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CUSTOMER HABITS IN A B2B CONTEXT: IMPACTS ON CASH FLOW LEVEL AND VOLATILITY

Porto Alegre
2019

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Dissertação apresentada no Programa de Pós-Graduação em Administração da Universidade Federal do Rio Grande do Sul, como requisito parcial para a obtenção do título de mestre em Administração.

Orientador: Prof. Dr. Fernando Bins Luce

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Porto Alegre

2019

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RESUMO

Hábitos estão presentes em uma grande parte do dia-a-dia das pessoas. À medida que são repetidas ações com resultados satisfatórios em contextos estáveis, as respostas para ações futuras começam a ser ativadas automaticamente na memória de um indivíduo. Com o tempo, as decisões tornam-se menos impulsionadas por objetivos e intenções e, desta forma, um hábito é formado. Medidas empíricas de hábitos baseadas em dados de transações de clientes foram desenvolvidas pela área de marketing e vincularam comportamentos habituais de pessoas na hora da compra e o impacto financeiro nas empresas. Esta dissertação tem como objetivo analisar o impacto de comportamentos habituais no contexto B2B de transações entre fabricantes e varejistas. O responsável por efetuar uma compra em uma empresa pode comparar especificações, preços e avaliar os concorrentes antes de fazer um pedido. No entanto, é praticamente impossível avaliar todos os produtos sempre que for necessária uma compra para reabastecer estoques ou para solicitar um item vendido no catálogo por um vendedor dentro da loja. Portanto, espera-se que com o tempo, uma parte das transações que são realizadas começam a ser conduzidas por comportamentos habituais de alguém envolvido no processo de compra. Esta dissertação propõe medir os hábitos de compra e promoção em um banco de dados de transações e aplicar análises quantitativas para avaliar como os hábitos impactam os níveis de fluxo de caixa e a volatilidade dos mesmos. Uma análise posterior é proposta para comparar como os clientes habituais se relacionam com os clientes mais valiosos da empresa e uma simulação é proposta para analisar o impacto de uma eventual aquisição de clientes. Os resultados mostram que os hábitos mais fortes de compra aumentam os níveis de fluxo de caixa, mas também afetam positivamente a volatilidade do fluxo de caixa. Em contrapartida, os hábitos de promoção, com o passar do tempo, tendem a gerar fluxos de caixa menos voláteis que os hábitos de compra, mas com a desvantagem de diminuir os níveis dos mesmos.

Palavras-chave: Hábitos, Fluxo de Caixa, Volatilidade do Fluxo de Caixa, Customer Equity, Comportamento do Cliente

ABSTRACT

Habits are widespread in most of life. As people repeat actions with satisfactory outcomes in stable contexts, responses start to become automatically retrieved in memory. Over time decisions become less driven by goals and intentions, and therefore, a habitual behavior is formed. Empirical measures of habits based on customer transactions data were developed by marketing scholars and have linked habitual behaviors of people when purchasing and their impact on firms' performance. This dissertation aims to analyze the impact of habitual behaviors in the context of business-to-business transactions with manufacturers and retailers. The responsible for buying in a firm may compare specifications, prices and assess competitors before making a purchase. However, it is unfeasible to evaluate all products every time it is required a purchase to replenish stocks or to order a sold item in a catalog by a sales employee. Therefore, it is expected that over time, a portion of repeat transactions start to be driven by habitual behaviors of someone involved in the process of buying. This dissertation proposes to measure the Purchase and Promotion Habits in a database of transactions and to apply quantitative analyzes to evaluate how habits affect cash flow levels and their volatility. A later analysis is proposed to compare how regular customers relate to the company's most valuable customers and a simulation is proposed to analyze the impact of eventual customer acquisition. The results show that stronger Purchase Habits increase cash flow levels, but also positively affect cash flow volatility. On the other hand, Promotion Habits, over time, tend to generate less volatile cash flows than Purchase Habits, but with the disadvantage of reducing their levels.

Keywords: Habits, Cash Flow, Cash Flow Volatility, Customer Equity, Customer Behavior

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1 INTRODUCTION

"There is a curious similarity in the way managers at Lands' End and McDonald's articulate marketing goals. They each talk not about selling products but about keeping customers" (BLATTBERG; DEIGHTON, 1996, p.136). Managers spend a considerable amount of time thinking about strategies for retaining customers. However, in many ways, the purchase process is automatic, regardless of the efforts of the firm. The purchase order is sent without much thinking.

The present dissertation aims to explore a topic that has gained spotlight in the academy within the area of purchase behavior: the habit, addressing it on the perspective of customer equity in business-to-business (B2B). Customers can be stimulated to generate positive shopping habits or can develop behaviors that do not create an optimal performance for firms, as customers that wait for promotions to buy or that consistently return products, defer payments or buy loss leader items. One of the ways that marketing researchers might analyze customers' performance is by their cash flow level and volatility. A customer who brings the same revenue in a more stable way to the company, *ceteris paribus*, is worth more as an asset than a customer who has high volatility generating this cash flow.

Habits are relevant in this environment since they may explain a significant portion of everyday purchases, as when people purchase the same brands in different shopping trips or the same amount of a specific item across several visits to a store (WOOD; NEAL, 2009; VOGEL; EVANSCHITZKY; RAMASESHAN, 2008).

Customers' habits are an essential driver of shopping behavior and they could severely impact firms' performance, as the 8,640 brick and mortar stores closings in the US (2017) that are primarily due to new shopping habits (RUPP *et al*., 2017; NOGUCHI, 2017; ANSON, 2018).

The relationship between past behavior and future behavior can be guided by intentions in a predetermined route or become spontaneous when successfully practiced behaviors lead to habituation (OUELLETTE; WOOD, 1998; VERPLANKEN; ROY, 2015). Drolet and Wood (2017, p.275) argue that "[…] experience sampling studies have shown that around 43% of everyday behavior is performed in a routine way, and much of this is done while thinking about something other". People with habits to eat popcorn at the movies, when triggered by the environment of the cinema, consume approximately the same amount of popcorns regardless of whether it is fresh and stale or liking it or not (NEAL *et al*., 2011).

The challenge to marketers is that habits become a consistent non-attitudinal component of buyers' behavior that makes intentions and goals less influential guides when performing shopping decisions (OLSEN *et al*., 2013; CARDEN; WOOD, 2018). Stimuli through marketing actions may be imperceptive through the lack of attention or ineffectual by not considering alternative options (WOOD; RÜNGER, 2016). Nevertheless, habitual relationships with customers can turn to real competitive advantage to firms. The human brain loves automaticity in such a noisy and overwhelming world and, therefore, turning the firm’s proposition into a habit more than a choice might be an essential outcome of marketing strategies (LAFLEY; MARTIN, 2017).

In promotional campaigns to stimulate cross-buy, the understanding of customer’s habits has a crucial role in minimizing adverse outcomes as shown by the work of Shah *et al.* (2012). Liu-Thompkins and Tam (2013) shed light on differences in consumer response to marketing stimuli. Not every repeat purchase has a driver on loyalty, where persistent favorable brand evaluation is present. Habitual customers reacted negatively to generic promotions that aimed to stimulate migration to new categories of products, making the promotion less effective and even reducing the amount spent in the old category.

According to Van Heerde and Neslin (2017), US consumer-packaged goods (CPG) firms spend almost 75% of their marketing budget on sales promotions. The long term impact of these deals could generate a sales lift, increase brand awareness and brand switching but also stockpiling, new reference prices and also develop new behaviors, e.g., stimulate cherry-picking consumers. Frequent exposure to promotions has a changing effect on behavior (AILAWADI; GUPTA, 2014), which could foster the creation of habits.

Habits are highly resistant to change because the responses become integrated into memory with the context that predicts them. Thus, contextual cues must be changed so that people can leave the automatic mode (NEAL *et al*., 2011). Time and efforts costs can be critical factors in generating convenience, which might function as a precursor of habit, but as long as the habit is formed in a routinized and automatic process, the consumer no longer considers the time and effort costs at each purchase (LIU-THOMPKINS; TAM, 2013). According to Neal *et al*. (2011, p.1428), when people have a strong habit, they may even deactivate alternative responses. Therefore, people may not even remember that other options were available.

A famous campaign in California to stimulate people to eat healthier food at the beginning of the ‘90s aimed to increase the knowledge of the benefits of eating more fruits and vegetables. Result: people were more aware of healthier food and intentions of eating healthily increased. However, ten years after, people continued to eat the same amount of fruits and vegetables. That represents a disconnection between thinking and doing. As it is present in alimentation, most of the purchase behavior is also highly influenced by habits (WOOD, 2018).

What about when transactions occur between firms, is there any chance the people involved in the purchase process are acting on habitual behaviors? In organizations, habits are present through routinized behavior, as Ohly, Sonnentag, and Pluntke (2006) state that through repeated execution or practice, the performance of a task becomes faster and mental resources are freed so that the attentional load on that task is reduced. Then habits tend to evolve to an ordered, structured action sequence that is prone to be elicited by a particular context or stimulus (PIÓRKOWSKA, 2017). Tasks that involve higher mental processes or more complex forms of social behavior can also be enacted automatically when triggered by certain environmental cues, ignoring conscious will (BARGH; FERGUSON, 2000).

The literature in organization buying has started to bring the importance of including non-rational perspectives that capture with more realism the complex path of the business-to-business buying process. As Van Zeeland and Henseler claim, (2018a, p.73) “Over the past years, the role of emotion, subconscious processes and implicit heuristics slowly found its way into the rational world of B2B marketing”. The external volatility and internal time pressures pose a burden on buyers that need to purchase products to resell with minimal mistakes. The impact of such a scenario plus endless buying options “make gathering, structuring, and extensively analyzing data before making a purchasing decision often difficult if not impossible” (KAUFMANN; WAGNER; CARTER 2017, p.82). As Simon (1971, p.6) brilliantly stated, “Wealth of information creates a poverty of attention.”

Information concerning costs and characteristics of products, payment options, estimated time of arrival, support for ad campaigns, along with the abundance of supplier options creates “customers that are overwhelmed by information and choice [...] and often more paralyzed than empowered” (TOMAN; ADAMSON; GOMEZ, 2017, p.4). Specifically, when sole decision-makers may have 50, 100 or 200 suppliers under their surveillance and are mostly their duty to compare prices and technical characteristics of every product they have to purchase. Items that are more representative might consume time to search, compare and check at what price competitors are selling. Some procurement or acquisition processes require a higher level of involvement (KUMAR; GHOSH; TELLIS, 1992), however when it is considered the whole portfolio, some items under the scrutiny of the buyer might become overlooked over time.

This scenario may stimulate that people engaged in the buying or supply chain management area in organizations may routinize some purchase tasks. The context generated with some suppliers that involve repetitive purchases and satisfactory outcomes may turn into habitual behaviors. It may be represented by, e.g., relaxing some products and supplier comparisons, making the purchase order an automatic contextual outcome. It would be like an owner of a furniture store ordering every month an amount of mattress of a specific brand. Initial negotiations involved the exchange of commercial information and technical attributes. Additional orders of this product might even not consider competitors price or new product launches.

The work of Shah, Kumar, and Kim (2014) tested an empirical measurement of habit that takes into account frequency and temporal consistency of past behavior in a longitudinal dataset of customers. So, the habit strength of customers could be quantified along a continuum.

In this way, Shah *et al*. (2014) analyzed four different patterns of habits: Purchase, Promotion, Low-margin and Return Habit. Furthermore, they evaluated the power of habits on firm performance in the context of a retailer in the United States. Shah, Kumar, Kim, and Choi (2017) went further to analyze the impact of customers' habits on the volatility of cash flow, as well as the level of these inflows. Their study found that a 1% increase in customers' purchase habit generates a 1,83% decrease in the future cash flow volatility and a 4,62% increase in the future level of the cash flows, in the period analyzed of 4 years.

This dissertation aims to apply the measures of habits designed by Shah *et al*. (2014) in a B2B transactions context. Subsequently, customers that develop habits in accordance to the proposed measures can be assessed in the way they affect firm performance through the level and volatility of cash flows they generate, as proposed by Shah *et al*. (2017).

Much of the work in marketing has traditionally explored the consequences of an increased level of cash flow on firm value (SRIVASTAVA; SHERVANI; FAHEY, 1998). The volatility of cash flows is a much less frequent unity of analysis by marketing scholars (SHAH *et al*., 2017). Cash flows that are more stable hold less risk because firms can forecast better, avoiding incurring in more expensive external capital financing. Besides, investors could take an excess of volatility as poor firm performance or dependence of risky markets (ROUNTREE; WESTON; ALLAYANNIS, 2008).

Demand overly inconstant is a typical generator of more volatile cash flows. It makes the whole operation more unpredictable affecting delivery shipments, production setup times and inventory of raw materials. Therefore, it is crucial for marketing researchers to explore the characteristics of customer behavior that are prone to generate more stable flows of cash to firms. It is necessary to expand the knowledge on how volatility works in a business-to-business context where retailers buy products to resell. Manufacturers could have no control over how retailers deal with macroeconomic shocks or manage their operations in a competitive landscape with online retailers. It is also a key aspect to evaluate how formed habits affect the volatility within the existing rules of pricing and promotions sales.

Marketing research could benefit from exploring the impacts and consequences of habits on shopping behavior that goes beyond the business-to-consumer (B2C) scenario. Transactions between firms were responsible for $24.6 trillion in the US economy (2017); meanwhile, consumer spending reached $13.7 trillion (PIPLOVIC, 2018). Just in e-commerce, B2B transactions in Brazil reached the amount of R$ 2.04 trillion in 2018 (STATISTA, 2019).

The proposed framework of the analysis is the following: customers are seen as a measurable asset of the company (customer equity). Take one customer's purchase behavior that might operate habitually in distinctive patterns and strength. Such flow may unroll consequences in the cash flow of the company, and enriching information could be gathered by analyzing this inflow of resources is by its variability or volatility.

1.1 DELIMITATION OF THE STUDY, PROBLEM DEFINITION AND JUSTIFICATION

The work of Ehrenberg (1972) over repeat buying brought some critical statements concerning B2C purchases going as far as to say that in frequently-bought items the major part of consumer behavior is influenced by the previous average purchase frequency. According to Best and Papies (2017), in the past decades, social psychology has accumulated substantial evidence that intentions are good predictors of infrequent behaviors (e.g., choosing a university or new apartment), but intentions are poor predictors of behaviors that happen routinely in the same context. The repetition of purchases within the habit perspective incorporates the context and the automaticity of decisions.

Differing from the work of Shah *et al*. (2014) and Shah *et al*. (2017) that serve as the underpinning of this dissertation, the scenario analyzed will be a B2B context. Therefore, the primary goal is to assess how the proposed measures of habits influence B2B transactions and how they affect firm performance. In this context, manufacturers sell furniture products to retailers through their sales representatives.

Marketing scholars, in recent works, advocate for more academic attention to B2B market studies, extending the research in a context with much fewer customers, but with more relevant transactions and with purchasing processes that involve more agents (LILIEN, 2016;

GREWAL *et al.*, 2015; MORA CORTEZ; JOHNSTON, 2017). The behavior of B2B buyers is one of the research priorities of the Institute for Study of Business Markets (Pennsylvania State University), one of the major research institutes in the world for industrial marketing studies.

The literature over organizational buying behavior had in the 1960s and 1970s the creation of three works that laid the conceptual foundation of the area as the *general models for understanding organizational buying behavior* (WEBSTER; WIND, 1972) and the *model of industrial buyer behavior* (SHETH, 1973). The third and maybe the most known, the *Buy Grid Framework*, consisted on the understanding of three dimensions of the buyer behavior: situation (new task on the first buy, modified rebuy or straight rebuy), process (clearly defined phases) and the buying center, that were related to individuals, committees and groups responsible for purchasing decisions (ROBINSON; FARIS; WIND, 1967). Johnston and Bonoma (1981) extended the concept of buying center to a social communication network with different levels of involvement, starting to expand the coverage of the theories with a broader range of constructs and types of relationships. Recently, B2B buying literature started to involve ongoing processes in networks of dynamic actors inside and outside firms (e.g., social media, regulations, technology, global competition, fiscal pressures). However, it is rare in the organizational buying literature studies that go beyond strategic decision-makers always focused on the optimal economic outcomes. As Mier (2016) explores, rarely it is recognized the B2B buyer as someone who has worries, frustrations and inertia, whom might take a few milliseconds to create a trust-building process on a product or seller (VAN ZEELAND; HENSELER, 2018b).

So, how a B2B buyer or an owner of a retailer firm, who might be responsible for purchases, could act automatically when making a purchase order? The setting under study involves transactions between firms that produce furniture items to retailers, who will place these items in the showroom to resell to final customers. Catalog or brochure sales also occur; consequently, retailers might sell products they do not have in stock. Thus, in this B2B setting, frequent purchases or replenishment orders are made from several firms in the market, with no contracts or exclusive supply agreements. Also, there are no strict rules for purchasing like formal protocols or bureaucratic audit that allow purchases only within forecasted parameters. Buyers have the autonomy to acquire whatever brand or amount of product they find necessary to meet derived demand (GREWAL *et al.*, 2015).

These are some examples where habits may be present in the context of this research: a B2B buyer in his office room that repeatedly order a product “A” that his inventory management system is requesting and no comparisons or further negotiations are necessary. So, the sales force of the firm offering this product "A" is not activated to negotiate or to bargain prices. In a parallel way, the presence of a sales representative may also enable habitual purchases with someone in the organization during a customary visit. The sales representative and the buyer may start the informal talk of every visit, drink a cup of coffee and it does not take a long time to the buyer say that "x" amount of that item can be ordered.

