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The break of brand exclusivity in Brazilian credit card acquiring: effects and markup-cost decomposition in a price dispersion setting

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Keywords: credit cards, two-sided markets, price discrimination

JEL Codes: L41, L12, L13, D22

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1. Introduction

In July of 2006, the Central Bank of Brazil, the Secretariat of Economic Law of the Ministry of Justice (SDE), and the Secretariat for Economic Monitoring of the Ministry of Finance (SEAE) established a cooperation agreement to study the local payment card industry. The analyses carried by these authorities found high concentration and supernormal profit in acquiring activity, which was mainly performed by only two firms: Cielo[1], that had an exclusivity contract to acquire merchants for the Visa scheme, and Redecard, that although lacking a similar contractual position, in fact monopolized MasterCard acquiring.

As a result, the competition authority (CADE) promoted the extinction of exclusivity deals and, since July 1, 2010, both firms started acquiring for both brands, giving merchants some degree of choice. Other acquirers also entered the market, but they still have low market-shares.

Given the particular cost structure in the payment card industry, namely the interchange fee, we have information to identify markup and marginal cost in a setting with high price dispersion. This allows us to evaluate competition and cost impacts of the extinction of exclusivity, employing a unique dataset, with individual merchant data.

The next two subsections, respectively, explain the basic functioning of the payment card industry and draw the general picture of the Brazilian setting. Section 2 introduces the most relevant literature related to this paper. In section 3 we lay out two models and in section 4 we present the dataset we use to estimate them. In section 5 we show the specifications and results and in section 6 we conclude.

1.1. The payment card industry

The payment card industry is understood to be a two-sided market, which enables the interaction of two groups of agents: buyers and sellers. Each agent will only be interested in participating as long as there is participation on the other side, making a relevant set of transactions possible.

[1] Formerly Visanet.

There are three main agents[2] in the card industry. Issuers add cardholders to the network and serve them, while acquirers add and serve merchants, and the scheme owner performs brand management and, especially, establishes rules and security standards.

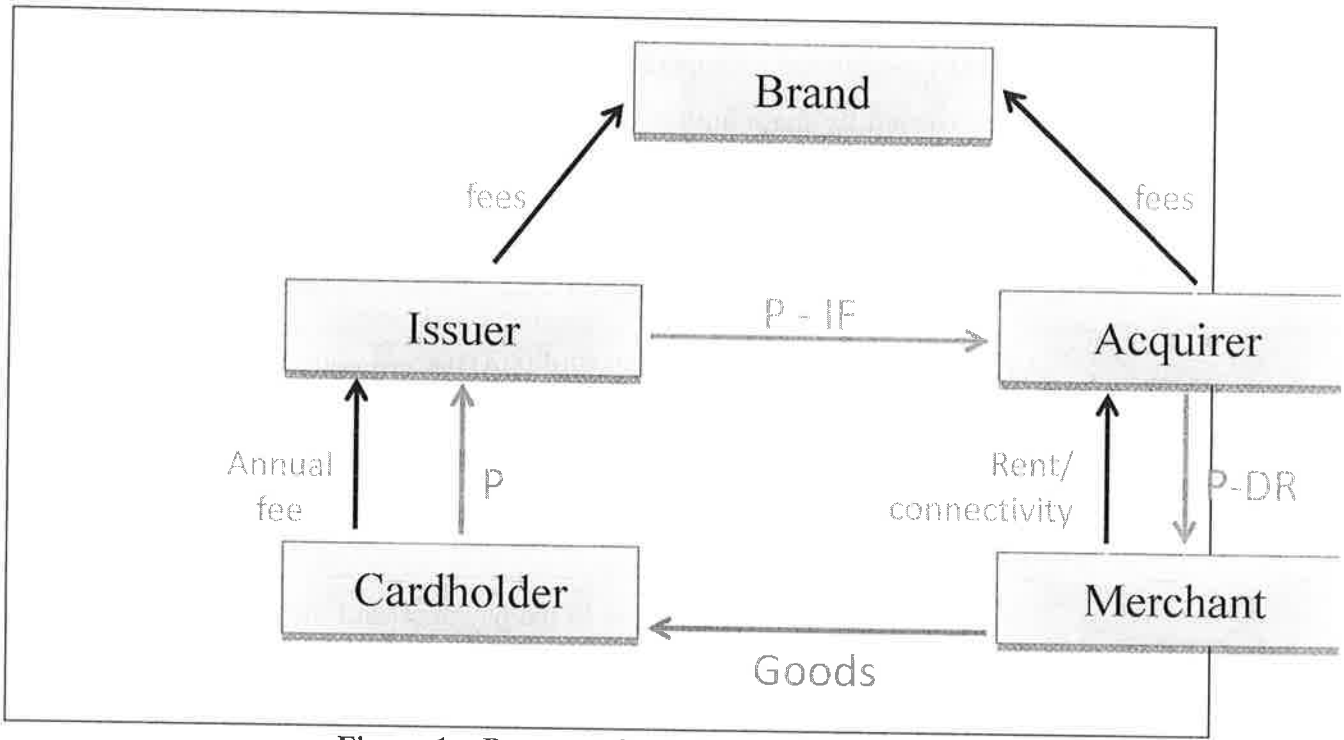

Figure 1 – Payment Card Scheme Functioning

Figure 1 contains the flow of a payment through a card scheme. Merchandise is sold at price P, for which the cardholder will pay to the issuer of her card (in case of a credit card, in a future date). That value is transferred to the merchant´s acquirer after discount of a percent value, the interchange fee (IF)[3]. Finally, the acquirer pays the merchant, discounting another percent value, the discount rate (DR). The arrows in black represent other charges that may exist.

