \beta_n = 0$ for all three models, which means that they are valid and so further interpretation of the regression coefficients is allowed (Brooks, 2008; Janssens et al. 2008).

Again, the logged sales in the previous year are an important predictor of the logged sales in the current year. An improvement of $Ln(SALES_{t-1})$ by one percent results in an increase in $Ln(SALES_t)$ by 0.994% in Model 1 and 0.995% in Model 2 and 3. Besides, the effect of the business cycle variable is significant and negative (-2.566%) in Model 2 only, which confirms the findings in the previous chapter.

The impact of the high price point dummy variable is insignificant in Model 1 and 3. This partly contradicts the results of the main research, in which $PRICE_H$ is significant (α = 0.10) in Model 1. Besides, in contrast with the previous findings, the influence of the durable goods dummy variable is significant in Model 2. In case a brand operates in one of the durable goods markets, its sales are 5.7% higher than that of brands which are in a non-durable goods industry. The fact that the impact of the variable is significant may be explained by the absence of the product category dummies. In the original Model 2, there are three product industry variables whose effect is negative and significant; *CAR*, *JUI* and *LAU*. This means that the sales of brands are significantly lower in two out of three non-durable goods markets. Since the product category dummy variables are not included in the robustness model, the former may be captured by the durable goods variable.

Variable	Model 1	Model 2	Model 3
Constant	0.038 (0.026)	0.018 (0.029)	0.009 (0.032)
Ln($SALES_{t-1}$)	0.994^{***} (0.003)	0.995^{***} (0.003)	0.995^{***} (0.003)
BC_t	-0.691 (1.230)	-2.566^{**} (1.225)	-2.380 (1.729)
$PRICE_H$	0.031 (0.019)		0.016 (0.026)
DUR		0.055^{***} (0.019)	0.040 (0.027)
BC_t*$PRICE_H$	0.742 (1.740)		-0.373 (2.446)
BC_t*DUR		4.477^{**} (1.733)	3.371 (2.446)
$PRICE_H$*DUR			0.003 (0.037)
BC_t*$PRICE_H$*DUR			2.206 (3.458)

*Table 7: Regression Coefficients Robustness Checks. *** $p < 0.01$, ** $p < 0.05$*

More important, the effect of BC_t*$PRICE_H$ in Model 1 is positive but insignificant, which confirms the findings in the main analysis. In case I ignore the insignificance, an improvement of BC_t by one percent would result in an increase in demand for high price point brands that is 0.742% larger than the increase in demand for low price point brands. So, again the analysis provides statistically insignificant initial evidence for Hypothesis 1.

Additionally, the effect of BC_t*DUR* is positive and significant. In case the business cycle variable improves by one percent, the increase in (the logged) sales of brands in the durable goods markets is 4.477% larger than the increase in sales of brands in the non-durable goods industries. This suggests that the demand effect of the business cycle is larger for durable goods than for non-durable goods, which confirms the findings in the previous analysis and supports Hypothesis 2.

Finally, the impact of $BC_t*PRICE_H*DUR$ is positive, yet statistically insignificant. This supports the results of the main analysis. In case I neglect the insignificance of the effect, an increase of BC_t by one percent would result in an increase in (the logged) sales that is 2.206% larger for high price point durable brands than for high price point non-durable brands. This suggests that the demand effect of the business cycle is larger for premium priced durable goods than for premium priced non-durable goods. So, I find statistically insignificant initial evidence for the validity of Hypothesis 3.

To sum up, in case I ignore the product category-specific effects, the exact same hypotheses are rejected. The evidence for Hypothesis 2 is statistically significant, whereas the support for Hypothesis 1 and 3 is not. However, in case I ignore the insignificance, I observe the expected effects that are found in the main analysis as well. So, overall, the findings in the original models are supported by the results of the robustness checks.

However, as presented in Appendix 4, the same OLS regression assumptions are still being violated. Again, I will discuss the implications and the possible solutions of these violations in the *Limitations* and *Recommendations* chapters.

Chapter 5: Discussion

5.1 Conclusions

This thesis is about the demand effect of the business cycle. More specifically, I investigate whether the demand for high price point brands compared to the demand for low price point brands over the business cycle differs for durable and non-durable goods. To the best of my knowledge, this combination of product durability, relative price points and the business cycle has not been investigated in the exact same way before.

The underlying assumption is that consumers care about their relative position in society. Instead of the consumption of particular types goods (Kamakura & Du, 2012), I propose that social status can be obtained by the acquisition of premium priced brands. In case peers can afford high price point brands, one would want to purchase products from brands at a comparable price level himself to maintain or obtain an equal position in society.

Kamakura and Du (2012) argued that relative consumption is especially relevant for products that are less essential in nature. Since the disposable income decreases during economic contractions (Estelami et al. 2001), less consumption would be needed to maintain the same social standing. For that reason, I predict the demand effect of the business cycle is larger for high price point durable brands than for high price point non-durable brands.