Another trace of habitual behaviors might emerge when a salesperson inside the store develops preferences of products when they present or show it to customers. Repeating this behavior, it ends up becoming habitual presentations of products (e.g., a salesperson that got used to present Samsung smartphones first to everyone demanding a smartphone that enters the store). This behavior of the sales associate will result in sold items that need another purchase order that the B2B buyer might send it to the supplier without further actions.

Habitual purchases might emerge under several forms, and they may also be present altogether or overlapped. Therefore, habits might have been the generator of a purchase order by any agent involved (e.g., buyer, the owner or sales associate). The precursor of a habitual behavior could be convenience, satisfaction, desire to change a supplier or just to grab a convenient promotion offer. Shah *et al*. (2014, p.730) define Purchase Habit as the "customer's general tendency to repeatedly buy from the firm".

Stimulating frequent purchases that might turn habitual could be a product of marketing actions as a fierce presence in the media with massive investments in advertising. However, in this context, very few brands are known outside the furniture world and with rare exceptions, companies in this setting will not appear on television or in an ad on Facebook. Marketing actions generally involve a catalog, the visit of a sales representative and the eventual participation in furniture fairs.

It is also worth mentioning that habitual behaviors might be present as a barrier if the buyer is habituated to a competitor. Then, it might be reasonable to understand why some customers instantly accept some offers and others may take several meetings to begin to start listening to a deal proposal. Though habits are not insurmountable, when they are confronted in the same context, an extra amount of effort by the offeror may be required.

In the work of Shah *et al*. (2017), B2C transactions were analyzed under the context of a US retailer that sells home improvement goods, furniture and home appliances where customers must make a shopping trip in order to reach the store (excluding online purchases). The setting where B2B transactions occur is usually under the same physical area. Mostly the buying department holds its operations in offices, stores or warehouses. Therefore, the environment in B2B settings might even be more stable, since these are the places where people go every day to work.

Time constraints, stress and pressure (WOOD; NEAL, 2009) that cue habitual behaviors in individuals when filling their shopping cart at Walmart, might apply as well to a scene where B2B transactions occur. The overload of information, choice, and pressure are burdens of many business-to-business buying processes (TOMAN; ADAMSON; GOMEZ, 2017). Besides, one buyer probably does not spend their entire day of work comparing products specifications and prices, searching for alternative suppliers and negotiating prices. Their regular job is also dealing with incorrect invoices, delay of suppliers' shipments, or even requiring suppliers for more support in a TV ad campaign. These professional duties might consume time and cognitive effort, which might generate automatic responses when dealing with issues of some suppliers. Hence, the literature over habits (WOOD; RÜNGER, 2016) could fit these B2B and B2C settings.

Shah *et al.* (2017) found several kinds of habits in a database of transactions with 666.992 customers, as people who persistently used the same self-service counter or bought in the approximately same time of day. Among these habits, four recurring behaviors that supposedly had a financial impact on the retailer were studied: customers' habitual purchase behavior (Purchase Habit), deal-prone customers that may only buy when the firm has promotions (Promotion Habit), customer that persistently buy items with steep discounts that have prices below the retailer cost (Low-margin Habit) and customers that have consistently returned previously purchased products (Return Habit).

Considering the idiosyncrasies of B2B transactions (LILIEN, 2016) and the particular characteristics of the sector where these transactions occur, this work proposes to analyze two groups of customers:

a) Purchase Habits: customers that make more repeated purchases in a certain amount of time showing temporal consistency of behavior;

b) Promotion Purchases: customers that systematically buy items in promotion that have lower margins than ordinary transactions.

The option for not considering the Return Habit is because returns in this B2B context are inexpressive and highly case-by-case. There is technical support for a wardrobe that the retailer received, and a shelf is missing from the package or has a defective painting. The firm will send a repair piece to the retailer, so there is not a return process of the whole product. It also does not follow the strict rules of B2C transactions, where the supplier is usually obliged to accept the return within some days after the purchase. Also, the option of not considering

Low-margins Habit is because transactions with negative margins happen in rare occasions in this context, usually when firms discontinue a product, and a large amount of this item rests on stock for an extended period. One potential habit that might be present: the recurring delay of payments that a retailer makes. Limitations over the database restrict this analysis, as it was not possible to capture if the motive of the delay was deliberated to adjust the cash flow management, the invoice that had an error or indeed a recurring behavior of someone who got used to default.

The Return and Low-margins Habits harmed the firm's cash flow, as they showed how people systematically perform actions not profitable for the company (SHAH *et al*., 2017). In a B2B context, however, managers can deal with adverse habits that have a negative impact on firms' finances with a more active approach. There are several ways to negotiate and even dismiss customers, whereas, in a B2C context, it is probably forbidden to deny the access of a particular customer from entering the store.

Thus, how the proposed two groups of customers (Purchase and Promotion) interact with customers that apparently do not create habitual behavior in purchasing from the firm and score low into the habit strength model proposed by Shah *et al.* (2014)?

Quantitative analyses with econometric panel data models are proposed to assess how habitual behaviors affect firm performance. In the context of this study, the sales representative office will be considered as a generalization for the firm, as it intermediates the deals between manufacturers and retailers and has the record of all transactions. Habitual customers might buy more frequently and with more constancy than others might, but does that translate into more economic value to the firm? Do customers within the highest CLV decile are indeed the ones who have stronger habits?

What if habitual customers require less time and resources to be retained? What if these resources and time saved, could be applied among the prospection and acquisition of new customers? Does a specific sales policy contribute to stimulating habitual behaviors? If you have a customer that is supposed to have developed habits with one of your competitor, how can you change the context to have more attention paid to your negotiation proposal? How can good habits be rewarded? How repeated exposure to sales promotions affect profits?

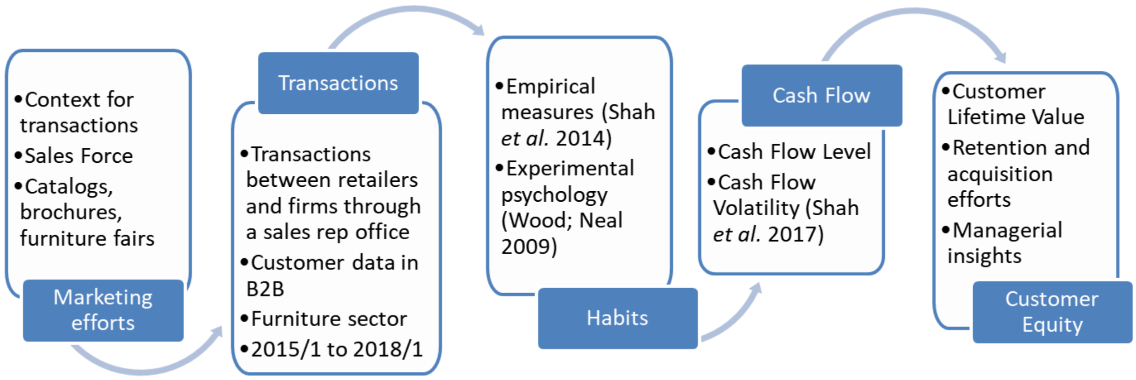
One important distinction is that the sales promotions present in this work are classified as trade promotions to retailers, and though indirectly affects consumers, are not directly aimed at them. The marketing research has a solid knowledge of sales promotions in over 30 years of academic works. However, there are still some gaps in trade promotions to retailers and the long term impact on profits for permanently available promotions. The role of promotions in this B2B context, can generate habitual behaviors that affect firm performance in what magnitude? The fact that the promotional offers are always present in this context and are not occasional could weaken the effect of stockpiling or forward buying (ZEELENBERG; PUTTEN, 2005) and offer new perspectives on the impact of cash flow level and volatility?

The need to explore automatic processes of purchase in organization buying is also intriguing. Many managerial insights could be generated to nudge or reward frequent and constant buyers that could be habit prone. Firms may also pay more attention to contextual issues that underlie habit formation. On the other hand, they could even test if the company is overspending time and efforts with customers that, as Ascarza (2018) proposes, would have bought anyway.

All the answers to these questions rely on a more comprehensive look to habitual behaviors in a business-to-business context. This dissertation does not aim to address all these issues at once. However, giving a step further in the direction of understanding and assessing the impact of this particular response mechanism that accompanies people in everyday tasks and decisions is the ultimate goal.

Therefore, the research question of this work is: how B2B transactions that are influenced by customers' habits affect firm performance through the cash flow level and volatility? The proposed chain of this work is the following:

Figure 1 – Main topics of the work



Source: author

1.2 GOALS

Next, the general and specific goals of this dissertation will be presented.

1.2.1 General Goal

To analyze how habitual behaviors present in the transactions of business-to-business customers affect firm performance.

1.2.2 Specific Goals

a) estimate the habit strength (Purchase and Promotion) of each customer as proposed by Shah *et al.* (2014) over the seven semesters of transactions;
b) evaluate how in magnitude and direction the strength of habits affect the cash flow level and volatility;
c) compare how the customers with the highest CLV interact with customers that have developed stronger habits;
d) simulate the financial impact of an expansion of the customer base that has more customers of a particular habit.

2 THEORETICAL FOUNDATION

The present chapter approaches the theoretical foundation of the topics that cover this dissertation. The logic of analyzing and measuring behaviors that affect customer performance, which can increase the overall value of a firm, has the customer-centric and customer equity views as the underlying subjects. Then, it will be presented a theoretical review of the importance of assessing the cash flow level and volatility, along with the topic involving habits within the customer perspective.

2.1 THE CUSTOMER-CENTRIC VIEW

Maybe even before the word "customer" began to be used in the 15th century (MERRIAM-WEBSTER, 2018), one of the most important ways of generating cash flow are the people you do business with. Even though the purpose of several businesses may not be generating cash flow, in case of needing it, it would better turn to customers. Peter Drucker (1973, p.63) already said: "Marketing is […] the whole business seen from the point of view of its final result, that is, from the customer's point of view."

Back in the 1960s, Robert J. Keith said "[…] no longer is the company at the center of the business universe. Today the customer is at the center." (KEITH, 1960). It was the beginning of the marketing revolution aiming at myopic executives who could not distinguish who took the customers away (LEVITT, 1960). In his seminal paper, Theodore Levitt (1960, p.56) signaled a direction the underpinnings of business should be set: " […] the entire corporation must be viewed as a customer-creating and customer satisfying organism".

After the somewhat controversial definition of Production Era, the beginning of the Marketing Era in the 1950s started to bring customer orientation as the primary driver of executive actions (KEITH, 1960; FULLERTON, 1988).

McNamara (1972) explored the marketing concept implementation reach as a business philosophy in the US, but only several years later the market orientation theory gained sound attention by marketing academia (KOHLI; JAWORSKI, 1990; NARVER; SLATER, 1990). It has brought the concept that companies must create superior value for its customers with market intelligence and organizational culture (DESHPANDE; WEBSTER, 1989) that generates additional benefits from minimizing costs. Marketing scholars then, turned their attention to the core capabilities to maintain good customer relationships (DAY, 1994; BOULDING *et al*., 2005).

Naver and Slater (1993) stated that market orientation is likely to lead to higher customer satisfaction, and consequently, repeat businesses (KOTLER; KELLER, 2015). In a parallel path, marketing also established the ACSI (The American Customer Satisfaction Index) as an acknowledged way to measure customer satisfaction (FORNELL *et al*., 1996). Alongside customer satisfaction, other customer-related factors gained momentum after the 1990s as customer loyalty (DICK; BASU, 1994; HALLOWELL, 1996), perceived quality (RUST; MOORMAN; DICKSON, 2002) and quality on service (PARASURAMAN; ZEITHAML; BERRY, 1985).

The consolidation of the mentioned topics inspired a better understanding of individual customer’s needs and what underpins the customer-centric view. Sheth, Sisodia, and Sharma (2000) and Shah *et al*. (2006) cast a light upon the path to surpass the product-centric view and reach the customer-centricity. It consisted in dealing with some organizational barriers: organizational culture (DESHPANDE; FARLEY; WEBSTER, 1993), organizational structure, processes [KORDUPLESKI; RUST; ZAHORIK (1993) show why it is not possible to achieve quality without linking internal processes to customer’s needs] and financial metrics.

Marketing academics and practitioners moved to a more relationship-oriented view of marketing, expressed in the Customer Relationship Management (CRM) literature. Payne and Frow (2005) and Boulding *et al*. (2005) stated that one of the central tenets of the CRM process is measuring the performance of customers to improve the value dual-creation process.

The customer-centric marketing main concept is the principle of looking and assessing each customer individually (SHETH *et al*., 2000), and is distinct from one-to-one marketing and the use of mass customization (PEPPERS; ROGERS, 1993) as it centers the needs, wants and resources of customers in the starting point of the planning process.

The heterogeneity of customers could be traced in a way that is more appropriate to marketing as technological advances and data techniques allowed collecting customer data in a less costly and precise way. Cutting-edge analytical tools softened the task of marketing analysts to link scattered information and draw conclusions.

Ascarza, Fader, and Hardie (2017) elucidate the differences of customer-centric to other product-centric orientations as the development of a culture of tracking individual customers over time; calculate forward-looking metrics like customer lifetime value (CLV) and taking the high CLV customers as the engine for growth.

It is worth noting that a different avenue proposed by some marketing scholars as Gummesson (2008a, 2008b), brings the concern that the customer-centric view is limited and a fuzzy concept that spoils customers when all firms implant customer orientation and no one attains competitive advantages. For example, Gummesson proposes a balanced centricity underpinned by the service-dominant logic (VARGO; LUSCH, 2004) and network theory (GUMMESSON, 2007). According to Osborne and Ballantyne (2012), one possible limitation of the customer-centric view is that the short-term logic of business keeps feeding commercial rules that perpetuate the firm-centric view despite newly proposed marketing frameworks. Despite the theoretical arguments of both sides, firms look to spend scarce resources in more productive ways. Deighton and Johnson (2013) showed how individual-level consumer data reduced inefficiency in matching producers and customers and is turning possible marketing to be more productive with efficient customer selection rather than persuasion.

Deighton (1997, p.348) argued that the Internet provided the tools to solve ‘the problem of consumer marketing's lack of customer intimacy” that for decades disconnected the actions of marketing in broadcast media to measures of consumer response and transactions. Then, it was opened the way for a newly proposed paradigm that Deighton (1997) called customer equity.

2.2 CUSTOMER EQUITY

Kumar and Shah (2009) define customer equity (CE) as the sum of the lifetime value of all customers of the firm. Wiesel, Skiera, and Villanueva (2008) show that the CLV result from several customer metrics (e.g., cash flows) generated by customers during their relationship with the firm (lifetime). To retain or acquire customers, firms must invest money (expenditures). CLV becomes forward-looking because it takes into account all the revenues and expenditures of a specific customer considering the patterns that will influence retention, acquisition or attrition. Therefore, the predicted profit that will be generated by a customer has an appropriate discount rate to make a net present value (KUMAR, 2008).

Customer equity is enhanced through drivers that, as brought by Villanueva and Hanssens (2007), encompasses customer satisfaction, loyalty programs, product offerings, channels and tactics of acquisition, word-of-mouth, brand equity and competition. Rust, Lemon, and Zeithaml (2004) underline value equity, brand equity and relationship equity as the primary drivers of CE. The impact of the drivers is influenced by industry and firm characteristics as empirically shown by the study of Ou, Verhoef, and Wiesel (2017). Hanssens, Rust, and Srivastava (2009) also allude to marketing capabilities as essential drivers, as expertise is vital to use the resources a firm has in the marketplace.

Kumar and Shah (2015) detail that in relationship businesses such as insurance and financial services, customer equity can be estimated through direct counting of customers and aggregation of their CLVs. However, when the direct-count approach is not possible or complicated, it is recommended to infer marketing's impact on customer equity at a more aggregate level, as Rust *et al*. (2004) proposed. There also models that contemplate customers that do not generate any direct revenue as in auction sites or job agencies (GUPTA; MELA; VIDAL-SANZ, 2006).

The work conducted by Silveira, De Oliveira, and Luce (2017) reached similar results when proposing a two-way measure of customer equity for firms in one particular context. One way through market-based data (top-down or aggregate-level approach) which is more simple and easy to implement, and the other with behavioral-based information (bottom-up or disaggregate-level) which is particularly helpful to identify customer equity drivers with the most impact in one market.

Models of CLV may incorporate the probability of a customer churn being unobserved (non-contractual settings) or when the customer "death" is observable (contractual settings), as brought by Fader and Hardie (2009).

The work of Jackson (1985) on the always-a-share and lost-for-good models introduced a feasible way to think and classify customer's relationship still used in CLV models (FADER; HARDIE, 2016). From one side of the behavioral spectrum, there are the always-a-share customers that part easily and have weak ties with any vendor. The opposite side, the lost-for-good customers, are always tied to only one vendor and have high switching costs, but as long as the relationship is over, they will probably never come back.

In real life, customers are a mix of these proposed models, and even with innovative analytical tools, firms still overspend in false positive customers driven by models of customer valuation that do not detect if a pattern of profitable transactions is just temporary (MALTHOUSE; BLATTBERG, 2005).

As Shah *et al.* (2017) propose, studies of individual customer behavior and its impact on customer value are common in the marketing literature (VENKATESAN; KUMAR, 2004). However, few studies have explored individual customer behavior through habit-based measures. Exploring and getting new insights into how habitual behaviors affects financial performance and how temporal stability of habits should be rewarded may help firms to build models that have higher accuracy. Then, managers can foster relationships that create more profitable and stable transactions that when aggregated, will increase the shareholder value.