The interchange fee is, to a great extent, interpreted as a lower bound for the discount rate, given that the acquirer's profit comes mainly from the difference between them. It is generally set multilaterally, so its value is independent of who is the acquirer-issuer pair involved in the transaction.

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[2] In some schemes and countries, it is common for firms to perform both acquiring and issuing functions.

[3] Thus, the acquirer pays the issuer, as is the case in the big international four party schemes. There are schemes in which the interchange fee flows in the opposite direction, but they are less common. An example is Australian EFTPOS local debit card scheme.

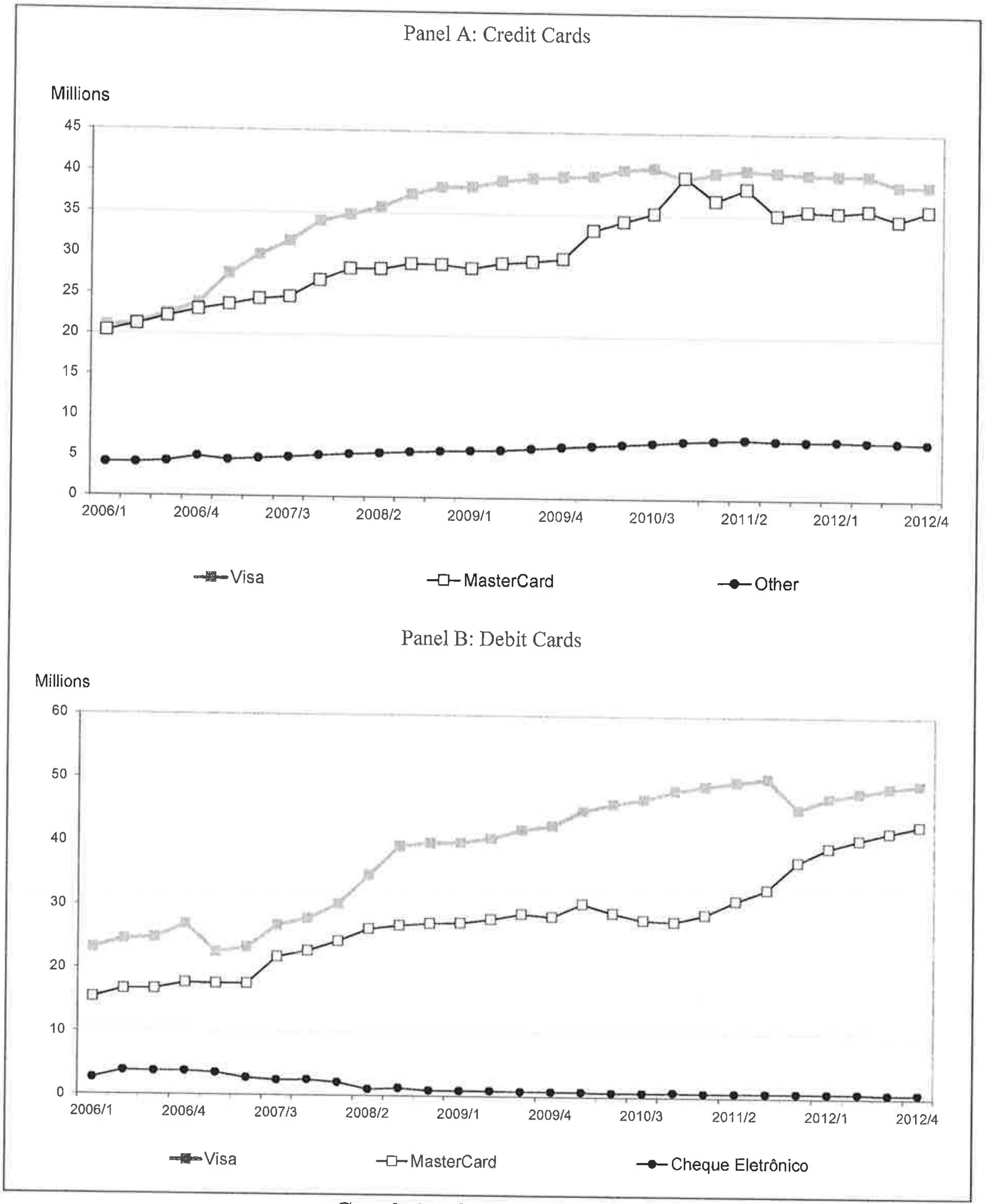
There are three and four-party schemes. In three-party schemes, the same firm performs issuing and acquiring roles, so there is no interchange fee. That is the case of American Express and Diners Club. In four-party schemes, like Visa and MasterCard, they are carried on by (potentially[4]) different firms. Worldwide, four-party schemes, had an advantage to expand over three-party ones, given the possibility of including new members, thus gaining access to their client portfolio.

