Customer habits in a B2B context: impacts on cash flow level and volatility

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Resumo

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 as a result, a habit emerges. This works aims to analyze the impact of habitual behaviors in the context of business-to-business transactions using empirical measures of habits developed by marketing researchers. 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 reorder a sold item. Therefore, it is expected that over time, a portion of repeat transactions between manufacturers and retailers start to be driven by habitual behaviors of someone involved in the process of buying. This work proposes to measure the Purchase and Promotion habits in a database of transactions in a furniture industry and apply quantitative analyses 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.

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

1 INTRODUCTION

The present work aims to explore a topic that has gained spotlight in the academy within the area of purchase behavior: the habit, 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 generate optimal performance for firms, as customers that just wait for promotions to buy or that consistently return products, defer payments or buy loss leader items.

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 (Wood & Neal, 2009). Habits are highly resistant to change because the responses become integrated into memory with the context that predicts them. Context, such as time and location, triggers habit-driven repeat purchases automatically without requiring supporting attitudes (Ji & Wood, 2007). Time and efforts costs can be important factors in generating convenience, which might function as a precursor of habit, but as long as the habit is formed the consumer no longer considers the time and effort costs at each purchase (Liu-Thompkins & Tam, 2013). 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 important outcome of marketing strategies (Lafley & Martin, 2017).

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.

What about when transactions occur between firms, what is the outcome when people involved in the purchase process act 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 organizational buying has started to include 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).

Information concerning costs and characteristics of products, payment options, estimated time of arrival, support for ad campaigns etc. 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, in addition to dealing with incorrect invoices, shipments' delay or any other issues that involve suppliers.

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, however when it is considered the whole portfolio, some items under the scrutiny of the buyer might become overlooked over time, e.g. relaxing some products and supplier comparisons.

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. Therefore, the habit strength of customers could be quantified along a continuum and categorized in four different patterns: 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 et al. (2017) went further to analyze the impact of customers' habits on the volatility of cash flow, as well as the level of these inflows.

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

Due to the idiosyncrasies of the context where firms and retailers have transactions (Lilien & Grewal 2012), two habitual behaviors are tested: Purchase and Promotional Habits. 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". The purchase habit takes into account all the orders a customer repeatedly purchase over time within a temporal consistency perspective.

The objectives of this work are: 1) quantify the habit strength of each customer over seven semesters of transactions involving manufacturers and retailers in a furniture sector; 2) evaluate how in magnitude and direction the strength of habits affect the cash flow level and the volatility; 3) assess how habits interact with a forward-looking profitability metric (CLV).

2 THEORETICAL FOUNDATION

2.1 Habits

In the marketing literature, some authors analyzing longitudinal data of customers' transactions started to observe that in certain cases 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 seen in the news linked to supposedly new shopping habits (Brooke, 2017). Labrecque *et al.* (2017) 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.

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.

2.2 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. Deighton, Henderson, and Neslin (1994) propose that the inertial effect on consumers makes the primary influencer of current purchase the past purchases.

In the business-to-business context of this work, a retailer could start buying more frequently from manufacturers 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. And then 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).

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. In this context, manufacturers offer trade promotions to retailers, which could anticipate future promotions and adjust purchase behavior (Ailawadi & Gupta, 2014). 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.

2.3 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 has 12 items that contemplate more than just past frequencies of behavior such as 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 to smartphone applications that monitor utilization frequency (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 and the results showed a high correlation. 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 important to mention the idiosyncrasies of habits that usually do not follow 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 mean 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).

2.4 Cash Flow Level and Volatility

Cash flow, as the net amount of cash being transferred into and out of a business 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 firm's accounting procedures than profits (Vorhies; Morgan & Autry, 2009). Customers are typically one of the fundamental and most important sources of a firm's cash flows 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).