It is worth mentioning that some scholars have researched the specificities of the business-to-business settings according to the use of customer equity tools. The work of Persson and Ryals (2010) highlights that managers make confusions between customer equity and customer assets terms since assets can be managed, but customer equity can only be measured. Nenonen and Storbacka (2016) relate why some industrial firms in Europe keep on utilizing retrospective customer profitability analysis due to the misunderstanding of these concepts. Some firms find troublesome to advance in customer-centric metrics when Wall Street keeps on requiring or evaluating performance in product-centric or aggregate metrics. Also, there is not a universal agreement of a standard formulation of CLV that conforms to audit standards. Nevertheless, the handbooks of Kumar and Shah (2015) and Lilien and Grewal (2012) bring great examples of how the framework of customer equity tools can be adjusted to the B2B peculiarities and lead to great improvements in the customer relationship management.

2.2.1 Resource allocation and marketing metrics

Management can take advantage of customer equity models to be able to better allocate marketing spending (REINARTZ; THOMAS; KUMAR, 2005). Kumar *et al.* (2008) explicitly show robust financial outcomes of customer-centric practices at IBM, increasing tenfold the revenues of a selected base of customers without any changes in the level of marketing investment.

It is worth mentioning that marketing actions may affect the firm's bottom line or stock performance in a direct way (SRINIVASAN; HANSSENS, 2009; JOSHI; HANSSENS, 2010) or an indirect way through changing the customers' mindset (PETERSEN *et al*., 2017).

A better allocation of resources can affect customer equity through retaining and acquiring new customers and through increasing share of wallet (COOIL *et al*., 2007; HANSSENS; DEKIMPE, 2017).

The culture of assessing customer performance can apply to not just spending resources, but as a way for selection of time and attention efforts. Casas-Arce, Martínez-Jerez, and Narayanan's (2017) research showed how a forward-looking customer-centric metric (CLV) could help novice employee catch up with experienced manager shifting attention toward more profitable client segments reducing arbitrariness. They demonstrate how this change helps the dissemination of more decentralized decisions, improving the productivity of the firm aligning the long-term value creation strategy of an organization with the short-term profit objectives of its employees.

Within the context of habitual behaviors, the allocation of resources is optimal if habitual customers are spotted and differentiated from customers that build their relationship over non-habitual preferences, as the study of Liu-Thompkins and Tam (2013) and Shah *et al.* (2012) show. Ascarza *et al.* (2018) demonstrated how standard retention efforts disrupted customers' habits that "awoke" and realized they were not satisfied with the relationship and churned.

For years, marketers looked in the finance literature of portfolio management support to manage resources' allocation. However, investing in customers is not the same as putting money into a real estate investment fund. According to Kumar (2018), investments in clients are non-linear, and U$ 1 spent in a high-CLV customer may result in different outcomes. Once investors buy a stock, they can hold it as long as they want. It is not possible to make that assumption with customers since they decide when they will leave. In case that stocks in the portfolio start performing poorly, someone may sell those stocks and rebuy them in the future. With customers, it is possible to abandon or reduce investments, but it is impossible to measure the consequences as negative word-of-mouth interfering in high-CLV customers. As Kumar (2018, p.4) highlights, "In other words, financial theories offer a passive approach to managing investments, whereas customer management requires an active management approach".

The primary objectives of the research in customer equity is the economic measurement of the value brought by customers and the identification of strategies that build profitable relationships (VILLANUEVA; HANSSENS, 2007). Therefore, habitual behaviors *per se* are not determinant to firm performance unless they become drivers of cash flows.

2.3 CASH FLOW LEVEL AND CASH FLOW VOLATILITY

Srivastava, Shervani, and Fahey (1998) start their seminal paper with a quote of Paul Anderson (1979) mentioning that if marketing does not take into account variables such as inventory levels, working capital needs, debt-to-equity (D/E) ratios, stock prices and only looks to sales and market share, it will be no less damaging than the marketing myopia proposed by Levitt (1960). One possible way marketing could reach a joint agreement with the C-level executives and with the shareholders is through the metric of cash flow.

Cash flow, as the net amount of cash being transferred into and out of a business (INVESTOPEDIA, 2018), has advantages as a measure of financial performance in that it is less influenced by accrual accounting methods and may be less vulnerable to idiosyncrasies of a firm's accounting procedures than profits (VORHIES; MORGAN; AUTRY, 2009). If appropriately applied, utilizing cash flow for a firm valuation estimate produces identical results as the residual income approach (PLENBORG; 2002).

Customers are typically one of the fundamental and most important sources of a firm's cash flows (SHAH *et al*., 2017), and expectations of future cash flows are the underlying root of shareholder value (HANSSENS; DEKIMPE, 2017). Marketing actions may enhance or accelerate cash flows, reduce their volatility and vulnerability, and increase their residual value through the creation of market-based assets that include customer relationships, channel relationships, and partner relationships (SRIVASTAVA; SHERVANI; FAHEY, 1997). Marketing may also generate higher cash flows acquiring additional customers or convincing current customers to spend more (HANSSENS; DEKIMPE, 2017).

Rao and Bharadwaj (2008) demonstrate that the effect of marketing initiatives on expected cash flows and shareholders' wealth is not straightforward, since actions when planned and executed may have no effect on expected sales and yet affect future expected cash flows. It is worth to note, as Rao and Bharadwaj (2008) remark, the firm's next period are determined jointly by the firm's choice of marketing initiatives but also by exogenous realities like the state of the economy.

Accelerating the speed of cash flows is important because earlier cash flows are preferred since time and risk reduce its value. Enhancing is possible through the increase in revenues with lower costs (SRIVASTAVA *et al*., 1997). However, the assessment of marketing strategies that aim at the reduction of the vulnerability or variability of cash flows are rare (SRIVASTAVA *et al*., 1998; SHAH *et al*., 2017). Fischer, Shin and Hanssens (2015) argue that cash flow volatility has not been a major concern to marketers, as it may generate conflicts between a common marketing objective (sales maximization) with a more operational and financial objective (stable revenues).

The low volatility of cash flows generates value to the firm by reducing the risk associated with cash flows, resulting in a lower cost of capital or discount rate. Cash flows that are more stable and predictable will have a higher net present value creating more shareholder value (SRIVASTAVA *et al.*, 1997). As Gupta (2009, p.177) underlines "If cash flow variability is not included in the model it is not clear if a customer who generates \$100±\$10 per period is better or worse than a customer who generates \$150±\$80". In the finance literature, the variance and range are a standard measure of variability or volatility of cash flows.

Rountree, Weston, and Allayannis (2008) found empirical evidence that investors negatively value cash-flow volatility with a 1% increase resulting in a 0,15% decrease in firm value. Minton and Schrand (1999, p.324) affirm that "higher cash flow volatility implies that a firm is more likely to have periods of internal cash flow shortfalls". Froot, Scharfstein, and Stein (1993) show that cash flow disturbs affect both investment and financing plans in a way that is costly to the firm, as when firms have to liquidate assets to make payments (OPLER *et al.*, 1999). Studies have connected the increase in cash flow volatility with higher cash holdings by US firms since the '80s, and this has led to a decrease in the trade credit to buying firms, creating more constraints to increase sales (BATES; KAHLE; STULZ, 2009; HARRIS; ROARK, 2017).

Badrinath, Gay, and Kale (1989) found that institutional investors prefer companies that have more stable variations in earnings. Smooth earnings ease the analyst's task of predicting future earnings (GRAHAM; HARVEY; RAJGOPAL, 2005). Nevertheless, there is a hot debate among some investors that refuse to take volatility as a proxy for risk (UDLAND, 2015). This argument may hold as markets or industries will always oscillate in response to macroeconomic shocks, laws to stimulate consumer spending, political turbulences or raise in interest rates but that do not automatically translate in a riskier customer or firm.

It is important to note that marketing looks to reduce cash flow volatility with the generation of economic value. In the finance literature, earnings smoothing can be targeted with the use of accruals. Managers may enter into futures, options, or swaps to mitigate expected cash-flow volatility. Opler *et al.* (1999) propose that hedging can reduce the variability in cash flows, increasing the value of the firm. However, according to Rountree *et al.* (2008), these processes do not add sustainable value to the firm. However, this is not the rule, since Graham *et al.* (2005) found that 78% of executives admitted sacrificing long-term value to preserve smooth earnings.

The volatility of cash flows is minimized when the relationship with customers and channel partners is arranged in a manner that promotes stability in operations, with fewer and smaller peaks and valleys in sales (SRIVASTAVA *et al.*, 1998). Therefore, the temporal consistency of particular habits as found by Shah *et al.* (2017) may contribute to firms attenuate expected cash flow variance. However, it remains an open question to assess if the context present in this work will hold the same results, as it is a business-to-business setting where manufacturers sell to retailers, which later resell to final customers. This chain might offer particularities as purchase orders could range thousands as well as complements or supplements of less than R$ 50,00.

Sometimes, the volatility of cash flow is an endogenous consequence of marketing actions. The study of Fischer *et al.* (2015) demonstrates how volatile marketing spending results in demand volatility. According to Srivastava *et al.* (1997, p.61), trade promotions might "encourage customers and channel partners to stock up and buy more sporadically than otherwise".

Lee, Padmanabhan, and Whang (2004) refer to the bullwhip effect, as the distortion in demand information that affects the coordination of the supply chain as production scheduling, inventory control, and delivery plans. Systematic increases in demand volatility occasion this effect. Consequently, amplified demand patterns implicate in extra costs with raw materials, additional manufacturing expenses, excess warehousing, and transportation. Unexpected overload of order fulfillment may generate several impacts with sales, customer service, and finance department, i.e., financial managers that may have to engage in extensive earnings smoothing (ALLAYANNIS; ROUNTREE; WESTON, 2005).

Fischer *et al.* (2015) bring some outcomes of high volatile scenarios, especially in the plummet times: more frequent hiring and firing generating higher costs of training, distress over the sales team, workers motivation and compensations of sales and executives.

The framework proposed by Srivastava *et al*. (1997) brings strategies for reducing the volatility of cash flows as customer selectivity, demand-driven flexible manufacturing and everyday low price (EDLP) versus price-promotions.

Nevertheless, Fischer *et al.* (2015, p.198) remark that "volatility is not bad per se. If it is driven by an upward sales trend, for example, then it might even be desirable. The unexpected variation around the forecasted trend line is the kind of volatility that is undesirable". Researchers found that in some cases customers that allocate a larger share of their purchases with a firm or that hold deep relationships offer more variable cash flows with also higher cash flows levels (TARASI *et al*., 2013).

Previous studies in the business-to-consumer found that repeat purchase with temporal consistency brings more stable revenues to firms (SHAH *et al*., 2017). This dissertation proposes to assess if, in the business-to-business context of this work, the results hold to the peculiarities of the relationships and transactions.

2.4 HABITS

One of the most prolific researchers of habit in the last decade, Wendy Wood (2018)[1] remarked that "on 43% of the time, what we do when we are working is repeating what we have done before and not thinking about what we are doing. It is automatic we are acting on habits".

In the introductory chapter of the JACR special issue over Habit-driven Consumer, Drolet and Wood (2017, p.275) define habit as:

> […]context-response associations in procedural memory that develop as people repeat an action for a reward. Once a habit forms, the response is automatically brought to mind by perception of the context. This analysis differentiates habit from more motivated dispositions, especially goal-directed actions. Once formed, habits are notoriously unresponsive to people's intentions.

Habit is a construct that can be researched from different domains as economical, clinical psychology, sociology and neuroscience, to name a few. In this dissertation and the work of Shah *et al.* (2014), the concept of habit bears on the research tradition of social and experimental psychology (WOOD; NEAL, 2009).

William James reserved an entire chapter to habit in his 1890's book, *The Principles of Psychology.* To emphasize the observed power of habits, he connected it with the laws of nature: "The moment one tries to define what habit is, one is led to the fundamental properties of matter" (JAMES, 1890 p. 64). James saw habits as a sequence of action and reaction that contemplates what people do for the most part of a day.

Clark L. Hull (1943) was a prominent author that developed studies over habits attaching it with extrinsic rewards in laboratory experiments with animals and humans. He thought on a shape of habits over time, as being an asymptotic curve in which automaticity of behavior increases consistently, although by smaller units after each repetition over time, until it reaches a plateau where it stabilizes.

However, as Wood and Rünger (2016, p.290) explain, "reinforcement-based models of habit were soon supplanted as the field embraced more purposive and cognitive perspectives". With the growing interest in cognitive processes and the overshadowing of behaviorism, habits

[1] Lecture on the inauguration of The INSEAD-Sorbonne University Distinguished Visiting Chair in Behavioral Sciences, January, 30 2018, Paris, France

disappeared from the research agenda of psychology. For much time, habits were seen as an empty construct.

Works in neuropsychology in the late sixties brought much of what it is known about habits today, with research involving humans with brain damage after an accident or with Parkinson's disease that even after severe amnesia still conserved untouched some habitual behaviors (FOERDE, 2018). Recently, with advances in technologies of neuroimaging and neurobiology, researchers are discovering specific brain areas that relate to learning, response to rewards and habits slips. As Amaya and Smith (2018, p.145) claim, "In the brain, ground-zero for habits is the dorsolateral striatum (DLS; primate putamen homologue), a basal ganglia input structure". The basal ganglia are one of the brain areas responsible for controlling voluntary behavior (YIN; KNOWLTON, 2006).

Studies involving habits started to gain momentum with interest in the principles of automaticity within social psychology in the late '90s (VERPLANKEN; AARTS, 1999). As Shah *et al.* (2014, p.727) expose, the renewed interest is based on "understanding how a person's goals, intentions, and dispositions (e.g., attitudes, personality) mediate habit formation and affect cognitive associations that trigger temporal consistency of repetitive behavior".

Wood and Neal (2009, p.580) posed a provocative question "How plausible is it that the relatively simple habit cuing mechanism drives consumer behavior?" Several studies in the marketing and consumer behavior area have been scrutinizing this topic. In July 2017, a complete edition of the *Journal of the Association for Consumer Research* was dedicated to the Habit-driven Consumer. Habits, for example, appeared in quite a different approach (GREEN; LANGEARD, 1975) but resurged in papers of *Journal of Marketing Research* (SHAH *et al*., 2014; SHAH *et al*., 2017), *Journal of Marketing* (SHAH *et al*., 2012; LIU-THOMPKINS; TAM, 2013), *Journal of the Academy of Marketing Science* (LABRECQUE *et al*., 2017) and *Journal of Consumer Psychology* (WOOD; NEAL, 2009). In the journal *Current Opinion on Behavioral Sciences*, a complete edition for habits and skills was released in 2018. Bas Verplanken, one of the most prominent authors of the area of social psychology, organized a book called *The Psychology of Habits* in late 2018.

In the marketing literature, some authors analyzing longitudinal data of customers' transactions started to observe that in certain instances some behaviors persisted with consistency over time even after more investment, personalized communication or cross-buying offers (SHAH *et al*. 2012). In marketing's long run to demonstrate return over its investments, another possible explanation for a parcel of ineffective spending was related to some habitual behaviors.

Purchase habits are deemed to be responsible for considerable changes that products, retailers or channels face during their existence. The migration to online shopping, the weak sales of traditional toys, beer, bar soap and products related to golf are often linked in the news to supposedly new shopping habits (BROOKE, 2017). Habits are formed and they can last for a long time. Labrecque *et al*. (2017, p.124) found that habits influence the introduction of new products with "consumers slipping back into old habits despite their favorable intentions", showing that if there is a conflict with existing habits a new product is unlikely to be used.

In the context of business-to-business transactions of this work, someone responsible for purchase decisions may consider "Well, I would like to buy something different for this showroom; we need new, different products as our customers search for novelties". The point is that as soon this person sits on his chair, turns on his laptop and check some news over the internet, the context may activate a habitual behavior and the necessary purchase to feed that available space or negative item on stock is sent to the usual supplier. No further research on alternative options happens. It is supposed that habitual behaviors towards purchasing's products to resell probably do not englobe the most sold and essential items. The logic is that when considered the whole portfolio of products and suppliers, some may become overlooked as purchase turns repetitive, and the context does not generate friction to the process.

As Ouellette and Wood (1998) explain, past behaviors when satisfactory practiced in constant contexts, can generate associations between behavior and contextual cues. That turns in to automatic responses and become habits. Otherwise, when behaviors are not well learned or when performed in unstable contexts, they call conscious decision making (deliberate processes) to execute the action. Lally *et al.* (2010) state that in the real world it would be almost impossible to repeat uninterruptedly a response every time someone has a context cue, and even with some missed opportunity, people still acquire habits in the long run. Their study also found how people take a different amount of time to develop automatic behaviors (e.g., in exercising): from 18 to 254 days to reach the automaticity plateau, with an average of 66 days.

Contextual cues refer to the many elements of the performance environment that potentially are present as actions are repeated. Those often associated with habits are people (e.g., alone or with shoppers around), physical location (e.g., office, home, store layout), preceding events or states (e.g., before going to run, mood) and time of the day (WOOD; NEAL, 2009; HERZIGER; HOELZL, 2017).

According to Wood and Rünger (2016), context cues change as people change of jobs, move to a new house or face a natural life transition because they reduce exposure to cues that used to trigger former habits. In B2B settings, it is reasoned that the change in key positions in the company hierarchy, as well as a new team in the buying department, could disrupt the context where a relationship is held between a seller and a vendor. Times of financial constraints can create stricter rules for purchase orders that add friction to the repetition of past behaviors. Similarly, friction can arise through new rules established by vendors as removing products in the portfolio, new pricing policy or new sales representatives.