1.2. Payment Cards in Brazil

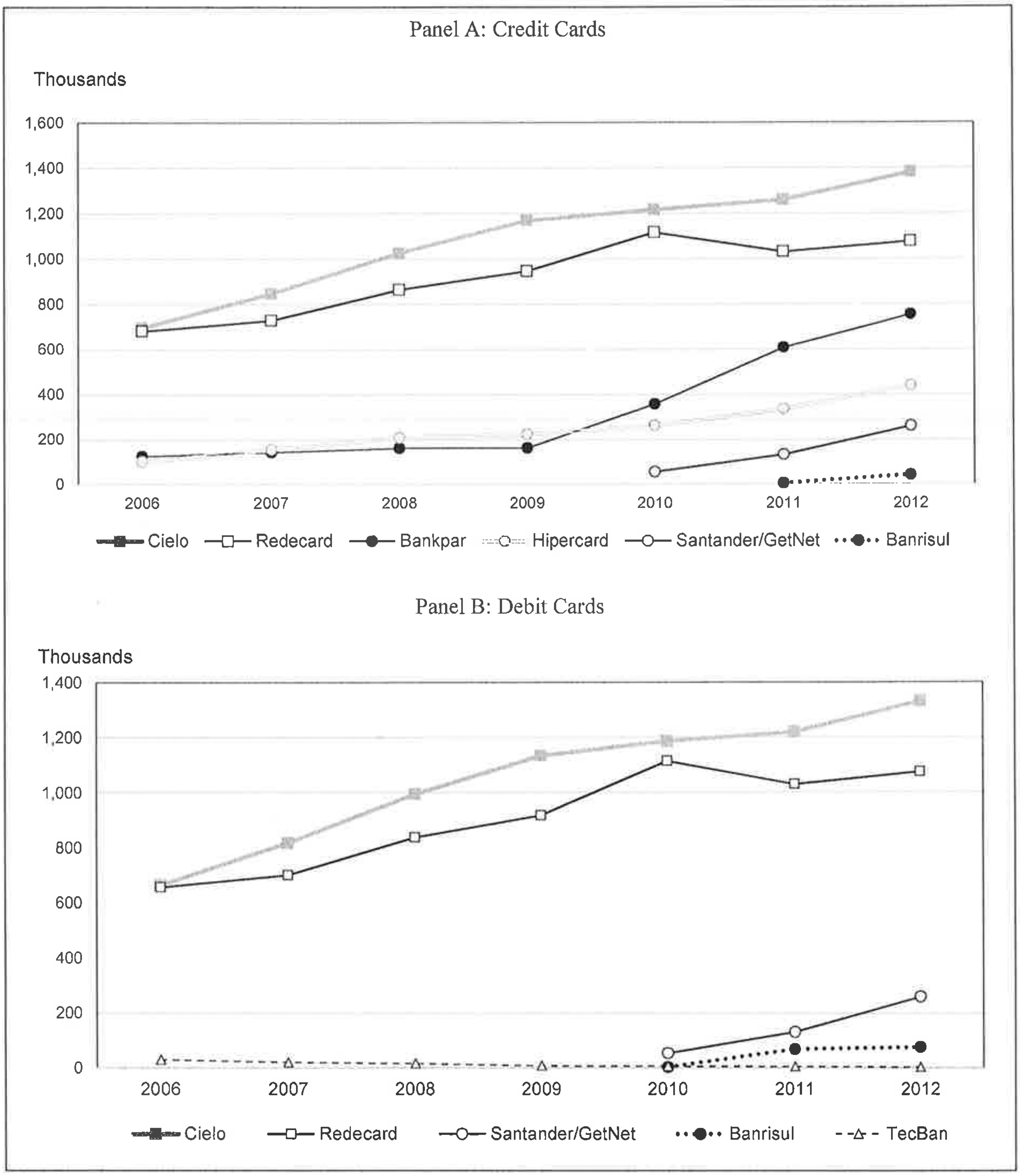
Considering the wide acceptance of payment cards, in Brazil, at the end of 2012 there were 81.5 million active[5] credit cards and 96.7 million active debit cards. Around 90% of these credit cards and almost all debit cards belonged to either Visa or MasterCard schemes. The evolution of these quantities is shown in Graph 1.

Credit card issuers in Brazil commonly charge fees from their cardholders[6]. The most frequent is an annual fee. There are also fees charged for specific services and interest rates charges over revolving credit lines. Even when a cardholder revolves, new transactions are entitled to have a grace period. The widespread reward programs may be regarded as a negative contribution to total credit card price. There are no fees charged for holding a debit card[7].

[4] These firms, generally banks, may perform both tasks. Occasionally, some transactions have cardholder and merchant tended by the same bank.
[5] "Active" cards are those involved in at least one transaction in the twelve previous months.
[6] Credit card fees were regulated in 2010 by National Monetary Council Resolution 3.919, with the objective of making services and charges comparable between providers. No caps were imposed.
[7] National Monetary Council prohibited the practice of charging such a fee since 2007, although it was not commonly used by banks before (Resolutions 3.518 and 3.919).