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 and cash flows that are more stable and predictable will have a higher net present value creating more shareholder value (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 (Shah et al., 2017). 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 peaks in sales. Fischer, Shin and Hanssens (2015) argue that cash flow volatility has not been a major concern to marketers, as it may generate conflicts with a typical marketing objective (sales maximization) with a more operational and financial objective (stable revenues).

3 METHOD

The collected data for the B2B context is based on a set of transactions between manufacturers and retailers in the furniture sector in the metropolitan area of Porto Alegre, Brazil for the period of seven semesters (2015/1 to 2018/1). The database consists of around 13,500 transactions of 373 retailers with three manufacturers that produce furniture items like kitchens cabinets, wardrobes, storage units, racks and complements such as bookcases and shelves. Data was collected through a sales representative office that intermediates the transactions and has contractual permission to be the unique seller of the manufacturers in the geographical region. 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 businesses. Some retailers are part of cooperative groups and a few are larger retail chains. The responsible for buying could be the owner of the business, the purchase manager or even a sales associate that sells a product through a catalog.

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. 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 action.

3.1 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*.

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

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

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

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

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 Mean Behavioral Intensity for each behavior (Purchase or Promotion). 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. Therefore, on Equation 4 a relatively large value of the numerator term and relatively small value of the standard deviation (denominator) would contemplate a strong repetition of behavior with temporal consistency.

The characterization of a promotion purchase is when the transaction generates a net cash flow 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. Promotions are available to all customers and are regularly launched by the firms involved in the database. It is important to mention that promotions and the sales force are the most important marketing actions in this context, where brands do not invest heavily in communication. Marketing spending is almost a fixed expenditure of manufacturers, which are catalogs, material samples and participation on furniture fairs and are available to all customers.

The commission generated in each purchase order by the sales representative office is considered a proxy for the net 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*).

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

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

3.2 Variables

Based on the model present in Shah et al. (2017) some adjustments are proposed to analyze the impact of habitual behaviors on firm performance on this B2B context. Papies, Ebbes and Van Heerde (2017) emphasize that including a set of control variables in the regression models is primordial in order to try naturally to address for endogeneity issues. 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, 2018, p.145). 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, 2018).

To account for exogenous environmental shocks to help to control for a portion of sales of furniture that could be due to the estate market rather than the sheer habitual behaviors of retailers, it is included in the model a macroeconomic factor (Housing_t). This index is computed with the Fipe-Zap collection of sales of properties and rentals in the city of Porto Alegre. The Fipe institute (*Fundação Instituto de Pesquisas Econômicas*) is a traditional supplier of financial and economic indicators in Brazil. 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 be related 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. It is argued that a sales representative could have a closer relationship with customers, and more possibilities to develop a relationship with premium customer service, friendship, management consulting, or all the possibilities that e.g., consultative selling can render (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, line or manufacturers as they can, generally are top performers. Therefore, a proposed variable tries to control for a dynamic sales representative effect that could generate a closer relationship over time that induces repeat purchasing. Sales Force_{it} can be set as the number of manufacturers that a customer buys in each semester from the sales rep.

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 variable that captures the general search or interest for furniture on the internet. A proxy relating to it can be derived from the Google Trends for specific words of furniture sought: Internet Search_t. It is computed the general search for furniture relating to the word "*móveis*" in the period of 2015/1 to 2018/1 in the state of Rio Grande do Sul. The data that Google discloses for download has measures of every 9 days, starting on January 4, 2015, and ending on June 24, 2018. 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).

3.3 Dependent variables and models

The dependent variable of the Cash Flow Level needs to be transformed into a logged variable in order to account for a skewness that affects many marketing and financial data as sales or financial index. Therefore, the functional form of this model turns into a log-linear model. Along with the computation of Cash Flow Volatility (6), the proposed models can be specified as:

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

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

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) and 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 purchased by customer *i* 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 Panel data

The dataset was collected in a panel data form. The main motivation for exploring a panel data format is the opportunity to measure change at the individual level. 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". 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 (2010) 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 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 $i \rightarrow \infty$, and generally, this format of panel offers fewer complications than models where $t \rightarrow \infty$ (Wooldridge, 2010). The fact that panel format comprises only three years is especially important for the assumption of time-invariant factors to be controlled to reach a more convincing causal explanation (Rossi, 2018).