As Simon (1997) suggest, habits are a solution that people utilize because we do not have either the mental capacity or time to compare and decide every issue that surge in life. However, the optimal tool is also a double-edged sword: habits could be so ingrained in memory that they become a considerable challenge to marketers. Even after consumers approved and found attractive a new visual brand change for Tropicana juice in focus groups, in the shelves, the context was disrupted and an immense sales failure led customers to look for alternatives to replace the old familiar brand image (HARRINGTON, 2017).

2.4.1 Purchase and Promotion Habits

In consumer packaged goods, consumers tend to buy the same brands on different shopping trips or the same amount of a product during repeated visits to a grocery store (WOOD; NEAL, 2009). As Ehrenberg (1972) asserts, the nature of repeat purchases could be different for a market-leader or small-seller product, but empirically it follows regular patterns across brands, products or periods of time. As shown by Ji and Wood (2007), several products tend to be repeatedly purchased over time. For example, Seiler (2013) found that in 70% of detergent purchases, customers failed to search for alternatives and were unaware of the price. As Deighton, Henderson, and Neslin (1994) propose, the inertial effect on consumers makes the primary influencer of current purchase the past purchases.

Marketing scholars studied repeat purchase of consumers using probability models as the negative binomial distribution (NBD), used to characterize repeat-purchasing in numerous markets, especially in fast-moving consumer goods. The study of Wilkinson *et al*. (2016) found a good fit between NBD models and future customer purchase patterns in a B2B database of industrial transactions of raw materials.

In the business-to-business context of this research, as retailers need to resell acquired goods, there may be several drivers of repeat purchases that possibly differ from the reasons one firm continuously buy A4 paper sheets for the office or screwdrivers for the assembly line.

Retailers could start buying more frequently from firms that offer fast delivery, a better finishing on furniture or a differentiated design. Others might look mostly to price to match the demand for a new category or to battle competitors in a specific product. Besides, repeat purchases could be stimulated through the connection with the sales forces, which spur more transactions with, e.g., earning the trust of the buyer, feelings of presence and support in difficult times or friendship.

Positive attitude, risk minimization, satisfaction with first transactions or preference toward a brand may be the precursors of repeat purchases that might turn to attitudinal loyalty if there are a clear exercised preference and constant favorable evaluations or, it may become an automatic behavior if activated by contextual cues (LIU-THOMPKINS; TAM, 2013). The literature over the concept of inertia might overlap with some aspects of habits. As Liu-Thompkins and Tam (2010) explain, inertia is a mechanism where past action influences future actions. It can be driven by habits or by attitudinal loyalty. Habits may share this relation of past-future actions, but besides behavior, it is also a proved psychological mechanism.

Shah *et al*. (2014, p.729) define promotion habit “as the general behavioral tendency of a customer to selectively purchase items that are offered to customers as deals”. Marketing researchers investigated the repeat purchase of promotions through utilitarian economic ways (e.g., using time and efforts costs), psychological (e.g., hedonic) or socio-cultural approach (e.g., demographics). Recurring deal purchases stimulated researchers to find a pattern or rationale of this kind of customer. Bawa and Shoemaker (1987) analyzed the deal proneness of customers using coupons and found unexpected results that linked higher income and educated citizens with higher coupon proneness. Blattberg *et al.* (1978) utilized a utilitarian model in that household and firms would make the same kinds of inventory/costs decisions. Chandon, Wansink, and Laurent (2000) looked for an explanation for consumer response to promotions and found that customers valued a mix of hedonic and utilitarian benefits within a deal, instead of only monetary savings. Deal seekers might do recurring spatial searches across stores or temporally search deals across time (GAURI; SUDHIR; TALUKDAR, 2008).

Kwon and Kwon (2007) also proposed several arguments for customers continuously looking for deals, and some were related to the cognitive abilities, shopping experience, and skills developed by the buyer when making comparisons and dealing with prices. Therefore, it may be reasonable that a buyer in a B2B context, after recurring purchases of promotions, could have mastered skills for picking opportune deals.

Sales promotions might generally span three classes: manufacturers offer *trade promotions* to retailers with permanent discounts or funding to co-participate in advertising efforts, then, retailers can offer a price reduction on a "special Wednesday deal" to consumers known as *retail promotions*. Manufacturers can offer coupons or rebates directly to consumers in *consumer promotions* (AILAWADI; GUPTA, 2014).

A promotion can generate an immediate market response increasing sales of the promoted item, but also it could "steal" from other brands or even increase the sales of the whole category (BLATTBERG; BRIESCH; FOX, 1995). It generally affects the store traffic and even makes consumers switch the place they make their customary shopping to grab a new deal. Within the long term, promotions could alter the reference prices sensitivity changing the frequency and amount of future purchases (WINER, 1986). It is possible that some promotions accelerate sales that would happen in the future with stockpiling (ZEELENBERG; PUTTEN, 2005). As Van Heerde and Neslin (2017) show, it is always important to analyze whether the future purchase came from the same product or if it borrowed a sale from other brands.

In the context of this work, it is important to define as trade promotions the deals that retailers pass through to consumers. Retailers generally prefer discounts on the invoice and manufacturers usually prefer to generate a bonus after the achievement of an objective or performance (amount of items sold). Retailers could pass through the incentives straight to the manufacturer's product or allocate it across the category. Forward buying could be prejudicial to manufacturers that will accelerate sales, not increasing them in overall (AILAWADI; GUPTA, 2014). However, it could generate a positive impact on repelling competitors as they protect their space on a retailer.

Moreover, understanding of different types of repeated consumer behavior is vital for brand and financial reasons as it might increase repeated purchase and consumption affecting customer lifetime value and share of wallet (WOOD; NEAL, 2009). Thus, "repetition, and more specifically habits, may characterize a significant segment of consumer behavior that is linked to important marketing outcomes" (WOOD; NEAL 2009, p.579).

2.4.2 Measuring Habits

In Psychology, habits can be estimated by self-report surveys, as the Self-Report Habit Index (SRHI) that regards habit as a psychological construct (VERPLANKEN; ORBELL, 2003). The SRHI scale has 12 items that contemplate not just past frequencies of behavior, but also the difficulty of control, lack of awareness and efficiency. Alternatively, there are other methods of measuring habits that range from a pure self-reported frequency of behavior (OUELLETTE; WOOD, 1998) to smartphone applications that monitor utilization frequency or even geo-location mapping for contextual purposes (CARDEN; WOOD, 2018).

Shah *et al*. (2014) proposed a method to infer the habit strength empirically using observed transaction behavior. It was confronted with the SRHI and with measures that take into account only frequency-based or inertia-based purchases. The results showed a high correlation between the proposed measure of habit and the existing measures. The benefit of applying the proposed habit measure and using only customer data, it is to take advantage of the lower costs and the feasibility that does not require surveying customers of the firm or using experimental studies with hypothetical scenarios that misrepresent the context which habitual responses are triggered (HERZIGER; HOELZL, 2017). It is crucial to mention the peculiarities of habits that usually do not follow the intentions and goals of respondents that might not retrieve correctly when and how they performed an action.

The work of Liu-Thompkins and Tam (2013) and Shah *et al.* (2014) does not treat habits as a pure frequency of past behavior. Although, in a quite distinct way, both studies incorporates temporal consistency as a means to differentiate habits from other attitudinal behaviors of loyalty. Therefore, authors found a statistical relationship between past and future behavior that once a behavior has been sufficiently repeated with patterns of temporal consistency; they indeed might have turned into habits (VERPLANKEN; ORBELL, 2003).

The challenges to collect repeat responses from customers during time have historically destimulated marketing and consumer research into habits (DROLET; WOOD, 2017). As Liu-Thompkins and Tam (2013) affirm, marketing benefited from the development of more straightforward empirical measurement of habit strength using a person's transaction history that increases the practical relevance of habit as applied in the study by Shah *et al*. (2014) and Shah *et al*. (2017).

2.4.3 Organizational Habits

The context of this dissertation is under the business-to-business environment and therefore, it is vital to extend the research on habitual behavior into organizational behavior. Several studies over routinized tasks are related to habitual behaviors, but regarding complex activities that involve more cognitive effort, they are scarce in the literature.

As Verplanken and Orbell (2003, p.10) expound, “The efficiency of habits appears in particular under conditions of heavy load, such as exhaustion, time pressure, distraction, or information overload”. Wood and Rünger (2016) add stressful moments to these conditions where people increase their reliance on habits. Therefore, it is supposed that these characteristics in the environment that may facilitate the occurrence of habitual behaviors are also found in many organizations.

Polites and Karahanna’s (2013) study shows how habits are essential in the adoption of intelligent systems in the workplace, demonstrating the example of firms that invest highly in business intelligence (BI) tools but employees keep on making analyses via spreadsheet software. They argue that “continued use of an information system (IS) over time is largely a function of habit rather than conscious intentions” (POLITES; KARAHANNA, 2013, p.222).

Ohly *et al.* (2006, p.274) found that “the automaticity involved in routine tasks might promote performance on other tasks that need more cognitive resources, such as the production of novel and useful ideas (i.e., creativity)”. It is worth noting that the task involved in purchasing can be split in moments of comparisons and collection of information, negotiating with suppliers and choosing among several products and models; and the subsequent period, where the conditions are set and the buyer just repeat orders to suppliers in order to keep the supply chain network flowing. Therefore, it expected that repetitive purchases within a stable context and with temporal stability (consistency) over time, might be cued to happen with traces of automaticity.

3 METHOD

Methodological procedures for data collection and analyses will be described in this section.

3.1 THE DATASET

The dataset is based on a set of transactions between manufacturers and retailers in the furniture sector in the metropolitan area of Porto Alegre, for the period of seven semesters (2015-1 to 2018-1). The database consists of around 15,000 transactions of 334 retailers with three manufacturers, obtained through a sales representative office that intermediates these transactions and has contractual permission to be the unique seller of the manufacturers in the geographical region. Each purchase order is from a sole manufacturer with one retailer. The data contains a mix of existing and acquired customers in the period observed.

3.1.1 Retailers

The retailers that constitute the database are stores that sell furniture products and eventually, electronics or home improvement items. They are a multi-brand store since they do not have exclusive supply agreements. Most retailers in the database have one store branch and are small business. Some retailers are part of cooperative groups. In this situation, these units have autonomy of buying products from any supplier they decide, but they need to follow some rules of shop façade, monthly impress ads, agreements with credit card operators and ERP systems. There are also large retailers in the portfolio that have several branches in the state of Rio Grande do Sul, Santa Catarina and Paraná that sell furniture, appliances and electronics.

3.1.2 Manufacturers

The manufacturers in the dataset produce furniture items like kitchens cabinets, wardrobes, storage units, racks and complements such as bookcases and shelves. These firms operate in the same segment, which has a serial production of a high amount of items that are later sold to retailers. Manufacturers in this context are generally low intensive in the use of technology, are labor-intensive and with low penetration in international markets (GALINARI; JUNIOR; MORGADO, 2013; VEIGA; RIOS, 2016). It is important to observe that the manufacturers in this dataset do not have an association with each other; they just help to constitute a larger dataset for analysis. Two of them are from the state of Paraná, and one of the manufacturers is from the state of Rio Grande do Sul. The fact also that there is more than one manufacturer gives the results of this work more generalizability since the habitual behaviors observed are less probable to be due to one firm-specific actions.

3.1.3 Sales representative

The sales representative office is the point of contact between manufacturers and retailers. In some contexts, the relationship between the sales reps and customers have a strong link. Besides constituting the salesforce of the firms; they are responsible for the negotiations, customer service and selling visits. The same salespeople conducted the transactions for the whole period of the dataset, and no turnover was present.

3.1.4 Transactions

Each transaction of the dataset has the following information:

a) customer: name and identification of the retailer;

b) manufacturer of the furniture items;

c) date of the generation of the invoice since 01/01/2015;

d) condition of payment in days;

e) the total value of the invoice with taxes;

f) net profit of the invoice (commission of the transaction);

g) percentage of net profit of the invoice: from 0% to 4% it is identified as a promotional transaction. For net profits over (> 4%), it will be considered as an ordinary transaction;

h) amount of categories of products in the invoice: kitchen, bedroom, living room or complements.

The characterization of a promotion purchase is by the net profit margin when the transaction generates a net profit of 4% or less. Promotions in this B2B context are primarily a reduction in the price of a product or line of products to retailers. Purchase orders above such net profit percentage are considered ordinaries because they usually occur with standard negotiations and discounts. Both parts previously establish these terms and often only change them once in a year when firms may stipulate their new pricing policies or when there is a need to readjust prices due to macroeconomic shocks.

The commission generated in each purchase order by the sales representative office is considered as a proxy for the net profit of manufacturers in each transaction. The more a sales representative gives discounts, the less they will earn and the manufacturers. This amount also captures the discounts relative to the condition of payment (payment term).

Marketing spending is almost a fixed expenditure of manufacturers, since every year catalogs, material samples, pens and blocks with firm logo and participation on furniture fairs are the most expressive and are available to everyone in the portfolio. Most manufacturers of this sector do not invest heavily in brand communication and this pattern of the expenditure of the marketing mix is similar among the manufacturers of this database. Prior studies on this furniture sector in Brazil have acknowledged the characteristics of a low technology industry with commodity players that offer more accessible serial furniture items, differing from manufacturers as Todeschini and Unicasa that operate in high-end segments (GALINARI; JUNIOR; MORGADO, 2013; VEIGA; RIOS, 2016). Customers that have an extra advertising claim for a specific purpose such a new store façade, a new product for showroom or a free sample get this request amount conceded as a discount on the invoice, and as a result, the transaction (commission) captures this information. It helps to have a clear vision of individual customer profitability. Manufacturers rely on the sales force to be the most powerful component of marketing actions.

3.2 THE HABIT FORMULATION

The first step, following the model proposed by Shah *et al.* (2014), is to measure the habit strength of each customer. It is computed the intensity of each of the two recurring behaviors *k* (Purchase and Promotion) for each customer *i* on each semester *t*.

$$\text{Intensity of Promotion Purchase}_{\text{it}} = \frac{Number\ of\ Promotion\ Purchases_{it}}{Total\ Number\ of\ Purchases\ Incidences_{it}} \tag{1}$$

$$\text{Intensity of Purchases}_{\text{it}} = \frac{Total\ Number\ of\ Purchases\ Incidences_{it}}{Number\ of\ Days_{t}} \tag{2}$$

$$\text{Mean Behavioral Intensity}_{\text{ikt}} = \frac{\sum_{t=1}^{N} Intensity\ of\ Behavior\ (Promotion\ or\ Purchase)_{ik}}{N_i} \tag{3}$$

$$\text{Habit Strength}_{\text{ikt}} = \frac{Mean\ Behavioral\ Intensity_{ikt}}{1\ +\ \sigma_{\ ikt}} \tag{4}$$

Where,

Number of Promotion $\text{Purchases}_{\text{it}}$ = number of transactions with net profit lower than 4% for each customer *i* on each semester *t*;

Total Number of Purchase $\text{Incidences}_{\text{it}}$ = number of all transactions made by customer *i* on each semester *t;*

Number of Days_{t} = number of days of semester *t;*

N_i = number of semiannual measures over which the corresponding intensity of behavior *k* for a customer *i* is observed;

$\sigma_{\ ikt}$ = standard deviation of the semiannual measures of Intensity for each behavior (Purchase or Promotion). The importance of this division is that it represents the temporal consistency of the recurring behavior. The number 1 is added to the denominator to safeguard when all the measures of Mean Behavioral Intensity are the same ($\sigma_{\ ikt} = 0$) and for the purpose to have always values in the denominator that are larger than 1, so the overall measures will be placed along a scale of habit strength that ranges from 0 to 1. The standard deviation computation starts from the second semester of each customer so that it has two observations at least.

The model proposed by Shah *et al.* (2014, p.730) empirically quantify “habit strength to be high when the customer exhibits not only a high degree of the recurring behavior over time but also a high level of temporal stability". Therefore, in Equation 4, a relatively large value of the numerator term and relatively small value of the standard deviation (denominator) would contemplate an intense repetition of behavior with temporal consistency.

The computation of the habit scores is processed with the utilization of pivot tables on *Microsoft Excel*. First, all transactions are summarized within the semesters, and then each customer can have a sum of all transactions that occurred in that particular period. Each customer must be a row and the columns represent the number of transactions in each semester. Then, all the calculations for Intensity of Behavior, Mean Behavioral Intensity and Habit Strength can be computed for promotions and general purchases.

3.3 CASH FLOW LEVEL AND VOLATILITY

As previously mentioned, the commission generated in each purchase order by the sales representative office is considered the cash flow of the transaction. Therefore, all the orders a customer makes in a semester are aggregated so that each customer *i* has a semiannual intake of cash flows. Based on Shah *et al*. (2017), the observation of cash flow volatility is calculated by dividing the standard deviation of individual cash flow level by the absolute value of the mean level of cash flow over the same period (in each semester *t* for each customer *i*). That is the formulation of volatility found in other marketing works as Tarasi *et al*. (2013) and Gruca and Rego (2005).

$$\text{Cash Flow Level}_{\text{it}} = \text{Cash Flow generated by customer } i \text{ on semester } t \tag{5}$$

$$\text{Cash Flow Volatility}_{\text{it}} = \frac{\sigma_{\ Cash\ Flow\ Level_{it}}}{Mean\ Cash\ Flow\ Level_{it}} \tag{6}$$

3.4 MODEL SPECIFICATION

In order to gauge the impact of the habitual behaviors on the cash flow volatility and level of each customer, the structure of the models follow those in Shah *et al.* (2017). Nevertheless, due to the idiosyncrasies of the B2B context (e.g., the retention rate), as well as the fewer number of individuals in comparison with B2C studies (SHAH *et al.*, 2017) that makes the forecasting or explaining future outcomes harder, this works prioritizes an investigation over the general relationship of the variables. Therefore, the analyses spot a light in the behavior over time of habits than a look in the prediction of the future generation of cash flow (the perspective of future profitability will be analyzed with the Customer Lifetime Value approach in section 4.4).