Graph 1 – Quantity of active cards
Data source: Banco Central do Brasil

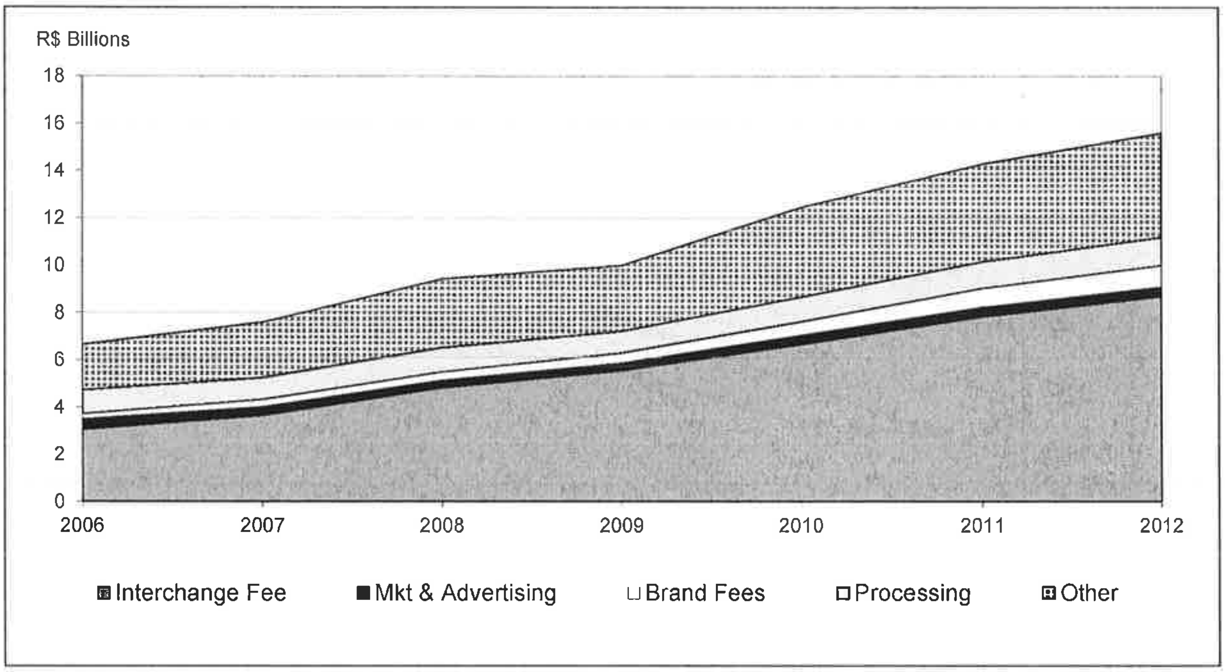


Graph 2 – Quantity of active acquired merchants
Data source: Banco Central do Brasil

Acquirers charge merchants a rent for POS terminals or a connectivity fee[8], and the percent discount rate over transaction value. They also perform other services, the most remarkable of which is credit card accounts receivable funding. In Brazil it takes on average 30

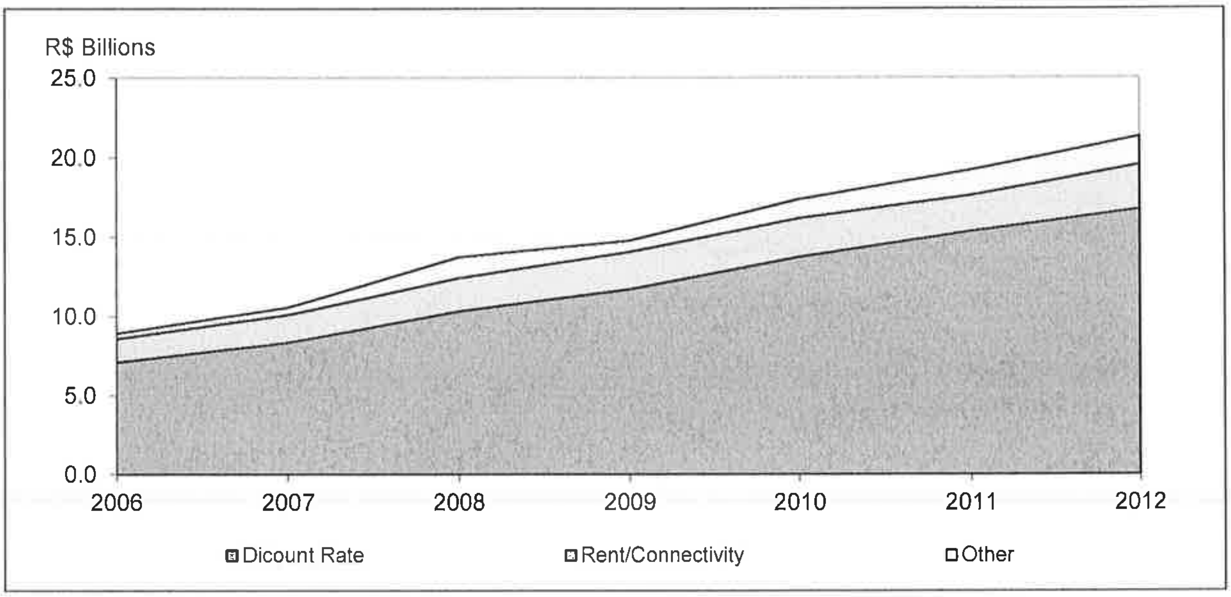
[8] POS terminals, typically used by small merchants, belong to acquirers. Large merchants generally employ another solution, called PDV, integrated to checkout. In this case, there is no rent, but still a connectivity fee is due.

days from the day of the purchase for a merchant to receive the payment[9,10]. Another local particularity of this industry is the possibility that the merchants offer their clients to split the price of the purchase in monthly installments. In that case, the merchant will only receive the payments as installments are due. Discount rates and interchange fees vary with the number of installments[11]. Graph 2 depicts the evolution of the number of active acquired merchants, which are defined as the ones that took part in at least one transaction in the 180 previous days. Graphs 3 and 4 display acquirers' revenue and cost. We can grasp the relevance of interchange fee cost and discount rate revenue from these graphs.



Graph 3: Composition of acquirers' cost
Data source: Banco Central do Brasil

[9] On average, the issuer pays the acquirer 28 days after the date of the transaction. That is on average longer than it takes the issuer to get paid by the cardholder.
[10] For debit cards, it takes two days.
[11] It is common to find purchases split into up to 10 installments.



Graph 4: Composition of acquirers' revenue
Data source: Banco Central do Brasil

BCB, SEAE and SDE(2010)[12] report that discount rates vary with merchant market segments[13], and, within each of them, fall as the size of the merchant increases. Furthermore, in the case of credit cards, they increase with the number of installments of a purchase. The report indicates the existence of price discrimination and highlights its relationship with the network value of merchants (the fact that large stores create more cardholder participation interest than small ones).

The evolution of the average discount rate[14] in card schemes that operate in Brazil is depicted in Graph 5. The dashed lines mark the second quarter of 2010, the last one with exclusivity. Notice that there is a perceptible change in the trajectory of average credit card discount rate. It is this break that we wish to analyze with our econometric exercise. On the other hand, for debit cards the change is less perceptible. For this reason, among others that we explain later, we do not study the products together, and use only credit card information.