The sample covers six product categories; carbonates, juices, coffee, dishwashers, laundry appliances and vacuum cleaners. The first three industries represent the non-durable goods, whereas the final three product sectors do so for the durable goods. For each product industry I pick the four cheapest and the four most expensive brands to represent the low and high price point brands respectively.

Hypothesis 1 states that the demand for high price point brands, compared to low price point brands, increases in case the economy expands. It turns out that I do not find any statically significant support for this claim. However, if I ignore the insignificance of the effect, I do observe that the sales of premium priced brands grow more than that of the cheapest brands in the sample during economic expansions. This means that I provide statistically insignificant initial evidence for a larger demand effect of the business cycle for high price point brands than for low price point brands.

In Hypothesis 2, I propose that the demand for durable goods is more affected by shocks in the business cycle than the demand for non-durable goods. In this case, I do find statistically significant evidence that supports this proposition. For that reason, I conclude that the demand effect of the business cycle is indeed larger for durable brands than for non-durable brands.

In the final hypothesis, I propose that the demand for high price point durable brands (relative to low price point durable brands) increases more than the demand for high price point non-durable brands (relative to low price point non-durable brands) in case the economy expands. As is the case for Hypothesis 1, I do not find any statistically significant support for this proposition. However, in case I ignore the insignificance, I do observe the expected effect. It turns out that the impact of the business cycle on sales is larger for premium priced durable brands than for premium priced non-durable brands. This means that I find statistically insignificant initial evidence for a larger demand effect of the business cycle for high price point durable brands than for high price point non-durable brands.

To judge the generalizability of the results, I perform some robustness checks in which I ignore the product category-specific effects. In other words, I approach the market for durable goods as a single, homogeneous market. I do the same for the non-durable goods industry. It turns out that the robustness checks confirm the findings of the main analysis. Hypothesis 2 is supported, whereas the evidence for Hypothesis 1 and 3 is statistically insignificant.

5.2 Limitations

As is the case for almost every research, this thesis is subject to some limitations. To start with, Passport provides brand-specific sales information from 2008 till 2017 only. Since I include a lagged variable of sales ($SALES_{t-1}$) in the regression model, the observations of the dependent variable ($SALES_t$) start in 2009. As the trough of the most recent financial crisis was in 2009 as well (NBER, 2012), this means that I include data from years in which the economy grew in absolute terms only. For that reason, the generalizability of the results to years in which the economy shrank may be limited.

Additionally, the assumption that the classification of brands over the relative price point categories does not change over time may be arbitrary. Since there is no historical price data available on Passport, I assume that in case Brand A is more expensive than Brand B nowadays, this was also the case in the past. In other words, I suppose that the distribution of brands over the low and high price point category is constant over the sample period. However, this may be incorrect, since other researchers have shown that companies respond to shocks in the business cycle in different ways. In case the economy is in a recession, some firms lower their prices, whereas others do the opposite to compensate for the lower sales volume (e.g. Chevalier & Scharfstein, 1996).

Next to these practical issues, there are some limitations regarding the OLS regression assumptions as well. To start with, the assumption of homoscedastic error terms is rejected. Although the presence of heteroscedastic residuals does not affect the estimated coefficients, it does influence the standard deviations. For that reason, the inferences made may be incorrect and misleading (Brooks, 2008; Long & Ervin, 2000).

Also, the assumption that requires the absence of autocorrelation may also be violated in this thesis. As is the case for the heteroscedasticity assumption, autocorrelated residuals do not affect the estimated regression coefficients. However, it may result in wrongly estimated standard deviations, which harms the reliability of the results. Besides, autocorrelation may cause an overestimated explanatory power (R^2) of the model (Brooks, 2008).

Finally, the assumption of normally distributed residuals is not supported. Again, the violation of this assumption may lead to underestimated standard errors. However, this is mainly the case for small sample sizes (Maas & Hox, 2004). Since the sample size of this thesis is not necessarily too small, violating the normality assumption may not be too problematic.

5.3 Recommendations

The first way to improve my thesis is by extending the sample period, as the current sample only consists of years in which there is a positive growth of the economy. This would require a database that contains brand-specific data over a longer period of time. Although Passport offers data from 2008 till now, one should search for some other databases that provide information about the sales and strategies of companies during prior years.

Additionally, it may be good to search for price information over time. Since Passport only provides current price levels, I assume that the relative pricing of brands did not change during the sample period. As discussed earlier, this assumption may be arbitrary. To avoid this proposition, one should search for a database that contains historical, brand-specific price data.