In order to present how the models will be estimated, it is followed by the procedures found in the Wooldridge (2010). Consider the following panel data model to be estimated:

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

where $v_{it} = c_i + u_{it}$ In the manner that $\boldsymbol{x}_{it}$ is a $1 \times K$ 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 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. One option for estimation is the Random-Effect estimator that is a generalized least squares (GLS) estimation procedure that considers individuals' effects a random variable and requires the regressors and the individual effects to be uncorrelated in all periods . It considers the c_i part of the composite error, assuming that $\mathrm{E}(c_i|\boldsymbol{x}_i) = 0$. Alternatively, the Fixed Effect estimation relax this assumption and let c_i to be correlated with $\mathbf{x}_{it}$.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 do the within transformation with the average demining in the equation (10) in order to eliminate the individual effect c_i (Wooldridge, 2010).

The analyses will be conducted with the software *R* with the package *plm* (Millo & Croissant, 2019) that offer a solid and spread utilization of panel data econometric models.

4 RESULTS

Following the computation of the measures of Habits and Cash Flow Volatility, the final sample consists of 219 customers. Customers that do not have an observation on at least two semesters and that did not purchase at least two times in a semester were removed from the analyses due to the impossibilities of calculation of the indices. The variables utilized in the empirical model are described in Table 1. The variable Cash Flow Level has a great 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.

Table 1 - Descriptive Statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Sales Force	1,022	1.552	0.696	1	1	2	3
Seasonality	1,022	-	-	1	1	2	2
Cash Flow Level	1,022	1,037.526	3,717.672	2	220.3	913.5	73,073
Purchase Habit	1,022	0.054	0.070	0.002	0.015	0.070	0.682
Promotion Habit	1,022	0.162	0.212	0.000	0.000	0.249	1.500
Housing	1,022	64.704	10.426	51.010	54.790	71.470	83.720
Internet Search	1,022	60.586	4.198	55.620	56.880	64.330	68.130
Cash Flow Volatility	1,022	0.977	0.427	0.116	0.706	1.146	5.461

4.1 Correlation Matrix

The Correlation matrix in Table 2 shows all the variables that will be in the panel data regressions. The variables Cash Flow Level and the Purchase Habit offer a strong correlation and a moderate link to the Promotion Habit. The Volatility of Cash Flows seems to correlate in a close way with both habitual behaviors. Internet Search and Housing offered almost a zero correlation with Purchase Habit.

4.2 Econometric panel data tests

If the individual component (c_i) is not present in the specified model, a Pooled Ordinary Least Square estimation can be consistently obtained. The results of the tests in Table 3 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].

Table 2- Correlation Matrix

	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*

Table 3 - Tests for individual effects (Poolability)

	F Test	Breusch-Pagan
log(Cash Flow Level)	F(218, 797) = 3.259 [$p < .001$]	normal = 12.777 [$p < .001$]
Cash Flow Volatility	F(218, 797) = 3.959 [$p < .001$]	normal = 16.031 [$p < .001$]

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

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). The results of the test shown in Table 4 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.

4.3 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 4, the Hausman test ($p < 0{,}05$) rejected the null hypothesis of a Random-Effect model, indicating that the Fixed-Effect model is recommended to the dataset. Nevertheless, as a matter of comparison and robustness, the results of both estimations will be shown in the final estimation table.