We discuss other relevant features of the Brazilian payment card industry while laying out the model for the impact decomposition, so we can show specifically how these features are incorporated into the analysis.

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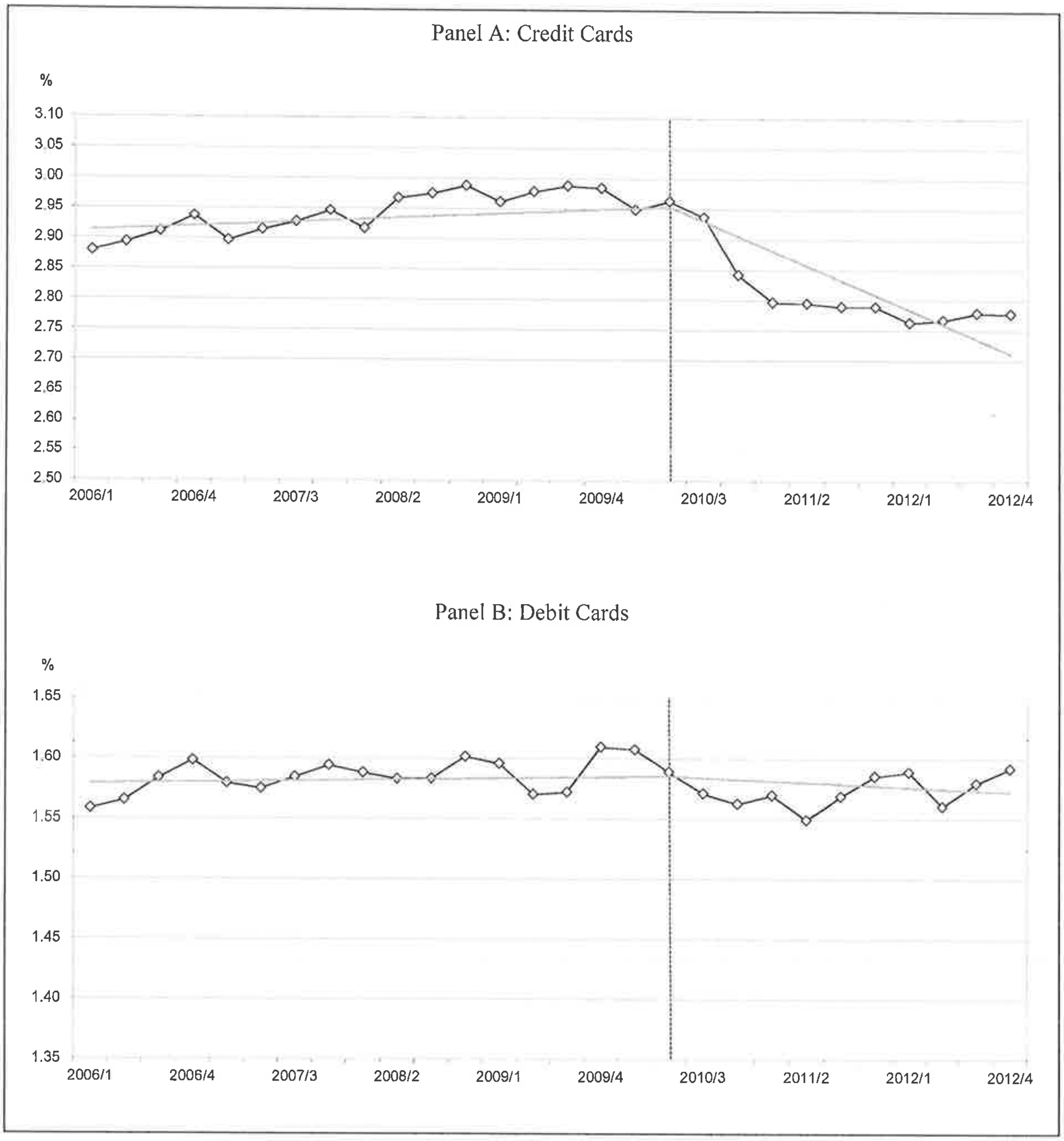
[12] This document is a thorough diagnostic report of the industry by BCB (Central Bank of Brazil), SDE (Secretariat of Economic Law of the Ministry of Justice), SEAE (the Secretariat for Economic Monitoring of the Ministry of Finance.

[13] We explain the exact meaning of this below.

[14] This is a weighted average, using transaction values as weights.



Graph 5: Average Discount Rate
Data source: Banco Central do Brasil

2. Literature

To evaluate the impact of the end of exclusivity on the acquirers activity, we need a model that captures its basic features and allows to compare its operation before and after the break. The most relevant characteristics of the industry relate the present paper to the two-sided market and the price discrimination literatures.

Although the literature about platforms has evolved significantly in the last few years, the number of empirical articles is quite limited. One of the possible causes for that is the scarcity of datasets. Applications usually fall into two sets: publications (working as platforms for readers and advertisers) or payments. In the first set, we find Kaiser and Wright (2006) and Sokullu (2012) who study the magazine industry in Germany, while Argentesi and Ivaldi (2005) do it for France. Argentesi and Filistrucchi (2007) analyze the newspaper industry in Italy.

As for the payment industry, relevant references are Carbó-Valverde, Liñares-Zegarra and Rodríguez-Fernández (2012) who study feedback loops (marginal network externalities) in both sides of the market in Spain, and Rysman (2007) who studies the cardholder side in the US using regional data. The use of regional data in these articles is one of the main factors allowing the identification of network effects.

The main common element between these papers and the present one is the introduction of controls for network effects between cardholders and merchants, although their measurement is not our focus and our dataset is not particularly fit for that. Even so, the introduction of controls is important to avoid some possibility of biased estimation of the impact of the intervention[15].