Also, one should correct for the violations of the OLS regression assumptions. To start with, the most straightforward technique to solve the heteroskedasticity problem is to transform (some of) the independent variables or to use the Generalised Least Squares method. This method weights the variables by the factor that causes the heteroscedasticity. However, since the form and magnitudes are unknown in most cases, this method is not always feasible. For that reason, more sophisticated techniques are available that use heteroscedasticity-consistent standard error estimates (Brooks, 2008; Long & Ervin, 2000).

Next to the heteroscedasticity issue, the no autocorrelation assumption is also violated. Since the presence of autocorrelation could result in incorrect inferences, one should correct for this. A popular way to do so is to apply the Newey-West procedure, which produces HAC (Heteroscedasticity and Autocorrelation Consistent) standard errors that fix the autocorrelation and heteroscedasticity problem (Brooks, 2008; Newey & West, 1987). Although this procedure is originally developed for time series data only, panel data versions are available as well. Especially in Stata (Hoechle, 2007).

Finally, one should pay attention to the normality assumption, which requires that the error terms are normally distributed. A commonly used technique to deal with the violation of this assumption is a (logarithmic) transformation of the dependent variable. However, although the independent variable is log transformed in this thesis, the error terms are still non-normally distributed. Another remedy could be to increase the number of observations (Brooks, 2008). As I mentioned before, I recommend to extend the sample period, which would automatically result in more observations and so the violation of the normality assumption may be solved. However, even if it would turn out that the residuals are still non-normally distributed after extending the sample period, this may not be too tragic. The Gauss-Markov theorem states that OLS regression is still the best linear unbiased estimator in case the residuals are non-normally distributed (Halin, 2014). For that reason, failing to correct for this violation should not be a breakpoint.

To finalize, this thesis provides a good starting point for other researchers who want to study the demand effect of the business cycle for goods or brands that differ in relative price points and durability. I provide initial, statistically insignificant evidence for the claim that the effect of shocks in the business cycle on the demand for premium priced brands differs for durable and non-durable goods. In case the statistical limitations are solved in follow-up research, more specific and reliable conclusions could be drawn.

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Appendix

Appendix 1 – Data Description per Product Category

Carbonates

The carbonates industry in the U.S. is a relatively competitive market. There are a few big players who call the shots, but the number of smaller brands is extensive. As can be found in Figure 7, the low price point brands and high price point brands that are captured in the sample cover 32.89% of the total market in 2017.

The sales volume is measured in millions of litres. In 2009, the market size was approximately thirty-six million litres, whereas it has shrunk to thirty-two million litres in 2017. This means that the demand for (off-trade) carbonates decreased over the period of interest.

Although there is no specific price information available for private label brands, I still include them in the sample. Other researchers have shown that private label brands usually are cheaper than national brands (Kumar & Steenkamp, 2006; Lamey et al. 2007). For that reason, I consider them as a low price point brand. I did so for the juices, coffee, dishwashers and laundry appliances sectors as well.