3.4.1 Variables

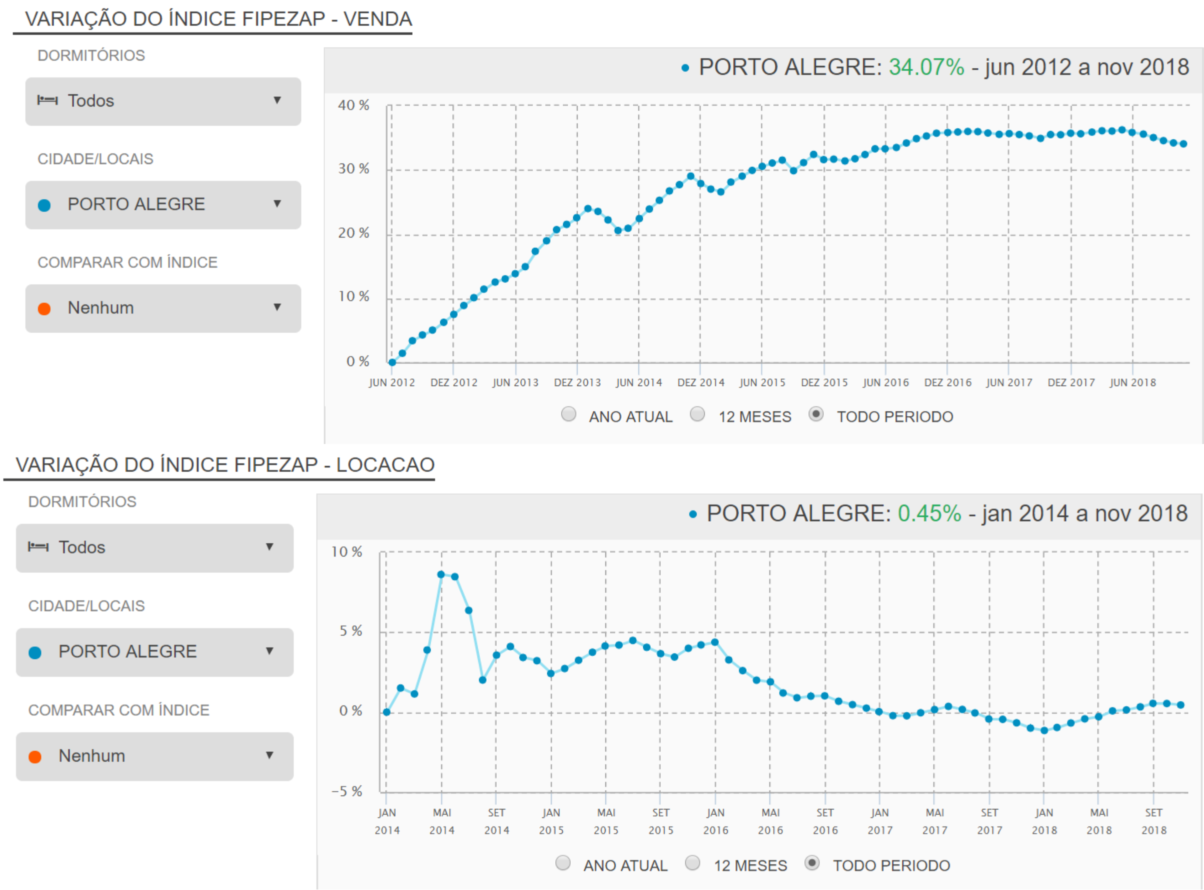
Papies, Ebbes and Van Heerde (2017) emphasize that including a set of control variables in the regression models is primordial to try to naturally address for endogeneity issues. To account for exogenous environmental shocks, it is included in the model a macroeconomic factor ($Housing_t$). This index is computed with the Fipe-Zap computation of sales of properties and rentals in the city of Porto Alegre, as shown in Figure 2. The Fipe institute (*Fundação Instituto de Pesquisas Econômicas*) is a traditional supplier of financial and economic indicators in Brazil. The insertion of this variable in the model helps to control for a portion of sales of furniture that could be due to shocks in the estate market or macroeconomic activity rather than the sheer habitual behaviors of retailers. The release of the indices is on a monthly base. Hence a transformation to semester basis was done.

The seasonality ($Seasonality_t$), which instead of summer and winter in the model of Shah *et al*. (2017), it is proposed as the first and second semester of the year to account for a possible bias of pre-Christmas sales and the factor of the thirteenth salary in Brazil.

As the variable Cross-Buy in the work of Shah *et al.* (2017), there is the need to incorporate and control for any possible additional dimension of the nature of the transactions not captured by the habitual behaviors. In the case of a B2C context, the evidence can relate to the sheer number of product categories that a customer purchases.

However, in the B2B context, the relationship is intermediated by a sales representative. Even if the same sales reps were responsible for the whole period of the transactions and time-invariant factors such as sales force skills, knowledge and adaptiveness can be accounted for with the panel format of the data; other possible dynamic factors could strengthen or weaken the relationships during the seven observed semesters.

Figure 2 – Fipe-Zap index of sales of properties and rentals in Porto Alegre



Source: Fipe-ZAP (2019)

It is argued that a sales representative could have a closer relationship with customers, and more opportunities to develop a relationship with premium customer service, friendship, management consulting, or all the possibilities that, e.g., consultative selling can render (LILIEN, 2016; LILIEN; GREWAL, 2012). Industrial buyers are generally busy and do not offer sales representatives much time to conduct the sale processes and sellers that get to sell as many products or manufacturers as they can, generally are top performers in the sales team. Therefore, a proposed variable tries to control for a dynamic sales representative effect that could generate a closer relationship over time that induces customers to buy more products of the portfolio, and indeed could stimulate more repeat purchasing despite the efforts of the manufacturers. The variable Sales Force$_{it}$ represents the number of manufacturers that a customer buys in each semester.

As a potential omitted variable problem in the model, it is necessary to account for the possible influence of consumers making transactions with retailers just because they are more interested in furniture products. That fact could naturally increase the purchases that retailers make with manufacturers. Therefore, one possible candidate for this would be a control variable that captures the general search or interest for furniture on the internet. A proxy relating to it can originate from the Google Trends for specific words of furniture sought in the metropolitan region of Porto Alegre: Internet Search$_t$. It is computed the general search for furniture in Google Trends relating to the word "*móveis*" in the period of 2015/1 to 2018/1. The data that Google discloses for download has measures of every nine days, starting on January 4, 2015, and ending on June 24, 2018, as shown in Figure 3. Also, requiring transformation for semester values. The organic search in Google for any specific word has been utilized by some researchers in the economic field as the work of Blake, Nosko and Tadelis (2015). Indeed, it remains an open question whether the interest of people who search for furniture on the internet differ substantially from the ones who conduct the purchase journey mainly in physical stores. However, there is a growing interest in showing how customers start researching in online channels and end up purchasing in brick-and-mortar stores in the multichannel shopping literature (DINNER; VAN HEERDE; NESLIN, 2013) and as well as for furniture products (SCHLANGENOTTO; KUNDISCH; WÜNDERLICH, 2018).

Figure 3 – Search for furniture words on Google Trends

Source: Google Trends (2019)

3.4.2 Dependent variables and models

The dependent variable of the Cash Flow Level (5) needs to be transformed into a logged variable (natural log) to account for a skewness that affects many marketing and financial data like sales, prices or promotions. Therefore, the functional form of this model turns into a log-linear model.

Along with the computation of Cash Flow Volatility (6), based on Shah *et al.* (2017), the proposed models to gauge the impact of habitual behaviors on manufacturer performance can be specified as:

$$\ln(\text{Cash Flow Level}_{it}) = \delta_1 Purchase\ Habit_{it} + \delta_2 Promotion\ Habit_{it} + \delta_3 Sales\ Force_{it} + \delta_4 Seasonality_t + \delta_5 Housing_t + \delta_6 Internet\ Search_t + c_i + \varepsilon_{it} \tag{7}$$

$$Cash\ Flow\ Volatility_{it} = \beta_1 Purchase\ Habit_{it} + \beta_2 Promotion\ Habit_{it} + \beta_3 Sales\ Force_{it} + \beta_4 Seasonality_t + \beta_5 Housing_t + \beta_6 Internet\ Search_t + c_i + \eta_{it} \tag{8}$$

Where

β, δ = parameters to be estimated;

η_{it}, ε_{it} = idiosyncratic error term (i.i.d over customers and time);

c_i= individual time-invariant term (unobserved effect);

t = semester (six-month time interval starting on 2015/1);

i = customer (retailer)

Cash Flow Volatility$_{it}$ = cash flow volatility of customer *i* at time t;

Log(Cash Flow Level)$_{it}$ = log of the level of cash flow of customer *i* at time t;

Purchase Habit$_{it}$ = purchase habit strength of customer *i* at time t;

Promotion Habit$_{it}$ = promotion habit strength of customer *i* at time t;

Sales Force$_{it}$ = number of different manufacturers customer *i* purchases at time t;

Seasonality$_t$ = first and second semester of a year indicator at time t;

Housing$_t$ = sales of properties and rentals in the city of Porto Alegre at time t;

Internet Search$_t$ = general search or interest for furniture on the internet at time t

3.4.3 Panel data

The dataset is in a panel form. This format allows the researchers to collect data on the behavior of several entities observed across time, and it offers several advantages over pure cross-section or time-series analysis. The main motivation for exploring a panel data format is the opportunity to measure change at the individual level. Panel data can comprise regular time intervals or irregularly time windows when, e.g., companies get a determined size or customers reach a membership status (CAMERON; TRIVEDI, 2009). Hsiao (2014, p.5) underlines that panel data gives "more informative data, more variability, less collinearity among the variables, more degrees of freedom and more efficiency". As Mizik and Pavlov (2018) posit, marketing researchers are usually trying to measure the development of intangible assets, but as strategic factors, they are generally unobservable or hard to measure. However, only controlling for those strategic factors, marketing researchers have the possibility to take stronger conclusions on the actions or interventions that affect firm performance.

The structure of the dataset offers an unbalanced panel, as customers may stop buying from the firm in one semester and return, or even quit a relationship forever. As Wooldridge (2015) underlines, the potential harm of unbalanced panels occurs when the data that is missing correlates with the idiosyncratic errors; otherwise, the unbalanced panel structure has no problems of estimation. The nature of transactions with retailers will always have customers that stop buying, move to competitors, close or face financial restrictions, as well as, new customers that start their relationship with firms.

According to Cameron and Trivedi (2009), the format of this dataset is a short panel where the periods of time (t) are shorter than the number of individuals (i), as t fixed and $i \to \infty$, and generally, this format of panel offers fewer complications than models where $t \to \infty$. With "large-N asymptotics it is convenient to view the cross-section observations as independent, identically distributed draws from the population" (WOOLDRIDGE, 2010, p.284). The fact that panel format comprises only three years and a half is especially crucial for the assumption of time-invariant factors to be controlled to reach a more convincing causal explanation (ROSSI, 2017).

Several possible models of panel data estimators appear in the literature of econometrics. Following the recommendation of Angrist and Pischke (2008) and specifically in the marketing area by the work of Germann, Ebbes and Grewal (2015), before choosing the estimator, the researcher should act as a regression engineer, and consider the formulation of the model and the relationships of time and individual effects in order to choose the proper estimators. In the other way, the applied econometric works tend to explore more the econometric tests for picking the appropriate estimators. These tests check the assumptions of the time-invariant factors as well as nuisances in the error term as serial correlation or heteroskedasticity.

The analyses will be carried out in the software *R* with the package *plm* that offer a solid and spread utilization of panel data econometric models. The package *plm* was created by the researchers Yves Croissant and Giovanni Millo, which originated the book Panel Data

Econometrics with R (2019**)** that offer researchers a comprehensive material for implementing the analyses in the software *R*. Most of the features of the *plm* package perform without further complications for unbalanced panel data sets. However, there are some limitations: the two-ways Random-Effects model where the error component has a time-invariant and an individual-invariant element works only for a balanced panel structure. Shah *et al*. (2017) utilized this estimator model in their work.

3.4.4 Endogeneity

Marketing scholars have developed increasing concern of the presence of endogeneity in marketing models, especially since the late 1990s (ROSSI, 2017). Endogeneity can arise if the explanatory variables correlate with the error disturbances. Generally, it has three causes (WOOLDRIDGE, 2010): omitted variables in the model or *self-selection*, where the agent chooses the value of the explanatory variable; measurement error; and simultaneity, where one explanatory variable can be simultaneously determined with the dependent variable. If a marketing manager wants to trust that an *x*% in one marketing variable translates in *y*% in performance, they need to be aware that parameters that show an endogeneity bias are going to produce misleading consequences (PAPIES; EBBES; VAN HEERDE, 2017). One of the most applied remedies for endogeneity issues is the use of instrumental variables. However, as stated by Rossi (2014), in marketing research, it is difficult to find candidates for instrumental variables that are not correlated with most used dependent variables as sales, customer satisfaction and profits. Randomization of customers to receive treatment (marketing actions) is generally not feasible in works dealing with marketing strategy, and Rossi (2017) argues that even when it is not possible to randomize individuals to analyze performance, with observable data to rule out endogeneity is a matter of good construction of the model. Then, if it is possible to “find covariates that are highly correlated with the unobservables…the results can indeed become less confounded with selection bias” (ROSSI, 2017, p.145). Therefore, in the marketing literature, the recent work by marketing researchers that tries to find remedies to the endogeneity problem, recommend as one of the ways, the exploration the benefits of a panel data format and the construction of a reasonable model (ROSSI, 2017; PAPIES; EBBES; VAN HEERDE, 2017; MIZIK; PAVLOV, 2018; RUTZ; WATSON IV, 2019).

The proposed models to gauge the impact of habitual behaviors on firm performance of this work could have as candidates for omitted variables bias the factors that are not in the model (section 3.4.2):

- Customers (stores): managerial ability, localization, size
- Sales Force: kindness, responsiveness, ability
- Manufacturers: product quality, operational efficiency, marketing actions
- Consumers that go to the stores: interest of customers in furniture

The general search for furniture, as mentioned previously, can be controlled with the proxy on the variable Internet Search$_t$. One possible factor that influences retailers to make more orders is the marketing actions of the manufacturers. However, as mentioned previously, promotions are available to all customers and are regularly launched by the firms involved in the database. The communication of a new deal might happen by digital means (as an e-mail or WhatsApp message) or delivered through the sales force. It is important to note that every customer has the opportunity to buy a promotional product. The panel structure of the data can control for the other omitted variables that are not expected to vary significantly in the seven semesters of observations, therefore holding them as time-invariant factors.

3.4.5 Econometric panel data estimators

To present how the models will be estimated, this work follows the procedures found in the Wooldridge (2010). Consider the following panel data model:

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + v_{it}, t = 1,2, \ldots, T; i = 1, \ldots, N \qquad (9)$$

Where $v_{it} = c_i + u_{it}$. In the manner that $\boldsymbol{x}_{it}$ is a 1 × K is a vector that of covariates that could vary across i and t; $\boldsymbol{\beta}$ a vector of $K \times 1$; v_{it} the composite error formed by an idiosyncratic component u_{it} and the unobserved time-constant variable c_i. This time invariant component captures individual (also unobserved heterogeneity or individual effects in the literature) characteristics that do not vary over time for an individual or organization. Examples could range from cognitive ability or family characteristics as well as factors as localization or organizational culture.

The first option to estimate the panel data model is to test the possibility of a pooled ordinary least squares (OLS) model that assumes that there is no presence of the unobserved individual effect (c_i) and all the data is pooled together, so the intercept and coefficients are constant across the units. However, to have a consistent estimation, in equation (10) it is necessary to hold the assumptions that the E $(\boldsymbol{x'}_{it}u_{it}) = 0$ and E $(\boldsymbol{x'}_{it}c_i) = 0$

$$y_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + c_i + u_{it}, t = 1,2, \dots, T; i = 1, \dots, N \quad (10)$$

If the assumptions are wrong, the omitted variable (c_i) will be part of the residuals, and it means that the residuals for any individual will be correlated across periods. For some contexts, this assumption may be too strong. Some authors propose that inference using pooled OLS requires the robust variance matrix estimator and robust test statistics (ANGRIST; PISCHKE, 2008). Hence, econometricians tend to choose two techniques that are more robust for panel data estimation: the Random-Effects and the Fixed-Effects models (WOOLDRIDGE, 2010).

The Random-Effects estimation must hold even stronger assumptions than Pooled OLS for the orthogonality of c_i and $\boldsymbol{x}_{it}$, however, "it exploits the serial correlation in the composite error, $v_{it} = c_i + u_{it}$, in a generalized least squares (GLS) framework" (WOOLDRIDGE, 2010, p.292). The GLS approach tries to deal with the serial correlation and heteroskedasticity trying to find a pattern: a scalar variance-covariance matrix of the errors. Other option would be the Fixed-Effect approach, considered the gold standard of econometrics (BELL; JONES, 2015).