Prior to this article, the determination of the discount rate for Visa and MasterCard schemes was studied in BCB, SEAE and SDE (2010), Annex C, using the merchant market segment data, coming from the same dataset we now employ. In that study, the average discount rate was regressed against average interchange fee interacted with a segment dummy and against a measure of concentration in the segment (participation of the 15 largest merchants in the segment total transaction value), using a 2006-2007 panel with quarterly information. The conclusion is that there was price discrimination between segments and that discount rate increased with interchange fee, with a coefficient larger than one in almost all segments. In addition, the discount rates fell with the increase in concentration.

Given that price dispersion is an important characteristic of the acquiring activity in Brazil, it is relevant to bring it into the model, to evaluate the impact of the end of exclusivity. It is not enough, for example, to use an average price for the whole client portfolio, especially because theoretical effects of competition on price dispersion are ambiguous, as shown in Holmes (1989) and Borenstein (1985).

[15] It is consensual that the number of cardholders should influence merchants' acceptance decision.

That brings us to the second set of papers to which our work relates: the price dispersion literature. A supplier charging different prices from separate sets of clients may result from either marginal costs or demand elasticities not being homogeneous. Only the latter reason is regarded as price discrimination. The hard empirical problem is to separate both sources of variation, as we do in this paper.

Two main strategies may be found in the literature to deal with this issue: the assumption of equal cost or equal demand between different firms or markets and the use of regressors related to these elements. Shepard (1991) and Busse and Rysman (2005) are examples of the first approach. The first one is applied to the US gas station market and the second studies the US yellow-page advertisement market. On the other side, Borenstein and Rose (1994) and Gerardi and Shapiro (2009) study price dispersion in the US airline industry, using mainly the second approach. Asplund, Eriksson and Strand (2008) also perform this kind of analysis, applied to regional morning newspapers in Sweden, a two-sided market.

Therefore, the present paper integrates this literature, although it is not our main focus. We allow markup and marginal cost to vary with merchant size and segment, and we find it is relevant to do so. It is interesting to draw attention to the fact that our approach has some advantages over the articles mentioned. That is because we have individual final client information, including prices and other covariates, and because of the structure of the industry, which makes unnecessary the assumption of equal marginal cost or equal demands between firms or markets. The fact that there are only one (national) market and two acquirers under analysis, which in other contexts might be disadvantages, actually relax the set of assumptions we need. On the other hand, there is the disadvantage of having only data for the largest merchants, so the conclusions we draw must be restricted to that group.

3. Models

We use two models for the empirical application we present in this paper. The first one tries to empirically identify a group of merchants that may be used as pseudo control groups, and determine the existence of an impact associated to the break of exclusivity. The second aims to decompose this impact into markup and cost elements, taking advantage of the interchange fee to identify them while incorporating other aspects of the industry.

3.1. Pseudo control group model

In this section we build an empirical model to identify the break in the panel of individual discount rates as a consequence of the end of exclusivity in acquiring. Our objective is to propose a way of controlling other systematic effects that might be mistakenly interpreted as resulting from the change in the market. For such task, we would ideally have a control group, that is to say, a set of merchants not exposed to the treatment (break of exclusivity in acquiring). In the case under analysis there was universal treatment, therefore such a set does not exist.

Our approach is to try to use an empirical strategy to identify a group for which the impact is weak. Although this may seem as somewhat endogenous, that group may be used to eliminate effects that might regularly vary across individual merchants within each type of discount rate they get. For example, suppose that for some unaccounted reason, cardholders had, along the years around the end of exclusivity, gradually lost interest in using their credit-cards Then we might erroneously credit markup reduction to increased competition when it actually might stem from a reduction in demand from merchants, who would no longer need to accept credit cards as much as before. This example was obviously not the case in Brazil, but it might be interesting to eliminate unaccounted factors of that form, and if they are homogeneous within a discount rate categorization, our approach will work.

Thus, we propose the following formulation for a discount rate equation:

$$d_{i,t} = \alpha_0 + \alpha_1 IF_{i,t} + \boldsymbol{\rho o}_{i,t} + \gamma_s dpost_t + u_{g,t} + \varepsilon_{i,t} \tag{3.1}$$

We index the cross-section unit with i, and time with t. We also use two other indexes to indicate groups to which i belongs: s stands for merchant market segment and g stands for a group of other common characteristics along which discount rates vary. Every cross-section unit belongs to some segment s and some group g.

IF represents the interchange fee. The observable characteristics to control for possible price discrimination or cost variation are included in vector $\boldsymbol{o}$, which has a vector of coefficients $\boldsymbol{\rho}$.

The main variable of interest is the dummy $dpost_t$, taking on value 1 since the fourth quarter of 2010[16], indicating there was no exclusivity from that period onwards. We allow temporarily its coefficient (γ_s) to be different for every market segment.

Finally, there are two unobserved components, u and ε. The latter is assumed to have zero expected value and to be uncorrelated with the regressors. On the other hand, u is a common component to every cross-sectional element belonging to the same group g. It varies along the time dimension and may be correlated with the regressors, in particular with IF or $dpost$, so incorporating it to the regression error could potentially result in estimation bias.

Now, suppose γ_s assumes value γ_c for the segment of each acquirer used as pseudo control group and γ_T for all the others. Define $\gamma \equiv \gamma_T - \gamma_c$. We intend to obtain a differential average impact between merchants not belonging to the pseudo control group and the average merchant belonging to it. Thus, we obtain the following equation:

$$d_{i,t} - \tilde{d}_{g(i),t} = \alpha_1\left(IF_{i,t} - \widetilde{IF}_{g(i),t}\right) + \boldsymbol{\rho}\left[\boldsymbol{o}_{i,t} - \tilde{\boldsymbol{o}}_{g(i),t}\right] + \gamma dpost_t + \check{\varepsilon}_{i,t} \qquad (3.1')$$

Function $g(i)$ returns the group g to which unit i belongs. Variables marked with tilde ($\sim$) correspond to pseudo control group averages, calculated at each point in time within group g. Pseudo control group merchant information is used only to compute these averages.