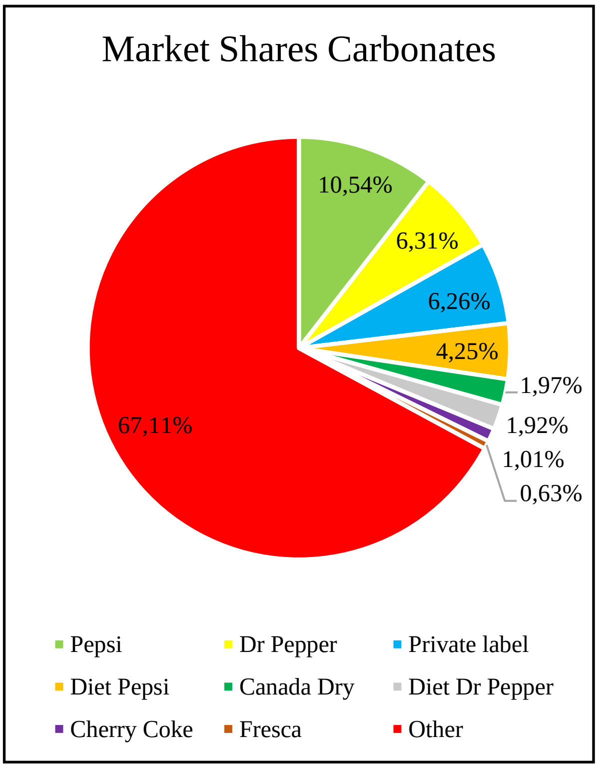


Figure 7: Market Shares Carbonates

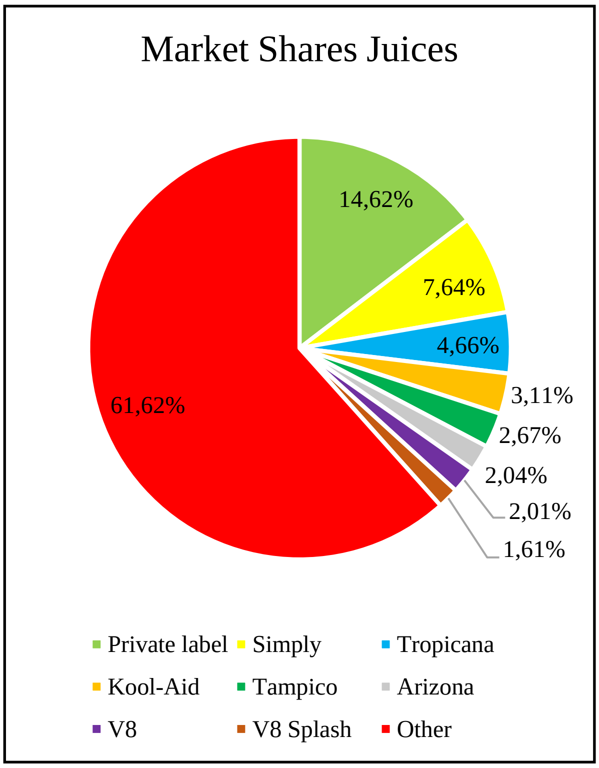


Figure 8: Market Shares Juices

Juices

The juices market is more cluttered than the carbonates industry. There is no clear market leader and there are a lot of brands that are more or less equal in size. As presented in Figure 8, the brands that I capture in the sample comprise around 38.38% of the total market in 2017.

In accordance with the carbonates industry, sales are measured in millions of litres. From 2009 (13.7 million litres) to 2017 (11.0 million litres), the overall amount of sales in the juices industry in the U.S. has decreased, suggesting that the demand for juices declined. However, the coverage of the brands in the sample remained relatively stable over the sample period.

Coffee

The coffee industry in the U.S. is very structured. When it comes to sales, Folgers outperforms its competitors by far. Although some other brands have a considerable market share as well, most firms only play a modest role. The brands in the sample cover around 26.00% of the total market in 2017 (see Figure 9).

The sales volumes in the coffee market are measured in tonnes. It turns out that, unlike the other non-durable goods categories in the sample, the coffee market has grown during the period of interest. In 2009, 732,402 tonnes of coffee were sold, whereas the overall sales volume was about 766,297 tonnes in 2017.