It is important to mention that the Random-Effects estimation due to stronger assumptions to avoid endogeneity issues, it has slightly been rejected in political science and with econometricians (ANGRIST; PISCHKE, 2008). The Fixed-effects, for some applications, can eliminate a substantial amount of information that pertains to individuals as Bell and Jones (2015) explain. If researchers have the main variables in $\boldsymbol{x}_t$ that do not vary much over time, they may be "forced to use Random-Effects estimation in order to learn anything about the population parameters" (WOOLDRIDGE, 2010, p.326). Both methods have pros and cons.

In the next subsection, it is presented the basic structures and requirements of both estimators:

3.4.5.1 Random-Effects

Following Wooldridge (2010), Random-Effects estimation requires the following assumptions:

RE.1: $\mathrm{E}(u_{it}|\boldsymbol{x}_i, c_i) = 0$, $t=1,...,T$ and $\mathrm{E}=(c_i|\boldsymbol{x}_i) = \mathrm{E}(c_i) = 0$

RE.2: Rank E $(\mathbf{X'}_i\Omega^{-\mathbf{1}}\mathbf{X}_i) = K$

RE.3 $\mathrm{E}({u^2}_{it}|\boldsymbol{x}_i, c_i)= \sigma_u^2$ and $\mathrm{E}(c_i^2|\boldsymbol{x}_i)= \sigma_c^2$

RE.1 represents contemporaneous exogeneity conditional on the unobserved effect assumption, RE.2 requires a rank K and that the unrestricted variance estimator Ω be nonsingular. RE.3 requests in the first part the homoskedasticity and serial uncorrelatedness of u_{it} conditional on $\mathbf{x}_i$ and c_i; and in the second part the homoskedasticity of c_i .

Therefore, following the GLS format, the matrix **Ω** must have the random-effects structure where $\mathrm{E}({v^2}_{it}) = \sigma_c^2+\sigma_u^2$ and $\mathrm{E}(v_{it}v_{is}) = \sigma_c^2$ so that it is possible to have consistent estimators of the variance matrix:

$$\begin{pmatrix} \sigma_c^2 + \sigma_u^2 & \sigma_c^2 & \cdots & \sigma_c^2 \\ \sigma_c^2 & \sigma_c^2 + \sigma_u^2 & \cdots & \vdots \\ \vdots & & \ddots & \sigma_c^2 \\ \sigma_c^2 & \cdots & \sigma_c^2 & \sigma_c^2 + \sigma_u^2 \end{pmatrix}$$

Generally, the format of **Ω** is not known previously and it is necessary that **Ω** is estimated first, so that $\widehat{\Omega} \equiv \hat{\sigma}_u^2 \mathrm{I_T} + \hat{\sigma}_c^2 \mathbf{j}_T \mathbf{j'}_T$.

Using the estimated variance matrix above the feasible generalized least squares estimator can be implemented. First $\hat{\sigma}_u^2$ and $\hat{\sigma}_c^2$ need to be obtained and they can be taken as a pooled OLS residuals $(\check{v}_{it})$. It is easier to find $\hat{\sigma}_u^2 = \hat{\sigma}_v^2 - \hat{\sigma}_c^2$:

$$\hat{\sigma}_v^2 = \frac{1}{(NT-K)} \sum_{i=1}^{N} \sum_{t=1}^{T} \check{v}_{it}^2$$

$$\hat{\sigma}_c^2 = \frac{1}{[NT(T-1)\,/\,2-K]} \sum_{i=1}^{N} \sum_{t=1}^{T-1} \sum_{s=t+1}^{T} \check{v}_{it}\,\check{v}_{is}$$

Therefore, it is possible to estimate:

$$\hat{\beta}_{RE} = \left(\sum_{i=1}^{N} \mathbf{X'}_i \widehat{\Omega}^{-\mathbf{1}} \mathbf{X}_i\right)^{-1} \left(\sum_{i=1}^{N} \mathbf{X'}_i \widehat{\Omega}^{-\mathbf{1}} \mathbf{y}_i\right)$$

And the asymptotic variance can be estimated as:

$$\widehat{Avar}(\hat{\beta}_{RE}) = \left(\sum_{i=1}^{N} \mathbf{X}'_i \hat{\Omega}^{-\mathbf{1}} \mathbf{X}_i\right)^{-1}$$

3.4.5.2 Fixed-Effects

The Random-Effects estimator considers the c_i part of the composite error, assuming that $\mathrm{E}(c_i|\boldsymbol{x}_i) = 0$. The main characteristic of the Fixed Effect estimation is to relax this assumption and let c_i to be correlated with $\boldsymbol{x}_{it}$. This is important, as it is possible to account for omitted variables that influence the relationship as long as this omitting be due to factors that do not change over time. One issue is that variables when are observables and constant in all *t* can not be inserted in $\mathbf{x}_{it}$, as there is no way to distinguish them from the unobservable c_i. Hence, one practical solution is to transform the equation (10) in order to eliminate the individual effect c_i.

The within-transformation starts with averaging the observations to get a cross-section equation:

$\bar{y}_i = \bar{\boldsymbol{x}}_i\boldsymbol{\beta} + \bar{u}_i + c_i$

Then, subtracting from the equation (10):

$y_{it} - \bar{y}_i = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)\boldsymbol{\beta} + u_{it} - \bar{u}_i + c_i - c_i$

or

$\ddot{y}_{it} = \ddot{\mathbf{x}}_{it}\boldsymbol{\beta} + \ddot{u}_{it}$

As stated in Wooldridge (2010), Fixed-Effects estimation requires the following assumptions:

FE.1: $\mathrm{E}(u_{it}|\boldsymbol{x}_i, c_i) = 0$, $t=1,...,T$

FE.2: Rank [E $(\ddot{\mathbf{X}}'_i\ddot{\mathbf{X}}_i)] = K$

FE.3 $\mathrm{E}(u_i u'_i|\mathbf{x}_i, c_i) = \sigma_u^2\mathbf{I}_T$

FE.1 represents contemporaneous exogeneity conditional on the unobserved effect assumption, FE.2 requires the rank K. FE.3 requires the homoskedasticity and serial uncorrelatedness of the idiosyncratic errors u_{it}.

So,

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N} \ddot{\mathbf{X}}'_i\ddot{\mathbf{X}}_i\right)^{-1}\left(\sum_{i=1}^{N} \ddot{\mathbf{X}}'_i\ddot{\mathbf{y}}_i\right)$$

The variance of this estimator can be asymptotically valid as

$$\widehat{Avar(\hat{\beta}_{FE})} = \hat{\sigma}_u^2 \left(\sum_{i=1}^{N} \ddot{\mathbf{X}}'_i \ddot{\mathbf{X}}_i \right)^{-1}$$

where $\hat{\sigma}_u^2$ can be obtained in a similar form as utilized in the Random-Effects with the residuals of a regression using the Pooled OLS on $\ddot{y}_{it} = \ddot{\mathbf{x}}_{it}\boldsymbol{\beta} + \ddot{u}_{it}$. So that,

$$\hat{\sigma}_u^2 = \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\ddot{u}}_{it}^2 / [N(T-1)K]$$

3.4.6 Tests for panel data estimators

The choice of Fixed and Random-Effects models the in econometric literature offers researchers the trade-offs of each model and even with tests to select models, the choices are somewhat a matter of trust (WOOLDRIDGE, 2010). As Verbeek (2017, p.394) explains, “the choice between Fixed-Effects and a Random-Effects approach is not easy, and in many applications, particularly when *T* is small, the differences in the estimates for β appear to be substantial”. Baltagi (2005, p.19) adds that “In fact, the fixed versus random effects issue has generated a hot debate in the biometrics and statistics literature which has spilled over into the panel data econometrics literature”. Nevertheless, some tests can help the researcher to give more evidence towards one specific model.

The Fixed-Effect estimator is more consistent under the presence of endogeneity, but it does not make it possible to estimate the coefficients of the individual effects (c_i). Theoretically, it should be checked the assumption that H_0 (Exogeneity) $\boldsymbol{Cov}\ (\boldsymbol{x}_{it}, c_i) = \mathbf{0}$ and H_1 (Endogeneity) $\boldsymbol{Cov}\ (\boldsymbol{x}_{it}, c_i) \neq \mathbf{0}$, considering the c_i individual-specific component and $\boldsymbol{x_{it}}$ the individual observations. If H_0 is accepted, the Random-Effects model could be an efficient and consistent estimator. If H_0 is rejected, the Fixed-Effects model is recommended. The test most present in the literature and very famous among applied econometricians is the Hausman test (1978). It tests the differences in the Fixed and Random-Effects estimators, considering that any statistically significant differences should be interpreted as a violation of RE.1: $\mathrm{E}(c_i|\boldsymbol{x}_i) = \mathrm{E}(c_i) = 0$, as exposed by Wooldridge (2010). Obviously, the main caveat of this test is that it is necessary to assume that u_{is} and $\boldsymbol{x}_{it}$ are uncorellated for any *s* and *t*, otherwise, both estimations will be inconsistent.

The models utilized by Shah *et al*. (2017) are based on the work of German *et al*. (2015) that tries to define as Rich Models a Random-Effects estimation with an extensive list of control variables. They also call the Unobserved-Effect Models the approach with Fixed-Effects to eliminate the between-individual variance and account for the presence of the CMO (in their study) by the within-firm variation. German *et al*. (2015) coined these new terms for the estimation of panel data with various methods without an econometric test to decide which estimator to use. They choose to present all the results of several estimations as a robustness check.

4 RESULTS

In this section, results of the analysis of the data collected for this work will be presented. The script used in the *R* software along with an anonymous version of the data set will be available on a *GitHub* page with the name of the author.

4.1 DESCRIPTIVE STATISTICS

The initial dataset consisted of 334 customers that generated 14974 orders from 2015 and the first semester of 2018.

Customers of this dataset are spread almost as a Pareto distribution, where 80% of total cash flow income over the whole period pertains to approximately 25% of the customers. Therefore, following Fader and Toms (2018), the distribution of cash flow of this dataset is similar to many other studies in the marketing area of customer analytics (Table 1).

The presence of one major retailer with several branches helps to contribute with almost 33% of the sales. As each transaction of this retailer originates in one of the branches that have several sales employees, the process of selling is not much different from any other retailers of the dataset.

Table 1 – Distribution of customers in the generation of cash flow and sales

Customer#	Cash Flow	Sales
1	25,886%	32,888%
2	5,882%	4,134%
3	2,968%	4,337%
4	2,013%	3,117%
5	1,891%	1,342%
6	1,493%	1,434%
7	1,454%	1,358%
8	1,399%	1,321%
9	1,227%	1,249%
10	1,199%	0,888%
11-334	54,583%	47,927%
	100%	100%

Source: author – R output (2019)

Table 2 presents the revenue and cash flow sum of each semester and the number of purchase orders. Some semesters of the sample have a smaller amount of purchase orders that could be due to natural occurrences of macroeconomic factors or even stronger actions from competitors that the manufacturers faced.

Table 2 – Purchase Variables

Semester	Total Sales Revenue (R$)	Number of orders	Total Net Cash Flows
2015/1	2.379.379,68	1138	R$ 92.113,04
2015/2	3.324.723,44	1478	R$ 124.717,87
2016/1	3.415.407,18	2482	R$ 142.711,51
2016/2	5.306.929,37	3093	R$ 218.117,59
2017/1	4.201.202,93	2708	R$ 185.686,02
2017/2	4.676.170,21	2393	R$ 200.548,10
2018/1	3.074.019,15	1682	R$ 127.637,14
Total	26.377.831,96	14974	R$ 1.091.531,27

Source: author (2019)

In Table 3, all the orders are split between their promotion and ordinary nature. The promotions sales offer a higher sum of sales and fewer purchase orders; however, the sum of cash flows over the seven semesters offers a higher amount in ordinary sales.

Table 3 – Promotion and ordinary sales

	Promotion	Ordinary purchase
Total Sales	R$ 14.965.438,58	R$ 11.412.393,38
Total Sum of Cash Flows	R$ 478.729,14	R$ 612.802,12
Number of orders	5302	9672
Average Sales	R$ 2.822,60	R$ 1.179,94
Average Cash Flow	R$ 90,29	R$ 63,35
Std Deviation Sales	R$ 8.016,12	R$ 1.243,37
Std Deviation Cash Flow	R$ 257,30	R$ 64,50

Source: author (2019)

From now on, following the computation of the measures of Habits and Cash Flow Volatility, the final sample consists of 219 customers. Customers that do not have observations on at least two semesters and that did not purchase at least two times in the semester they were alive were removed from the analyses due to the impossibilities of calculation of the standard deviations of the volatility and habit scores. For example, 105 customers had less than seven purchase orders in the whole seven semesters of observation, including 68 retailers had just one semester of relationship before stop buying or closing operations. The customers out of the analysis (31% of the initial database) represent approximately 3% of the whole generation of cash flows for the seven semesters. It is important to mention that 58 customers did not make any promotion purchase during the observation window, but as they comply with the ordinary purchase requirements mentioned above, they are on the final data set.

In Table 4, it is possible to observe how the habits calculations are spread in their overall mean for each semester.

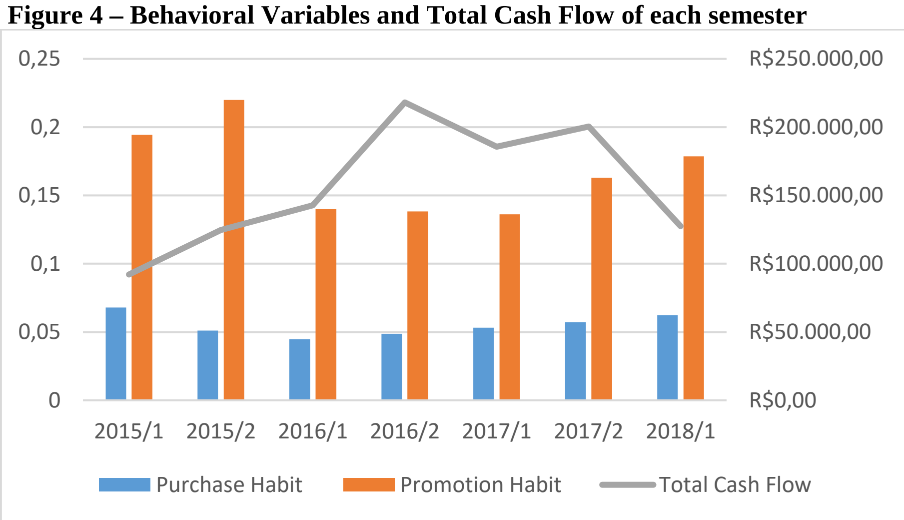
Table 4 – Behavioral Variables – overall mean for each semester

Semester	Purchase Habit	Promotion Habit	Sales Force
2015/1	0,0680	0,1944	1,2134
2015/2	0,0510	0,2198	1,6048
2016/1	0,0447	0,1400	1,5628
2016/2	0,0486	0,1382	1,6042
2017/1	0,0531	0,1361	1,5600
2017/2	0,0571	0,1628	1,5974
2018/1	0,0622	0,1787	1,5793
Overall mean	0,0537	0,1616	1,5518

Source: author (2019)

In figure 4, the longitudinal relationship of the overall mean of the habits scores with the sum of cash flows of the whole portfolio is presented.

Figure 4 – Behavioral Variables and Total Cash Flow of each semester



Source: author (2019)

The variables utilized in the empirical model are described in Table 5. The variable Cash Flow Level has a significant number of orders under R$ 1.000,00 and some higher purchase orders that generate a substantial amount of cash flow in the 75th percentile. As mentioned, after the computation of the habit scores and cash flow volatility (for each customer in each semester) the dataset has 1022 observations in the form of an unbalanced panel set. Some authors have proposed a measure of the “unbalancedness” of a panel. If the panel data is fully balanced, the measures of “gamma" (γ) and "nu"(ν) equal to 1. The more "unbalanced" the panel data, the lower the measures. Following Croissant and Millo (2019), the results of the test of unbalancedness have given the measures “gamma" (γ)= 0,8429 and "nu" (ν)= 0,8802. Therefore, the panel format of this dataset reaches a reasonable level of a full balanced panel.

Table 5 - Descriptive Statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Sales Force	1022	1,552	0,696	1	1	2	3
Seasonality	1022	-	-	1	1	2	2
Cash Flow Level	1022	1.037,52	3.717,67	2	220,3	913,5	73.073
Purchase Habit	1022	0,054	0,070	0,002	0,015	0,070	0,682
Promotion Habit	1022	0,162	0,212	0,000	0,000	0,249	1,500
Housing	1022	64,704	10,426	51,010	54,790	71,470	83,720
Internet Search	1022	60,586	4,198	55,620	56,880	64,330	68,130
Cash Flow Volatility	1022	0,977	0,427	0,116	0,706	1,146	5,461

Source: author – R output (2019)

In Table 6, the description of the Shapiro-Wilk normality test (W) and the respective p-value, Skewness and Kurtosis are presented. It presents a high Skewness for the variable Cash Flow Level. Hence, it is proposed, as mentioned previously, the transformation of this variable with the log function.

It is worth to note that the Normality Tests, especially the Shapiro-Wilk, has a high probability of rejecting the null hypothesis of normality in panel data or large data sets (ALEJO *et al*., 2015). The variables Seasonality, Housing, Internet Search do not have Skewness and Kurtosis analysis, as they are variables fixed by all individuals in each semester.