Table 4 - Tests for panel data estimation

	Wooldridge (2010)	Hausman (1978)
log(Cash Flow Level)	F = 3.7653 df1 = 1, df2 = 801 [$p =$ 0.05268]	$\chi^2 =$ 12.795 [$p =$ 0.04641]
Cash Flow Volatility	F = 0.89916 df1 = 1, df2 = 801 [$p =$ 0.3433]	$\chi^2 =$ 15.885 [$p =$ 0. 01438]

Note[1]: Alternative hypothesis: serial correlation
Note[2]: $H_0 : Cov\,(\boldsymbol{x}_{it}, c_i) = 0$

4.4 Results for Cash Flow Level

The main findings of this work highlight the strong and significant relationship between Purchase Habits on the cash flow level ($\delta_{1\text{FE}} = 9.443$, $p < 0{,}05$), as shown in Table 5. Confirming the findings of Shah et al. (2014, 2017) customers who develop a strong habit with the firm impact positively in the level of cash flow. 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 might pertain to a 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, or at least making the brand more widespread within the retailer or geographical region.

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. The stronger the relationship of a sales representative with customers could foster more transactions due to the good relationship and confidence.

Seasonality ($\delta_{4\text{ FE}} = 0.032$, $p > 0{,}05$) did not offer a significant strength 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 the positive significance 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 could be explained by customers that are indeed searching for furniture but ending up buying in online retailers or in competitors of the retailers in this dataset.

4.5 Results for Cash Flow Volatility

The results for Cash Flow Volatility (Table 5) 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 flow generated. 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. 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. Tarasi et al. (2011, 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". The expansion of the relationship could make retailers start to purchase a wider range of products, complements and supplements that offer a higher variability in the purchase orders. Alternatively, when a promotion is launched customers might anticipate future purchases with larger purchase orders, and therefore, less small value invoices are generated. This result is also robust when it considered sales volatilities in the place of cash flows volatilities.

On the other side, if managers are looking to reduce the volatility in the short-term they could explore launching promotions that require a minimum purchase value or within a more limited range of value. 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 addition, as the relationship becomes stronger, the buyers are confident and start to buy and purchase in a more convenient way.

The Sales Force ($\beta_{3FE} = 0.865$, $p < 0,05$) offered a positive and significant influence in creating more volatility within this framework analyzed. It is supposed that this result pertains to the similar reasoning of why Purchase Habits positively generated higher volatile cash flows. The variables of Housing, Internet Search and Seasonality did not have significant results in relationship with this dependent variable.

Table 5 – Results of estimations

	Log of Cash Flow Level		Cash Flow Volatility	
	Fixed-Effect(1)	Random-Effect (2)	Fixed-Effect (1)	Random-Effect (2)
Purchase Habit	9.443***	9.698***	0.865**	1.550***
	(0.937)	(0.555)	(0.390)	(0.248)
Promotion Habit	-0.499**	-0.337**	0.292***	0.547***
	(0.233)	(0.161)	(0.097)	(0.071)
Sales Force	0.345***	0.279***	0.045**	0.035*
	(0.052)	(0.044)	(0.022)	(0.019)
Seasonality	-0.032	-0.002	0.015	0.006
	(0.048)	(0.048)	(0.020)	(0.020)
Housing	0.022***	0.019***	-0.001	-0.0001
	(0.004)	(0.004)	(0.002)	(0.002)
Internet Search	-0.050***	-0.047***	0.001	-0.0002
	(0.008)	(0.008)	(0.004)	(0.004)
Constant		7.265***		0.769***
		(0.438)		(0.183)
Observations	1,022	1,022	1,022	1,022
R^2	0.222	0.352	0.035	0.127
Adjusted R^2	0.003	0.348	-0.237	0.122
F Statistic	37.902*** (df = 6; 797)	551.610***	4.782*** (df = 6; 797)	147.739***

Note: Standard errors are in parentheses. *p**p***p<0.01

4.6 Customer Lifetime Value (CLV) comparison

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

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

where, m stands for the contribution margin, as the average net 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). For this study, it is computed as the current interest rate (Selic) in Brazil in April 2019.