The error component, now $\check{\varepsilon}_{i,t}$, is given by the difference between $\varepsilon_{i,t}$ and its average in pseudo control group, computed in the same fashion. That introduces correlation between errors in the cross-sectional dimension, so it needs to be either modeled or dealt with employing heteroscedasticity robust estimators. The equation in differences in (3.1') eliminates the common error $u_{g,t}$.

3.2. Impact Decomposition Model

In this subsection, our main objective is to outline a model that enables us to replicate the acquirers' price making behavior and to separate markup and marginal cost. This is the greatest challenge in the interpretation of price variations as a consequence of competition. We

[16] In fact, exclusivity did not exist anymore since the third quarter, but using the fourth quarter showed to be more adequate in estimations. This may reflect the delay of merchants to perceive the change in the market and to react to the new setting.

will use this model to accomplish the main task in this article: evaluation of the impact of the change of environment on competition.

As we pointed out, there is relevant discount rate variation between market segments and between merchants of different sizes. Both the necessary requirements for there to be price discrimination are present: the service sold is not transferrable, avoiding the possibility of arbitrage, and there is some demand elasticity[17] variability between clients.

We might consider the possibility that the amount of transactions or their value were used for some form of second-degree price discrimination. However, that perspective would be inadequate, because in the payment card industry in Brazil the *honor all cards* rule applies, and it determines that, once a merchant decides to accept cards of a given brand, no cards of that brand may be turned down for any purchase[18,19], giving the cardholder the payment instrument choice. At the time this article was written, merchants were also not allowed surcharge card payments, especially the ones not divided in installments[20]. Therefore, given a card brand acceptance by a merchant, the amount of transactions and their value are exogenous to the discount rate. It is not possible for a merchant to choose between packages with different transaction number sizes. On the other hand, the amount of real-time merchant information obtained by acquirers is massive, containing transaction flows. Consequently, modeling this setting with third degree price discrimination is a more adherent choice.

Another important aspect of this market is the determination of interchange fee levels. They are set by scheme owners to "balance sides", meaning that it is intended to compensate part of the cost incurred by issuers to tend cardholder portfolio and bring new consumers to the scheme. In most of the period under analysis, interchange fees in Brazil were set at international levels, a practice criticized in BCB, SEAE and SDE (2010), which pointed out that it would be desirable that local factors were taken into account. Therefore, we consider the interchange fee as exogenous.

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[17] As mentioned in Borenstein (1985), discrimination may be based on substitution elasticity (between suppliers in the same industry) or on industry demand (price) elasticity ,i.e., the one that results from the possibility of not buying the good. Before the break of exclusivity, only the later possibility was available for merchants.

[18] This is a very important rule for the functioning of card schemes and it aims to warrant the cardholder the possibility of using her card, even if there is any mistrust regarding its issuer. We should highlight that, once a transaction is approved, it is the acquirer who owes the merchant, independent of cardholder default or issuer default. The rule has been under scrutiny by competition authorities in many countries and only bundling of different functions together (debit and credit) was removed. In Brazil, credit and debit acceptance may be hired separately.

[19] Even when there is the argument (according to anecdotes) that a merchant could turn down a card by faking a POS terminal malfunction, there is no evidence of systematic use of that strategy and it does not seem as possible relevant one for large merchants.

[20] Usually there is no price difference between purchases divided and not divided in installments. That is commonly advertised as "installments without interest".

Another feature is noteworthy when competition between card schemes is analyzed: multihoming. It consists of a cardholder or merchant participating in more than one scheme. Although that is not the focus of this paper, for the better understanding of the environment, it is in order to say that a large amount of merchants accept both Visa and MasterCard brands. That was confirmed by a survey included in BCB, SEAE and SDE (2010)[21], that shows that from a sample of 500 surveyed merchants who accepted card payments, 98.4% accepted Visa and 95.4% accepted MasterCard, implying great superposition of brands and of acquirers, who did not share infrastructure (not restricted to POS terminals).

Finally, after the break of exclusivity, it would be convenient to observe prices offered by different acquirers to the same merchants. This, however, is not possible in our dataset, which is probably its main drawback. Anyhow, we must draw attention to the fact that this intervention in the industry did not create perfect substitutes. Although Visa and MasterCard acceptance are now offered by both large acquirers, there are other brands which are not. An example of that is the national scheme Elo, offered only by Cielo. American Express and Hipercard (a local credit card scheme) are three party schemes who acquire directly, but the former has a partnership with Cielo, while the later has one with Redecard. There are also differences in other payment schemes, which use voucher cards (e.g. meal ticket cards), mostly given by firms to their employees. Merchants may also have an incentive to maintain contracts with both large acquirers to use one as contingency for the other, in the case of malfunction of connection devices. Furthermore, there are differences between acquirers' service, like the way in which they report information to merchants. All these facts enable acquirers to preserve at least some of their market power after the end of exclusivity, which is necessary for price discrimination, as highlighted by Holmes (1989).

Therefore, we assume acquirers are third-degree price discriminators. In our model, we use observable characteristics to sort merchants among categories, which pay different prices in order to maximize acquirer's profit. The estimated equation comes from the profit maximization condition, where the observables in our dataset (namely size and market segment) are introduced to parameterize categories and the interchange fee is evidenced and separated from the rest of the marginal cost. That is how we obtain an estimable equation that enables us to separate the main elements of markup (demand) from cost.