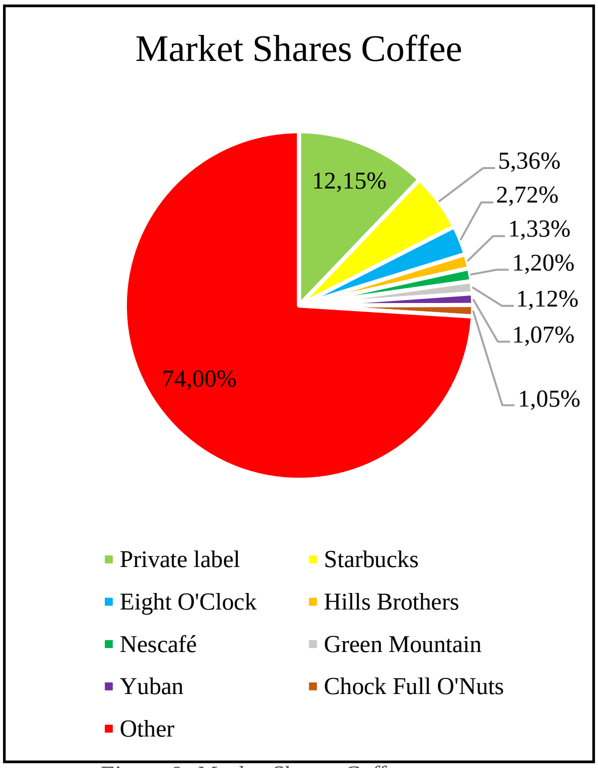


Figure 9: Market Shares Coffee

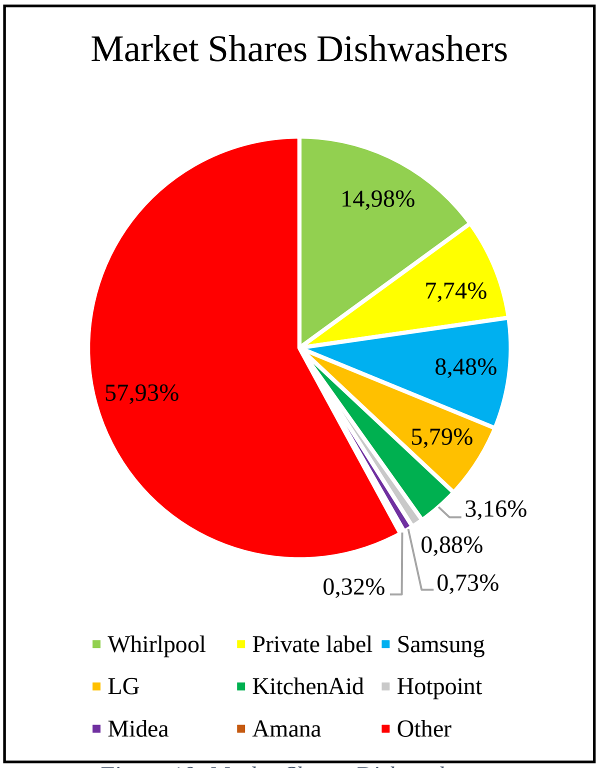


Figure 10: Market Shares Dishwashers

Dishwashers

In the United States, the dishwashers industry consists of three or four big brands, some medium sized firms and a few small competitors. In 2017, the low price point brands and high price point brands in the sample cover 42.07% of the total market. The exact market shares per brand can be found in Figure 10.

The amount of sales, as measured per thousands of units, has grown over the sample period. In 2009, approximately five and a half million dishwashers were sold, whereas the overall sales volume was around eight million units in 2017. The demand for dishwashers was relatively stable until 2012, however it grew explosively during the years thereafter.

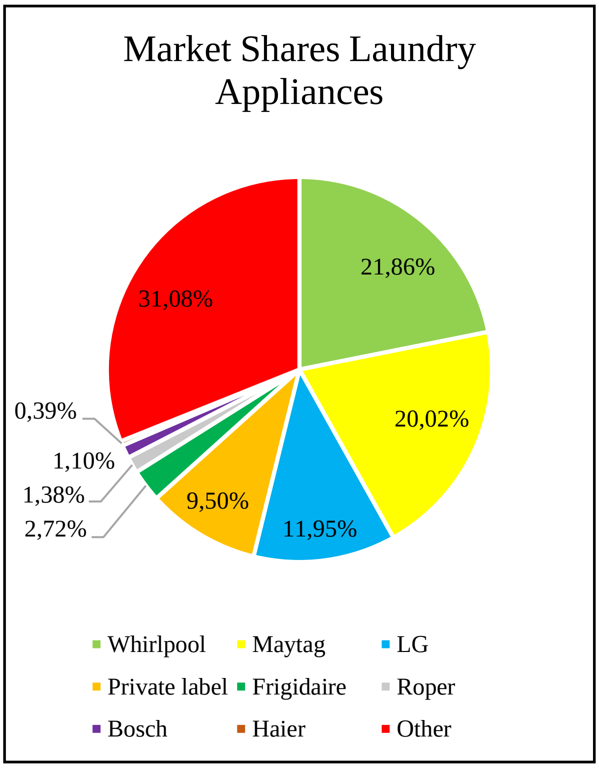


Figure 11: Market Shares Laundry Appliances

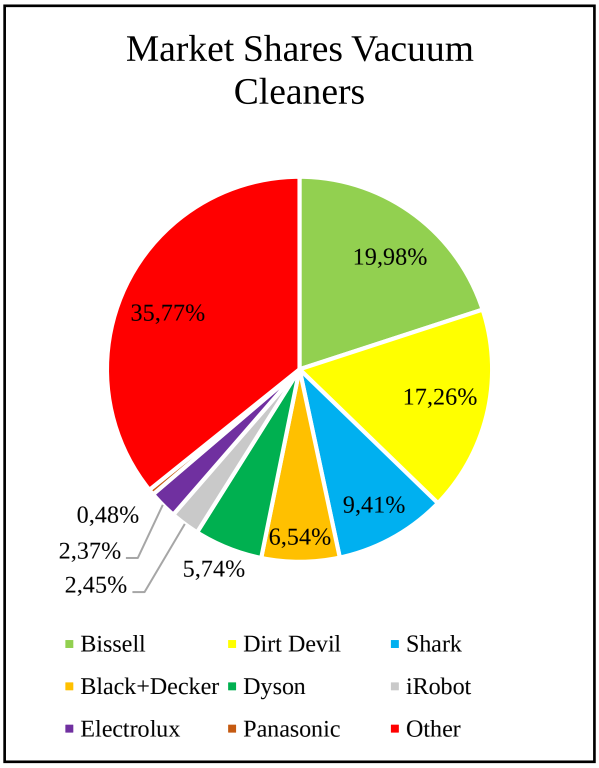


Figure 12: Market Shares Vacuum Cleaners

Laundry Appliances

There are two major suppliers in the laundry appliances market in the United States; Whirlpool and Maytag. Together they cover around 41.88% of the total market. Besides, there are three main competitors, whereas the number of smaller brands is relatively limited in comparison with the other product industries in this thesis. Combined, the brands in the sample capture 68.92% of the total sales in 2017. The exact market shares are presented in Figure 11.