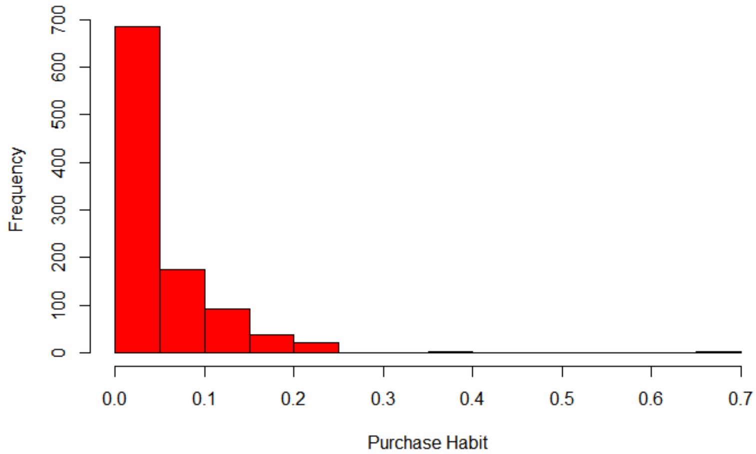
Table 6 – Variables Distributions

Variable	Missings	Skew	Kurtosis	W(p)
Sales Force	0,00 %	0,87	-0,5	0,72 (< 0,001)
Cash Flow Level	0,00 %	12,37	185,93	0,18 (< 0,001)
Purchase Habit	0,00 %	4,23	27,98	0,62 (< 0,001)
Promotion Habit	0,00 %	2,55	9,42	0,73 (< 0,001)
Cash Flow Volatility	0,00 %	2,32	15,45	0,87 (< 0,001)

Source: author – R output (2019)

As can be seen in the graphics of figures 5 and 6, Purchase and Promotional Habits are left-skewed.

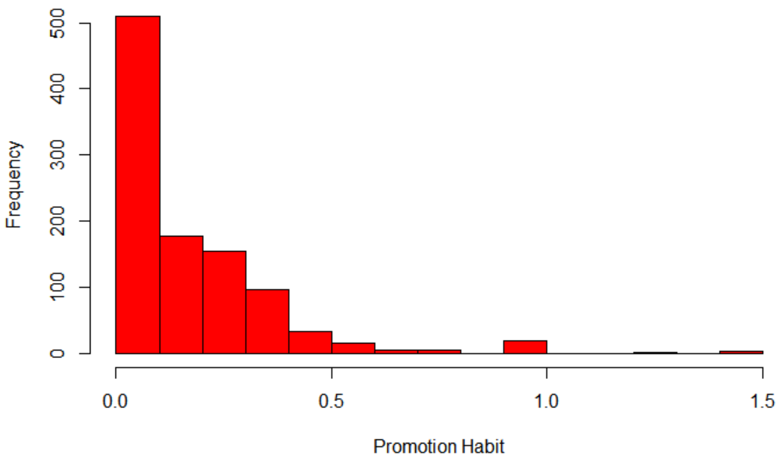
Figure 5 – Distribution of Purchase Habits



Source: author – R output (2019)

As a matter of the formulation, most observations are of a small magnitude. The Promotional Habits have some higher values as it is computed with the denominator of purchases incidences and not in days of the semester as it is with Purchase Habits.

Figure 6 – Distribution of Promotion Habits



Source: author – R output (2019)

4.1.1 Correlation Matrix

The Correlation matrix is presented in Table 7, with all the variables that will be analyzed in the panel data regressions. The variables Cash Flow Level and the Purchase Habit offer a strong correlation and a moderate connection with Promotion Habit. The volatility of cash flows seems to correlate moderately with both habitual behaviors. Internet Search and Housing offered almost a zero correlation with Purchase Habit.

Table 7 – Correlation Matrix of all variables in the analysis

	Purchase Habit	**Promotion Habit**	**Cash Flow Level**	**Cash Flow Volatility**	**Sales Force**	**Internet Search**	**Housing**
Purchase Habit	1	-	-	-	-	-	-
Promotion Habit	0,368	1	-	-	-	-	-
Cash Flow Level	0,720	0,377	1	-	-	-	-
Cash Flow Volatility	0,432	0,466	0,427	1	-	-	-
Sales Force	0,373	0,243	0,128	0,219	1	-	-
Internet Search	-0,002	0,075	-0,023	0,006	-0,068	1	-
Housing	-0,013	0,059	-0,017	-0,003	-0,081	0,817	1

Note: Pearson as the default method of correlation measure with function *cor* in *R*

Source: author – R output (2019)

4.1.2 Panel Data Tests

If the individual component (c_i) is not present in the specified models, a Pooled Least Square estimation could be a consistent option for estimation. In the Table 8, the results of the tests all rejected the null hypothesis of no significant individual effect in both estimations of Cash Flow Level (7) and Cash Flow Volatility (8). The tests conducted are the F Test (*pFtest* in *R*) and the Breusch-Pagan (*plmtest* in *R*) with the corrected version of Honda (1985) for unbalanced panels.

Tests for serial correlation (*pwartest* in *R*) of the errors are necessary as they may lead to inefficient estimates and biased standard errors. Following Croissant and Millo (2019) the test of Wooldridge (2010) verifies the existence for serial correlation for (the idiosyncratic component of) the errors in Fixed–Effects panel models. This test does not rely on large–T asymptotics and has, therefore, good properties in "short" panels. Furthermore, it is robust to general heteroskedasticity (CROISSANT; MILLO, 2019).

Table 8 - Tests for individual effects (Poolability)

	F Test	Breusch-Pagan
log(Cash Flow Level)	F(218, 797) = 3,259 [p < 0,001]	normal = 12,777 [p < 0,001]
Cash Flow Volatility	F(218, 797) = 3,959 [p < 0,001]	normal = 16,031 [p < 0,001]

Note: $H_0: \sigma^2{}_c = 0$

Source: author – R output (2019)

The results of the test shown in Table 9 indicate to accept the null hypothesis of no presence of serial correlation (p > 0,05), even though according to Wooldridge (2010) panels that cover a short time period this issue should not be a problem.

Table 9 - Tests for serial correlation

	Wooldridge (2010)
log(Cash Flow Level)	F = 3,7653 df1 = 1, df2 = 801 [p = 0,0526]
Cash Flow Volatility	F = 0,89916 df1 = 1, df2 = 801 [p = 0,3433]

Note: Alternative hypothesis: serial correlation

Source: author – R output (2019)

It is worth mentioning that in some literature concerning the models of econometric analysis of panel data (e.g., BALTAGI, 2005) it is possible to find the composite error with three elements. Besides the time-invariant individual specific component (c_i) and the idiosyncratic error (u_{it}), there could be an individual-invariant time-effect (λ_t) that represent the influence of aggregate trends which affect all individuals as e.g., an year of strike, a protection law in a particular year or a natural disaster. Therefore, a test [Lagrange Multiplier Test (time-effects for unbalanced panels)] is suggested by Croissant and Millo (2019). The possibility of the presence of the time-effect seems to have no significant effects (p = 0,2248).

4.1.3 Fixed or Random-Effects

After discarding the Pooled OLS estimation technique, the issue that arises among researchers that utilize panel data is the choice of Fixed or Random-Effects for estimation, considering both the most known techniques in the econometric literature.

In Table 10, the Hausman test with the *phtest* function in *R*, ($p < 0,05$) rejected the null hypothesis of a Random-Effects model, indicating that the Fixed-Effects model is recommended to the dataset. Nevertheless, as a matter of comparison and robustness, the results of both estimations will be shown in sections 4.2 and 4.3, though in the description in the text the coefficients of the Fixed-Effects estimation are presented.

Table 10 - Tests for correlated effects

	Test of Hausman (1978)
log(Cash Flow Level)	$\chi^2 = 12,795$ [$p = 0,04641$]
Cash Flow Volatility	$\chi^2 = 15,885$ [$p = 0,01438$]

Note: H_0: Cov $(\mathbf{x}_{it}, c_i) = 0$

Source: author – R output (2019)

4.2 RESULTS FOR CASH FLOW LEVEL

As presented in Table 11, the main findings of this work highlight the positive and significant relationship between Purchase Habits on the cash flow level of the firm ($\delta_{1\text{FE}}$ = 9,443, $p < 0,05$). Confirming the findings of Shah *et al*. (2017) customers who develop a strong habit with the firm impact positively the level of cash flow over time. Therefore, customers who score higher in the habit continuum are supposed to buy more frequently but also making purchases that offer greater inflow of resources to the firms.

The Promotion Habit offered a negative impact on cash flow level ($\delta_{2\text{FE}}$ = -0,499, $p <$ 0,05). The interpretation of this result can relate to the relationship of a customer that develops stronger Promotion Habits and its cash flow trend follows an opposite direction over time. The promotions offered to customers could be beneficial in other ways as preserving market share, satisfaction or loyalty that could affect the Purchase Habit. Promotions are an important generator of sales and cash flows. However, as results show, customers who develop higher Promotion Habits are migrating to less profitable deals. The explanation could pertain to customers that are not generating more purchases with higher profits, are spending less on each promotion or demanding more discounts that make promotions with even lower profit margins.

The variable Sales Force ($\delta_{3\text{FE}}$ = 0,345, p < 0,05) resulted in a positive relationship over time in cash flow level terms. One potential explanation for the result is that customers that create wider connections with sales representatives tend to specialize and resell more the products in the seller's portfolio, possibly by creating expertise and knowledge with good customer service in the backup. A strong connection of sales representatives with customers could foster more transactions due to the good relationship and confidence that might be crucial for the establishment of a solid context.

Table 11 – Results - Cash Flow Level

	Dependent variable:	
	Log of Cash Flow Level	
	Fixed-Effects(1)	Random-Effects (2)
Purchase Habit	$9{,}443^{***}$	$9{,}698^{***}$
	(0,937)	(0,555)
Promotion Habit	$-0{,}499^{**}$	$-0{,}337^{**}$
	(0,233)	(0,161)
Sales Force	$0{,}345^{***}$	$0{,}279^{***}$
	(0,052)	(0,044)
Seasonality	-0,032	-0,002
	(0,048)	(0,048)
Housing	$0{,}022^{***}$	$0{,}019^{***}$
	(0,004)	(0,004)
Internet Search	$-0{,}050^{***}$	$-0{,}047^{***}$
	(0,008)	(0,008)
Constant		$7{,}265^{***}$
		(0,438)
Observations	1022	1022
R^2	0,222	0,352
Adjusted R^2	0,003	0,348
F Statistic	$37{,}902^{***}$ (df = 6; 797)	$551{,}610^{***}$

Note*:* Standard errors are in parentheses,
$^{*}p^{**}p^{***}p<0{,}01$

Source: author – R output (2019)

Seasonality ($\delta_{4\text{FE}}$ = -0,032, p > 0,05) did not offer a significant impact in the relationship, as previously supposed that the second semester of the year could generate more effect on the cash flow level of firms due to the period of Christmas and the 13th salary in Brazil. Housing ($\delta_{5\text{FE}}$ = 0,022, p < 0,05) reflects a small but positive influence of macroeconomic factors in this particular retail sector.

Internet Search ($\delta_{6\text{FE}}$ = -0,050, p < 0,05) showed a negative relationship. This fact can pertain to customers that are indeed searching for furniture but ending up buying in online retailers or in competitors of the retailers in this dataset.

4.3 RESULTS FOR CASH FLOW VOLATILITY

The results for Cash Flow Volatility in Table 12, offered a new perspective than the one achieved in the work of Shah *et al.* (2017). The Purchase Habit ($\beta_{1\text{FE}}$ = 0,865, p < 0,05) and the Promotion Habit ($\beta_{2\text{FE}}$ = 0,292, p < 0,05) showed a positive impact of these behaviors in the volatility of the cash flows. However, the Promotion Habit had a smaller impact within this analysis. This opens a new insight of the possible causes of the magnitude of this relationship. Tarasi *et al*. (2013, p.121) study found a similar effect: “customers who purchase many different offerings, or allocate a large share of their purchases to the firm, have higher cash flow variability and higher average cash flows”. Indeed, there might be a trade-off in some B2B settings, whereas the more closer and habitual a relationships turns with customers, the incidence of high and low monetary value purchases could naturally arise. The expansion of the relationship could make retailers start to purchase a wider range of products, complements and supplements that offer a higher variability of monetary values. Alternatively, when a promotion is launched customers might anticipate future purchases with larger purchase orders, and therefore, less small value invoices are generated.

In the B2C context where the range of products’ value could be smaller, less volatile inflows may be more reasonable whereas purchases might concentrate under the possibilities of spending of each customer. In the context of this study, if a relationship between manufacturers and retailers becomes closer and with higher habitual scores, they start to trade any kind of product more frequently. As they could sell one product of R$ 100,00 today and make a larger purchase to replenish stocks of R$ 50.000,00 tomorrow. In addition, as the relationship becomes stronger, the buyers get confident and start to make purchases more conveniently. In another route, customers with lower Purchase Habits might tend to buy only products they have on showrooms or the same type of items and that limits that variation on the value of purchases.

Sales Force ($\beta_{3\text{FE}}$ = 0,045, p < 0,05) offered a positive and significant influence in creating more volatility within this framework analyzed. It is supposed that this result pertains to the similar the reasoning of why Purchase Habit positively affected higher levels of cash flows.

The variables of Housing, Internet Search and Seasonality, did not have significant results concerning this dependent variable.

Table 12 – Results - Cash Flow Volatility

	Dependent variable: **Cash Flow Volatility**	
	Fixed-Effects (1)	Random-Effects (2)
Purchase Habit	$0,865^{**}$	$1,550^{***}$
	(0,390)	(0,248)
Promotion Habit	$0,292^{***}$	$0,547^{***}$
	(0,097)	(0,071)
Sales Force	$0,045^{**}$	$0,035^{*}$
	(0,022)	(0,019)
Seasonality	0,015	0,006
	(0,020)	(0,020)
Housing	-0,001	-0,0001
	(0,002)	(0,002)
Internet Search	0,001	-0,0002
	(0,004)	(0,004)
Constant		$0,769^{***}$
		(0,183)
Observations	1022	1022
R^2	0,035	0,127
Adjusted R^2	-0,237	0,122
F Statistic	$4,782^{***}$ (df = 6; 797)	$147,739^{***}$

Note: Standard errors are in parentheses,
*p**p***p<0,01

Source: author – R output (2019)

4.4 CUSTOMER LIFETIME VALUE (CLV) ANALYSIS

The next step is to analyze the relationship between customers with higher Customer Lifetime Values (CLV) and their distribution among the particular habits and strengths. As the habit formulation does not include monetary values, the highest CLV's customers might not be the most frequent and consistent buyers. Here, it is followed the methods of calculation of the customer metrics as proposed by Farris *et al.* (2010) and lifetime value as Gupta and Lehmann (2003) propose [with the small correction of the expected value symbol of the CLV, following Fader and Hardie (2016)].

The utilization of CLV for managerial decision in the business-to-business contexts is not widespread (HOLM; KUMAR; ROHDE, 2012). Marketing researchers have tried to investigate why managers trust in heuristics and even get good results in comparison with stochastic models of CLV (WÜBBEN; WANGENHEIM, 2008). Differing from the multitude of direct marketing settings, some industrial relationships can last 100 years, and one customer might represent 40% of all the transactions of a firm (NENONEN; STORBACKA, 2016). Therefore, some firms tend to utilize more retrospective indicators as Customer Profitability Analysis as a tool for investment decisions, since the optimization of retention and acquisition management is less frequent due to the smaller amount of prospects in the market. In addition, there is the necessity of industrial markets to look towards the optimization of asset utilization and reducing customer-related costs and risks.

Nevertheless, the Customer Lifetime Value formulation takes several advantages in its prospective perspective on customer profitability. Following Gupta and Lehmann (2003), the formulation below:

$$E(CLV)_i = \sum_{t=1}^{\infty} \frac{m \cdot r^t}{(1+i)^t} = m\left(\frac{r}{1+i-r}\right) \tag{11}$$

Where, *m* stands for the contribution margin, as the average cash flow of customer *i* in the previous 3 semesters; *r* is the retention rate (the ratio of customers who continue their relationship with a firm in comparison to the last observed period); *i* is the discount rate to future revenues from a customer. Measures for the discount could range from treasury bonds or the weighted average cost of capital (WACC). The calculation of this study takes the current interest rate of 6,5% (Selic) in Brazil in April 2019, that is very close to the *TLP (Taxa de Longo Prazo)* of BNDS that is the rate of one of the primary means of financing enterprises in Brazil.

The deliberate choice of three semesters to calculate the *m* variable is because it is an attempt to capture and "punish" with more accuracy the significant number of customers that stay just one semester in the base.

The infinite time horizon is more straightforward as it is not necessary to specify the duration of the relationship of the lifecycle arbitrarily. Even if some authors have some doubts about the utilization of retention rates in non-contractual settings, in some business-to-business relationships, it is more evident the notion of a customer's "death". For example, when sales representatives inform marketing managers that a retailer has closed down, or when he/she stops visiting a customer, who receives less attention, no product or price updates and quickly becomes "dead". Generally, this fact happens after a sequence of dissatisfaction occurrences over product defection, prices disagreements or failure in choosing a successful product for reselling.

In Table 13, it is presented the computation of the customer metrics of the whole database. The acquisition rate is calculated as the number of new customers that start the relationship with the firm in the period *t* divided by the number of customers that were in the previous semester, *t*-1. The Churn rate as defined by Ryals (2009, p.3) is the "rate at which customers are lost each year (therefore, the inverse of customer retention)".