Table 6 – 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%

The infinite time horizon is more straightforward as it is not necessary to specify arbitrarily the duration of the relationship of the lifecycle. The correlation matrix in Table 7 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 measured 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 7 - Correlation Matrix

	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*

In Table 8, the mean of CLV of each Purchase Habit cohort is presented. The distribution of the highest habits scores is split in deciles to form the cohorts. The High Purchase Habit group has almost 6 times the mean CLV of the Medium Purchase Habit cohort.

Table 8 – Purchase Habit cohorts and CLV mean

	CLV mean	Promotion Habit mean
High Purchase Habit *(Deciles 1 to 2)*	R$ 7.787,84	0,262
Medium Purchase Habit *(Deciles 3 to 8)*	R$ 1.412,04	0,127
Low Purchase Habit *(Deciles 9 to 10)*	R$ 665,26	0,121

Note: Cohorts of habits, CLV and the average of Promotion Habit are over the seven semesters

5 FINAL CONSIDERATIONS

This work aimed at assessing how habitual behaviors, measured in accordance with the method proposed by Shah *et al.* (2014), apply 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 a portion of the nature of transactions that people or business do every day? There is a growing interest in marketing researchers to explain how unconsciousness and habits, that underlie a larger 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 more stable flows of income to firms, but the connection between habits and purchasing in industrial (B2B) scenarios may go through a different journey. Higher purchase orders, a wider range of complements and supplements to products and different kind of agents involved in the purchase process generated a new insight over this topic.

Purchase managers or sales associates could be developing behaviors that the literature over B2B marketing has not fully explored. Habitual purchasers might require less investment in retention efforts. 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.

The specific theme of promotions in this research must open new insights into how they are conceived. As shown, 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. The effect of in-store events and display, buy-one-get-one and coupons could offer a different result, but these practices are not common in this context of transactions. Therefore, the price reduction stimulated through constant 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 to this topic. It might be a challenge to achieve both high profits and low volatility in all types of relationships. Especially, if firms have a wide range of products with complements and supplements in the portfolio. Therefore, all the burdens that companies have to deal with higher volatile periods, may be a natural result of the development of stronger relationships. Nevertheless, firms could stipulate packages of products or higher minimum purchase orders in order to minimize such effect.

The CLV analysis of the customer base adds robustness to the work as it shows how higher deciles of the habit scores can correlate well with Customer Lifetime Values as well as with the level of the cash flows.

5.1 Managerial Implications

Strategies for retaining habitual customers might be different from the ones used for a traditional loyal customer. Habits are strong 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 or conduct major salesforce or customer service changes. Operational efficiency could be an important player in keeping habitual customers "on".

Managers could explore deals that link more aggressive promotions of products that retailers could easily resell in a bundle with higher margins products. 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 relationship with firm profits over time.

Concerning the volatility of cash flows, it is indeed an open quest in industrial marketing: is it possible to control for this metric as the relationship widens between manufacturers and customers? A partnership that gains strength might stimulate small and big purchases and with closer contacts with less determined periods. As the results of this work suggest, one way to stabilize cash flows could be the launching of promotions with a smaller range of prices, making customers purchase orders that will offer less volatile income to manufacturers.

Managers could even experiment alternative marketing actions with selected habitual portfolios and randomly allocate more or fewer resources comparing with control groups within the same portfolio to assess the consequences over time.

6 LIMITATIONS AND FUTURE RESEARCH

The context of this work in the furniture sector holds some characteristics that may facilitate the emergence of habitual behaviors: less technological products with attributes that do not change much over time. Indeed a more dynamic industry that offers a highly competitive scenario with weekly negotiations, promotions and product launches might not fit in the habit theory chain.

Further research could explore how good customer service, pricing strategies or any other marketing actions influence and generate habitual behaviors. 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. The macroeconomic turbulence that Brazil has faced in the last years, as well as a movement towards online shopping, could have bigger 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 economic cycles.

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