Again, the sales volume is expressed in thousands of units. In 2009, 14.4 million washing machines and dryers were sold, whereas the amount increased to 17.7 million in 2017.

As was the case for the dishwashers market, the excessive growth in the demand for laundry appliances started in 2012.

<u>Vacuum Cleaners</u>

The vacuum cleaners industry in the U.S. consists of two big players, a few medium-sized brands and some smaller companies. As can be found in Figure 12, the brands in the sample account for 64.23% of the total sales in 2017. In accordance with the other durable goods markets in this thesis, the sales volumes are measured in thousands of units.

In 2009, around 30.0 million vacuum cleaners were sold, whereas the market size increased to approximately 34.3 million units in 2017. Except for 2013, the demand for vacuum cleaners grew on a yearly basis.

Appendix 2 – Regression Output Preliminary Analysis

Business Cycle (Hypothesis 2)

Prod. Cat.	CAR	JUI	COF	DIS	LAU	VAC
Constant	0.099**	0.200**	0.236	0.179**	0.137	-0.191**
	(0.037)	(0.078)	(0.162)	(0.087)	(0.082)	(0.073)
Ln($SALES_{t-1}$)	0.982***	0.965***	0.973***	0.981***	0.981***	1.030***
	(0.005)	(0.013)	(0.016)	(0.015)	(0.012)	(0.010)
BC_t	-1.014	-0.803	-5.683***	2.446	1.326	2.261
	(0.812)	(1.486)	(1.992)	(3.186)	(2.535)	(1.493)

*Table 8: The Effect of the Business Cycle on Sales. *** $p < 0.01$, ** $p < 0.05$*

Price Points over the Business Cycle (Hypothesis 1 and 3)

Prod. Cat.	CAR	JUI	COF	DIS	LAU	VAC
Constant	0.036	0.171**	0.153	0.277***	0.091	-0.035**
	(0.044)	(0.079)	(0.160)	(0.081)	(0.085)	(0.139)
Ln($SALES_{t-1}$)	0.989***	0.970***	0.980***	0.948***	0.981***	1.046***
	(0.006)	(0.013)	(0.016)	(0.016)	(0.012)	(0.017)
BC_t	-0.517	-2.457	-4.010	5.152	-3.231	0.870
	(1.106)	(2.062)	(2.714)	(3.990)	(3.542)	(2.114)
$PRICE_H$	0.023	-0.008	0.030	0.154**	0.098*	0.064
	(0.018)	(0.032)	(0.042)	(0.067)	(0.054)	(0.043)
BC_t*$PRICE_H$	-0.905	3.306	-3.524	-3.645	9.119*	2.654
	(1.563)	(2.920)	(3.858)	5.687	(5.009)	(2.987)

*Table 9: The Effect of Price Points over the Business Cycle on Sales. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$*

Appendix 3 – Assumption Checks (Pooled) OLS Regression

In this appendix, I test whether the required assumptions of Pooled OLS Regression are met. A schematic overview can be found in Table 10, whereas I provide more detailed information about the procedures below. I use a book called '*Introductory Econometrics for Finance*' by Chris Brooks (2008) as a guideline for the assumption checks.

	Model 1	Model 2	Model 3
Zero Average Value Residuals	+	+	+
Homoscedastic Residuals	-	-	-
No Autocorrelation	-	-	-
Strict Exogeneity	+	+	+
Normally Distributed Residuals	-	-	-
Variable Scales	+	+	+
No Multicollinearity	+	+	+
Linear Specification	+	+	+

Table 10: Assumption Checks (Pooled) OLS Regression

Assumption 1: The average value of the errors is zero – $E(u_t) = 0$

This assumption is not violated in case a constant term is added to the model (Brooks, 2008). Since the models that test Hypothesis 1, 2 and 3 all contain an intercept, I conclude that the assumption holds.

Assumption 2: Homoscedastic error terms – $var(u_t) = \sigma^2 < \infty$

The variance of the error term has to be constant for each value of the independent variable. However, the White test rejects the null hypothesis of homoscedastic error terms for all three models. For that reason, I conclude that the error terms may be heteroscedastic, which means that the assumption is violated.

Assumption 3: No autocorrelation – $cov(u_i, u_j) = 0$ for $i \neq j$

This assumption requires that the residuals are uncorrelated with each other. In case the error terms are correlated, it is called autocorrelation or serial correlation (Brooks, 2008). Since the models contain a lag of the dependent variable ($SALES_{t-1}$), I use the Breusch-Godfrey test to check whether autocorrelation is present. For all three models, it turns out that the null hypothesis of uncorrelated errors should be rejected, which means that the assumption is violated.