Table 13 – Customer metrics

	2015/1	2015/2	2016/1	2016/2	2017/1	2017/2	2018/1
Active customers	96	173	208	224	204	190	168
Acquisition rate		80,21%	34,68%	15,38%	9,38%	6,37%	8,42%
Retention rate		100,00%	85,55%	92,31%	81,70%	86,76%	80,00%
Churn rate		0,00%	14,45%	7,69%	18,30%	13,24%	20,00%

Source: author (2019)

The correlation matrix in Table 14 provides the results of the correlation between CLV and the two habits scores. It is important to mention that this formulation takes into account the mean of Promotion and Purchase Habit of a customer over the semesters and naturally, only customers that have habits scores are compared. The correlation of 0,711 between Purchase Habits and the CLV represents a strong relationship between a metric that represents the future profitability of customers.

Table 14 - Correlation Matrix - CLV

	CLV	Promotion Habit	Purchase Habit
CLV	1	-	-
Promotion Habit	0,355	1	-
Purchase Habit	0,711	0,433	1

Note: Pearson as the default method of correlation measure with function *cor* in *R*

Source: author (2019)

In Table 15, the mean of CLV of each Purchase Habit cohort is calculated. It is possible to take the distribution of the highest habits scores in deciles and form the cohorts. The highest scores that are in the 1st and 2nd deciles form a cohort. Then the values between the 3rd and 8th deciles form the medium cohort, leaving the two last deciles to the lowest scores of Purchase Habits. The High Purchase Habit group has almost six times the average CLV of the Medium Purchase Habit cohort.

Table 15 – Purchase Habit cohorts and CLV mean

	Average CLV	Mean Promotion Habit	Mean Purchase Habit	Sum of Cash Flows
High Purchase Habit *(Deciles 1 to 2)*	R$ 7.787,84	0,262	0,108	R$ 714.603,31
Medium Purchase Habit *(Deciles 3 to 8)*	R$ 1.412,04	0,127	0,027	R$ 333.615,36
Low Purchase Habit *(Deciles 9 to 10)*	R$ 665,26	0,121	0,028	R$ 12.132,48

Source: author (2019)

In Table 16, it is computed the Customer Equity of the customers in the dataset. As previously mentioned, it is the sum of the CLVs of all customers. It is a proxy for the value of the firm value, at least considering only the geographical region utilized in this study (GUPTA; LEHMANN; STUART, 2004). The share of the 20% most valuable customers within the CLV perspective reaches 72% of the customer equity computation.

Table 16 – Customer Equity

Average CLV	R$ 2.542,99
Customer Equity	R$ 556.914,61
CLV sum of 20% of the most valuable customers	R$ 398.840,51
Share of 20% most valuable customers[1]	72%

Note: [1]-based on CLV

Source: author (2019)

4.5 SIMULATION OF EXPANSION OF THE CUSTOMER BASE

Following the segmentation of customers based on the Purchase Habit, it also possible to conduct the same process on Promotion Habits. Therefore, a simulation is proposed to assess whether the increment of some customers with a particular habit and habit strength would affect firm performance. This procedure can evaluate the effect of the possible acquisition of customers prone to develop habitual behaviors instead of a random acquisition of customers. Sometimes unfeasible in practical terms, since habitual behaviors develop over time and in B2B settings acquisition follow different rules in comparison to B2C or direct marketing approaches (FADER; TOMS, 2018), this step could stimulate customer level insights towards finding a pattern of where to find new habit prone customers. It may be difficult for manufacturers to go out in the market and look for acquisition based on predetermined characteristics of a successful business' owner or a good purchase manager. Firms have low control over it. However, searching for retailers that follow similar managerial style that conduct smart pricing policies or that have well-designed stores, could be a good starting point for the development of more transactions.

The simulation starts with the acquisition of ten customers randomly selected from the entire base. As the last semester of observations (seventh semester), 16 customers were acquired, and the acquisition rate has severely declined from the first semester (2015/1), the number of 10 customers is a close representation of the reality. All customers have a unique ID, which represents their identity in the database. Next, a list of random numbers is generated in *Microsoft Excel* with the function RAND. Then, these "new" customers enter the base, and it is possible to measure how these new customers change the CLV's overall mean of the entire base.

In a sequence, it was randomly selected ten customers inside each group of Purchase Habit, calculated previously for the Customer Lifetime Value analysis in section 4.4. In Table 17, the column "Variation in CLV" compares the impact of their acquisition with the randomly acquired customers. As the CLV calculation represents a forward-looking metric, the estimation of the effects of a new customer also represents the long term, not just in the following period. The impact of the simulation of acquisition for the higher habit group could generate an increase in the average CLV of the whole customer base of 4,89%. It is also interesting to note how the acquisition of customers that do not show the same characteristics of higher habitual scores could affect the average CLV of the customer base negatively. That could represent the customers that are first acquired, or the easiest ones, those that are highly responsive to firms' marketing actions. Moreover, it does not mean they are the most profitable to the firm (FADER; TOMS, 2018). Besides reducing the overall mean of CLV of the base, it is to mention that when they are acquired managers and sales rep need to provide customer service, selling visits and customer onboarding actions, requiring more time and effort of firms. In addition, acquisition costs are ignored and that could even make the results worse. That is why the acquisition of good customers based on characteristics of good profitability indicators instead of only demographics or firmographics is so important for firm performance (FADER; TOMS, 2018).

Table 17 – Results of expansion of customer base - Purchase Habits

Acquisition of customers	Average CLV	Sum Cash Flow	Variation in CLV[1]
Randomly	R$ 2.501,98	R$ 1.077.409,67	
Low Purchase Habit	R$ 2.459,39	R$ 1.064.470,29	-1,7%
Medium Purchase Habit	R$ 2.498,79	R$ 1.075.292,72	-0,12%
High Purchase Habit	R$ 2.624,54	R$ 1.216.466,74	4,89%

Note: 1 - in comparison with randomly acquired customers

Source: author (2019)

The results of the expansion of the customer base looking for patterns within the Promotion Habit scores are in Table 18. They show a moderate advantage in comparison to the way firms go with no previous information in the market for new customers. At least, if firms could search for customers that are not promotion prone they could achieve good results in comparison with going for customers that have a low Purchase Habit. If firms need to develop a specific promotional action to open new markets or as a way to reduce volatility in some regions, then the pattern formed by such behavior could serve as insights in the quest for new customers.

Table 18 – Results of expansion of customer base - Promotion habits

Acquisition of customers	Average CLV	Sum Cash Flow	Variation in CLV[1]
Randomly	R$ 2.501,98	R$ 1.077.409,67	
Low Promotion Habit	R$ 2.561,60	R$ 1.100.614,56	2,38%
Medium Promotion Habit	R$ 2.508,76	R$ 1.090.544,36	0,27%
High Promotion Habit	R$ 2.546,86	R$ 1.110.753,73	1,79%

Note: 1 - in comparison with randomly acquired customers

Source: author (2019)

5 CONCLUSION

This dissertation aimed at assessing how habitual behaviors, measured following the method proposed by Shah *et al.* (2014), fit to a business-to-business context regarding firm performance. If satisfaction alone is perhaps responsible for one-quarter of the variance in repeat purchase behaviors (SZYMANSKI; HENARD, 2001), what else explains the other portions of transactions that people or business do every day? There is a growing interest in marketing researchers to explain how unconscious behaviors (WILLIAMS; POEHLMAN, 2017) and habits (VERPLANKEN, 2018) that underlie a broader mechanism of inertia-based switching costs exert a long-term effect on customer retention (BECK; CHAPMAN; PALMATIER, 2015).

The previous works over habits in B2C contexts indicate that fostering habits among customers could generate higher and more stable flows of income to firms (SHAH *et al.*, 2017). However, it is important to note that in some consumer packaged goods or retailing sectors studies, consumers have a more stable pattern of consumption as a family that consumes four bottles of shampoo or one package of toilet paper every month, and that usually does not change unless someone leaves the house or the family expands. In B2B, the complexity of the operation might be higher, as manufacturers must face the volatility provoked by retailers but also by final consumers that might change the retailer they shop. Therefore, the connection between habits and purchasing in industrial (B2B) scenarios may go through a different journey. Higher purchase orders, a more comprehensive range of complements and supplements to products and different kind of agents involved in the purchase process, offered an opportunity to evaluate how such behavior affects managerial practices.

Purchase managers or sales associates could be developing behaviors that the literature over B2B marketing has not fully explored. Therefore, it is of primary interest of sales, marketing managers and scholars to start to include these new perspectives into the framework of strategic actions (LAFLEY; MARTIN, 2017). Nevertheless, the great challenge to everyone involved in customers relationships is how to keep and foster the habit strength of customers in a competitive landscape where you need to launch new products, update attributes, have salespeople that ask to leave and face competitors that operate aggressively. By no means, it is an easy task, but expanding the knowledge over the habit concept it could be a good departing point.

The results of this work acknowledge the importance of having fierce habitual customers inside the base and the potential of competitive advantage gains over firms that do not understand the power of habits. The complexity of some business-to-business purchase processes might hamper the creation of habits, especially if the decision of new purchases have new parameters every time. Nevertheless, in some contexts, there are routine transactions where retailers, supermarkets or distributors need to replenish the stocks easily and quickly.

The path to purchase must be straightforward, clear and with frictionless contexts that induce repeat purchases. Simplistic thinking that only a rational choice leads to a sale might lead to myopic way into managing profitable relationships in B2B. Houston, Blocker and Flint (2019) express that relationship in B2B must be viewed from a perspective that business buyers are people too. They are dealing with a massive amount of information and options to buy from; especially now with the establishment of B2B e-commerce platforms, where suppliers are available worldwide. Buyers or supply chain personnel are not chess players that master strategic actions all the time. They also must allocate time and efforts to their portfolio of suppliers. Some of them, that are well established and foster their context with a smooth and clear path to purchases, can navigate in the automaticity route. One time will come that the buyer will automate decision making for a supplier that is performing well so that he/she will move attention towards a new problem or task.

Marketing models could improve the misclassification problem in CLV models (MALTHOUSE; BLATTBERG, 2005) and incorporate new information about more complex behavioral metrics so that firms can avoid overspending in customers that would have bought anyway. Marketing researchers are also discovering how to deal with wrong cross-selling offers that change the context or the mental structure of a customer that “wakes up” and might even churn. Habits are active if the context holds the same. Therefore, customers that are showing a stronger habitual score should matter when are firms look to change commercial policies, alter logistics rules, conduct radical salesforce adjustments or customer service changes. Operational efficiency could be an essential player in keeping habitual customers “on”.

The index proposed by Shah *et al.* (2014) could be a straightforward key performance indicator of how firms are retaining and fostering behaviors that offer better financial performance. Some works by marketing researchers are recognizing and distinguishing different constructs of loyalty and commitment that are helping firms to conduct more personalized retention efforts (ASCARZA *et al.*, 2018).

The specific theme of promotions in this research must open new insights into how they are conceived. The inertia of repeat promotion purchases could create “blind” customers to another kind of products (that offer higher margins) and thus, they keep on buying more promotions over time. Promotions in the context studied are primarily a reduction in the price of a product to retailers, the type of trade promotions as state Ailawadi and Gupta (2014). The effect of in-store events and display, buy-one-get-one and coupons could offer a different result, but these practices are not standard in this context of transactions. Therefore, the price reduction stimulated through regular promotions might induce habitual behaviors for this type of deal. Exposure to frequent promotions can set a new reference price, with potential damage to ordinary purchases that can become less attractive. Creativity is crucial in designing promotions, especially in the business-to-business setting where products and relationships can last for a long time and to eliminate an item from the portfolio might become an inglorious task.

The volatility evaluation of this work has offered a possible new look onto this topic. Studies that deal with cash flow volatility are scarce in the marketing literature (FISCHER; SHIN; HANSSENS, 2015) and further research could amplify how covariates can moderate the marketing actions-volatility relationship. It might be a challenge to achieve both high profits and low volatility in all types of relationships as found by Tarasi *et al.* (2013). It is worth mentioning that this work did not establish if a behavior has high or low volatility in general terms because it is not a comparison of volatility levels with other markets or industries, results just show evidence that one behavior affects more than the other does.

The CLV analysis and the simulation of the expansion of the customer base add robustness to the work as they show how Customer Lifetime Value can correlate well with Purchase Habit scores. The first look into customer acquisition may bear on learning what kind of customer is more receptive to the marketing efforts or to the context of transactions a firm has created. Habit prone customers may not be easy to find in the initial phases of the relationship. Nevertheless, relying only on firmographics or demographics might turn to a trap after the acquisition. The capacity a retailer has to resell the firm's products properly with good customer service or an excellent customer experience could spur future habitual behaviors, and firms could explore and find customers with those characteristics.

It is also fundamental to expand knowledge developed in other contexts of the marketing practice and verify what holds or not. The use of data collected from an authentic ambiance of transactions involving more than one manufacturer is not trivial to obtain and could offer valuable insights to expand B2B empirical studies (RESTUCCIA; LEGOUX 2019; LILIEN, GREWAL; 2012).

5.1 MANAGERIAL IMPLICATIONS

Are there any specific investment, salespeople training models, product design or pricing policy that has led to stronger habitual relationships and that could be replicated? Customers that scored higher on the habit score: were they just born good or is it the product mix that they are selling? Is the sales force that visits these customers using some skills that could be spread to other salespeople? Are the marketing actions different to these customers? A good starting point for managers to foster positive habits is to look at what has been done with customers that show higher scores. What does it have in their context of transactions? The other route is where to find habit prone customers. In some settings, it might be hard to select and go after these people, in others; it could be just a matter of choice. Managers must be aware that fostering customers that make more *straight rebuy* purchases (ROBINSON; FARIS; WIND, 1967) might be a question of correctly setting up a proper context; discouraging customers who want to start from scratch every single deal.

This work did not investigate other possible consequences of habitual behaviors other than the financial outcomes. Some retailers that acquire good habits with more frequent and constant purchases could help in logistics and distribution issues, expanding the geographical coverage of manufacturers. In addition, referrals and word-of-mouth could be assessed. Managers should also pay attention to who intermediates the transactions. As mentioned in this work, salespeople or the marketing department sometimes negotiate and interact with CEOs, purchase or supply chain managers or sales associates. Firms could develop specific actions for each intermediate. For example, if a sales associate gets used to the brand and their line of products, they could turn into ambassadors of the brand. As when they leave their current jobs, they could work in another retailer and make referrals and recommendations to the new purchase staff, and then, helping indirectly with the acquisition process.

Managers should make sure if their current promotions practices of regular price reductions are not damaging long-term profitability. At least investigate if they are increasing the utilization of a product early on the lifecycle of the customer, strengthening brand awareness or gaining market share. Promotions are an essential generator of sales with customers intercalating promotions and ordinary purchases all the time, so the former should not be terminated just optimized in ways that are more profitable over the long term.

Managers could investigate which products are on consumer trends and explore deals that link more aggressive promotions in a bundle with higher margins products. That could tempt retailers to migrate to more profitable deals. Even if a ceiling effect could be a big issue in reselling, as retailers might not buy more due to their impossibilities to resell, correctly setting up a promotion campaign could minimize the possibility of a negative long term effect.

Firms could form a portfolio of customers segmented in habitual behaviors as created for the CLV analysis (TARASI *et al*., 2011). Then, they could run field experiments with alternative marketing actions within selected habitual portfolios, and randomly allocate more or fewer resources, and compare with control groups to assess the consequences over time. This procedure could achieve a better causal explanation of the relationship between habits and profits.

Managers also must be aware that the costs involved in fostering habitual customers need to be carefully evaluated. To encourage more repeat transactions and satisfactory experiences might come at a price. The work of Lee *et al.* (2015) investigated why companies that increase customer-centric actions with better customer service, hire more staff and expand the structure to offer higher and faster responsiveness do not have gains in firm performance, usually even having negatives outcomes. The benefits must outweigh the increase in costs. Steady habits could also be on the other side, with competitors. Firms could only wait to a context be disrupted or could try with small and timely actions to try to disrupt it by themselves.

6 LIMITATIONS AND FUTURE RESEARCH

The context of this work in the furniture sector hold some characteristics that may facilitate the emerging of habitual behaviors: less technological products, product characteristics that do not change much over time and a cultural characteristic of the country that show a weak long term orientation, opposing from e.g. for Nordic countries (BECK; CHAPMAN; PALMATIER, 2015). For how many centuries is the model of a furniture unit that we keep our clothes (wardrobe) almost the same? Indeed a more dynamic sector that offers a highly competitive scenario with weekly negotiations, promotions and product launches might not fit into the habit theory chain. A more innovative landscape could disrupt with more effectiveness the inertial behavior of buyers.

The limitations of this work concern the fact that it work analyzes transactions of one particular segment within the B2B world, in one particular geographical region. More works should test the measures of habit in other B2B contexts, considering the measures of habit strength were created for B2C transactions.

The macroeconomic turbulence that Brazil has faced in the last years could have increased the price sensitiveness of this product category and therefore, a higher search of promotions and lower prices items created an endogenous factor that naturally increased this type of purchases. It remains an open question if results are robust to economic growth times, for example.

The change in buyers positions or more strict financial policies for buying could alter the context where transactions occur, minimizing the effects of habitual behaviors. Future researches could investigate deeply how the owner of a business, a purchase manager or a sales associate affect the creation of habitual relationships. In addition, how good customer service, pricing strategies or any other marketing actions influence and generate habitual behaviors.

The movement towards online shopping may have more prominent effects within this industry that the sample analyzed in this work could not have detected; therefore, it remains a suggestion for future research to check if the results are robust to later periods. This work would benefit from an exploration of the roots of habits, with investigative qualitative work. How products, salespeople or operational efficiency build a proper context for transactions? Which actors are more important in habit creation? Also, a further study could amplify the causal relationship of habits and firm performance, in a field experiment with customers of higher purchase habits cohorts being randomly selected to alternative strategies and checked over time.

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