Assumption 4: Strict exogeneity – $cov(u_t, x_t) = 0$

This assumption states that there should be no relationship between the independent variables and the disturbance term (Brooks, 2008). To check whether this requirement is met, I look at the correlations between the independent variables and the residuals. It turns out that none of the correlations are significant, which suggests that the strict exogeneity assumption holds.

Assumption 5: Normally distributed residuals – $u_t \sim N(0, \sigma^2)$

I investigate whether the residuals are normally distributed by using the Jarque-Bera test. As can be found in Figure 13, the normality assumption is rejected for all three models.

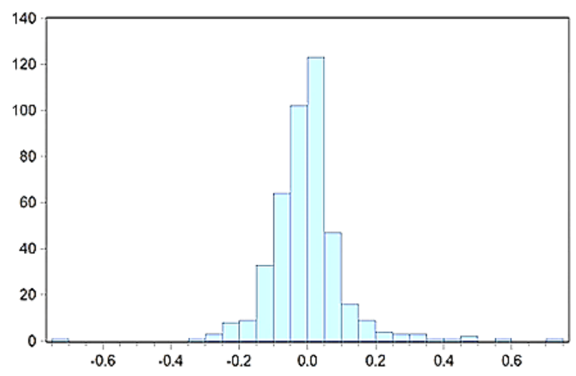
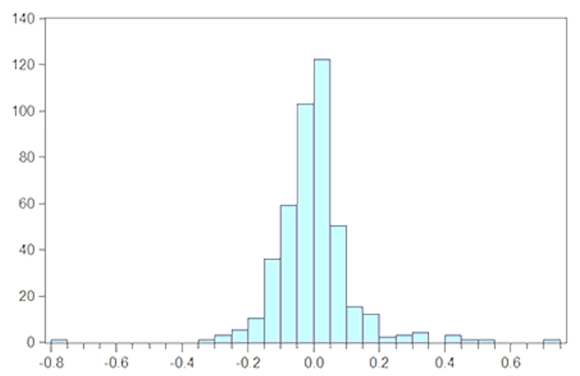
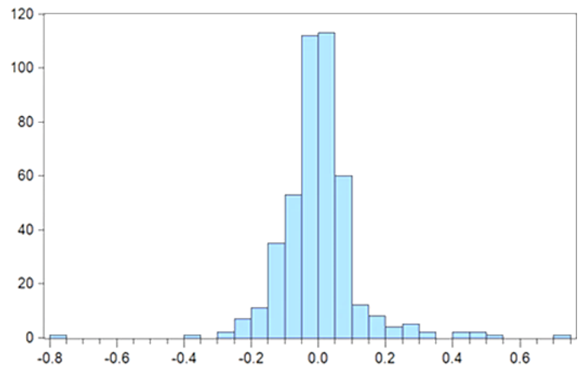
Model 1	Model 2
	
Model 3	Test Statistics
	Model 1: J-B 1852.458 Prob. 0.000 Model 2: J-B 2232.751 Prob. 0.000 Model 3: J-B 2178.952 Prob. 0.000

Figure 13: Distribution of the Residuals

Assumption 6: Scales of the (in)dependent variables

The dependent and the independent variables must be at least interval scaled. In case there are nominal scaled independent variables, they should be converted into dummy variables before they are added to the model (Brooks, 2008). All models meet those requirements. $Ln(SALES_t)$, $Ln(SALES_{t-1})$ and BC_t are ratio scaled variables, whereas *CAR*, *JUI*, *COF*, *LAU*, *VAC*, $PRICE_H$ and *DUR* are nominal scaled and converted into dummy variables.

Assumption 7: No Multicollinearity

This assumption requires a low correlation between the independent variables (Brooks, 2008). As can be found in Figure 14, there is a significant correlation between the dummy variables that capture the product category. This makes sense, since the dummy variables comprise the same aspect; product category. This is not problematic when it comes to multicollinearity.

Additionally, there is a significant correlation between the durable goods dummy variable and the product category dummy variables. This makes sense as well, since all brands that are in the dishwashers, laundry appliances or vacuum cleaners category are captured in the durable goods dummy, whereas the brands in the other product categories are not.

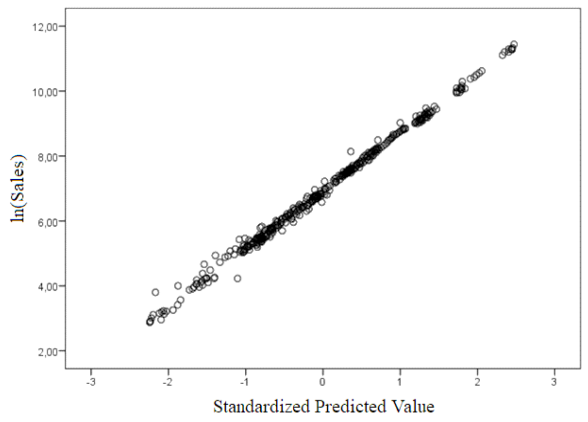
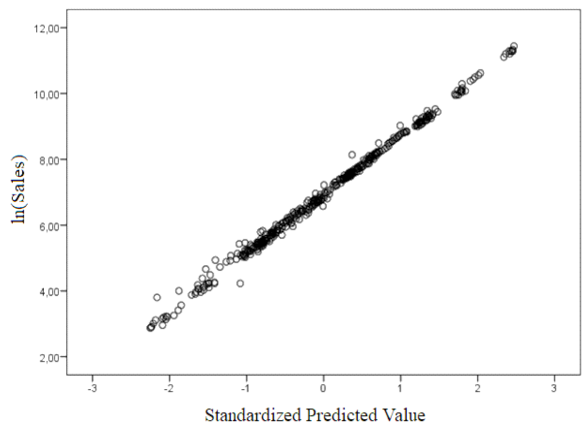
Finally, all the dummy variables in the models and the lagged sales variable ($Ln(SALES_{t-1})$) are correlated. This makes sense too, since the cross-sectional dummy variables are constant over time and they are used to explain the variability in the dependent variable. Since $Ln(SALES_{t-1})$ is a lagged term of the dependent variable, the same cross-sectional dummy variables can be used to explain some of the variance. Again, this is not problematic and so I conclude that the multicollinearity assumption holds.

Correlation Probability	LN_SALES...	BC	CARB	JUIC	COFF	DISH	LAUN	VACU	PRICE_H	DURA
LN_SALES_T_1	1.000000 -----									
BC	0.025249 0.6007	1.000000 -----								
CARB	-0.004524 0.9253	1.24E-18 1.0000	1.000000 -----							
JUIC	-0.218467 0.0000	7.21E-18 1.0000	-0.200000 0.0000	1.000000 -----						
COFF	0.682615 0.0000	6.60E-18 1.0000	-0.200000 0.0000	-0.200000 0.0000	1.000000 -----					
DISH	-0.468214 0.0000	8.04E-18 1.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	1.000000 -----				
LAUN	-0.101824 0.0344	9.89E-18 1.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	1.000000 -----			
VACU	0.110414 0.0217	9.69E-18 1.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	-0.200000 0.0000	1.000000 -----		
PRICE_H	-0.041285 0.3920	3.69E-18 1.0000	6.21E-18 1.0000	1.00E-17 1.0000	1.10E-17 1.0000	3.10E-18 1.0000	1.38E-18 1.0000	2.03E-17 1.0000	1.000000 -----	
DURA	-0.342584 0.0000	4.92E-18 1.0000	-0.447214 0.0000	-0.447214 0.0000	-0.447214 0.0000	0.447214 0.0000	0.447214 0.0000	0.447214 0.0000	0.000000 1.0000	1.000000 -----

Figure 14: Correlations Independent Variables

Assumption 8: Linear specification

This assumption states that the model is linear in the parameters. In other words, the relationship between x and y should be a straight line (Brooks, 2008). I check this assumption by looking at the graphs that contain the dependent variable and the (standardized) predicted value in Figure 15. For all three the models it holds that the graph displays a straight, diagonal line. For that reason, I conclude that the specification assumption holds.

Model 1	Model 2
	

Model 3

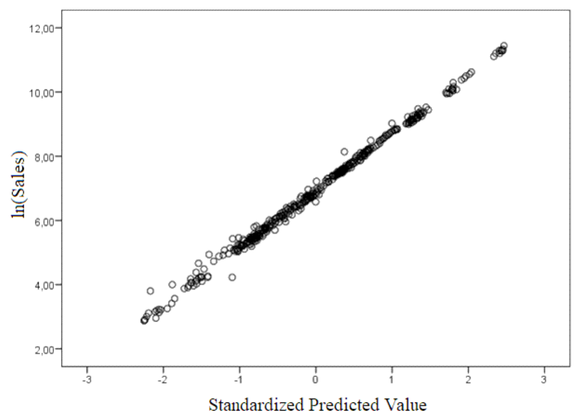


Figure 15: Specification Assumption

Appendix 4 – Assumption Checks Robustness Models

To check the validity and reliability of the robustness models, I perform the exact same procedures as for the original models. For that reason, I only provide a schematic overview of the assumption checks in Table 11. More information about the exact procedures and tests can be found in Appendix 3.

	Model 1	Model 2	Model 3
Zero Average Value Residuals	+	+	+
Homoscedastic Residuals	-	-	-
No Autocorrelation	-	-	-
Strict Exogeneity	+	+	+
Normally Distributed Residuals	-	-	-
Variable Scales	+	+	+
No Multicollinearity	+	+	+
Linear Specification	+	+	+

Table 11: Assumption Checks (Pooled) OLS Regression for the Robustness Models