The acquirers' profit is given by the following equation:

[21] Annex E. Data from 2008.

$$\Pi = \sum_j d_j q_j v_j - TC$$

Merchant categories are indexed by j, d_j represents discount rate, q_j is the number of merchants in j, and v_j is the value transacted by each of them. Note v_j is simply an observable feature of the merchant. TC represents total cost. We abstract from POS rent/connectivity revenue, since there is no disaggregated data for it[22].

We define marginal cost (MC_j) as the additional cost incurred by the acquirer to provide acceptance to one more j-category merchant. Therefore, we take the transaction profile of that merchant as given, and consider all the additional cost he brings about for the acquirer. Thus, the first order condition relative to the amount of merchants in category k, q_k, is:

$$\frac{\partial \Pi}{\partial q_k} = \frac{\partial d_k}{\partial q_k} q_k v_k + d_k v_k + n_k - MC_k = 0$$

where $\frac{\partial d_k}{\partial q_k}$ captures demand (inverse) price sensibility. n_k represents the network effect of adding one more merchant of category k to the portfolio. It would be positive if, for example, the cardholder's incentive in participation increased by acquiring this extra merchant. Then, the number of cardholders might rise, attracting more merchants at a given discount rate and thus elevating acquirer's profits[23]. Representing discount rate elasticity of category k merchants as ε_K, we have:

$$d_k v_k \left(\frac{1}{\varepsilon_k} + 1\right) = MC_k - n_k$$

$$\therefore$$

$$d_k v_k = M_k (MC_k - n_k)$$

[22] Generally, large merchants as the ones that constitute our sample use their own equipment (PDV) instead of rented POS terminal. Although we suppose they face smaller rent/connectivity costs than small merchants, we do not have any data to support that belief.

[23] In this example $n_k = \frac{\partial \sum_{j \neq k} q_j}{\partial c} \frac{\partial c}{\partial q_k}$, where c stands for the number of cardholders. There is also the possibility (covered by our specification) that there are different types of cardholders, with particular preference for merchants of certain categories and, at the same time, attractive to other categories of merchants. Since we expect the value of n_k to be positive, the sign of the difference $MC_k - n_k$ is theoretically undetermined. If there is no exclusivity, it is possible that the additional merchant was already a participant of the scheme, keeping the cardholder incentives unaltered.

The left-hand side of this equation represents total price charged from the merchant, while the right-hand side is the multiplication of markup M_k and marginal cost net of network effects.

Although we do not observe the categories, we have data on some of the merchants' observable characteristics. Imposing a functional form for category determination, we can use this information as markup, marginal cost and network externality determinants.

Hence, we can write:

$$d_k v_k = M_k(s, t_k, c).\left(MC_k(s, t_k, IF_k v_k) - n_k(s, t_k)\right)$$

IF represents the interchange fee, c is the number of cards in the platform (a control for network effects in k-category merchant demand for participation), t_k stands for the amount of transactions in which a k-category merchant takes part and s indicates its market segment.

We know, in particular, that interchange fee cost enters marginal cost in an additive fashion. Then, writing $MC_k(s, t_k, TI_k v_k) = TI_k v_k + f(s, t_k)$ we obtain:

$$d_k v_k = M_k(s, t_k, c)[IF_k v_k + f(s, t_k) - n_k(s, t_k)]$$

$\therefore$

$$d_k = M_k(s, t_k, c)\left[IF_k + \frac{g(s, t_k)}{v_k}\right]$$

Since we may not identify $f(s, t_k)$ from $n_k(s, t_k)$, we have aggregated them in function $g(s, t_k)$. Oh the other hand, the additive way in which IF_k enters marginal cost creates the possibility of identifying M_k, thus separating parameters originated in demand (price elasticity) from those coming from the supply side (costs) and network effects.

Furthermore, we are interested in verifying how markup[24] and marginal cost were affected by the break of exclusivity. Thus, we introduce time dimension, indicated by index t, and use $dpost_t$ to indicate periods starting in the fourth[25] quarter of 2010:

$$d_{kt} = M_k(s, t_{kt}, c_t, dpost_t)\left[IF_{kt} + \frac{g(s, t_{kt}, dpost_t)}{v_{kt}}\right]$$

[24] According to Bolt and Humphrey (2013), analyzing markup is an alternative form of using the Lerner Index.
[25] See footnote 16.

We assume linear forms for $M_k(\cdot)$ and $g(\cdot)$ and substitute segment dummies, b_s, for s. Naming S the set of segments, we obtain the form used in estimations:

$$d_{kt} = \left(\sum_{s\in S} \alpha_s b_s + \beta t_{kt} + \gamma c_t + \varphi dpost_t\right)\left[IF_{kt} + \sum_{s\in S} \theta_s \frac{b_s}{v_{kt}} + \mu \frac{t_{kt}}{v_{kt}} + \omega \frac{dpost_t}{v_{kt}}\right] \quad (3.2)$$

Our parameter of interest, which captures the average effect of the end of exclusivity on markups, is φ. If the change was effective to increase competition, we expect a negative statistically significant estimated value for φ. In that case, its magnitude will allow us to evaluate the intensity of the impact. Estimated value for control variables coefficients will allow us to evaluate adequacy of the model to industry's behavior.

4. Data

The dataset[26] we employ contains quarterly information from 2001: to 2013:2 reported by issuers and acquirers of wide acceptance card schemes. The dataset was originally built for the elaboration of studies under the cooperation agreement established between the Central Bank of Brazil, the Secretariat of Economic Law of the Ministry of Justice (SDE), and the Secretariat for Economic Monitoring of the Ministry of Finance (SEAE). In this section, we explain the portion of the data that we use in this paper.

As we mentioned, most of the empirical analyzes of two-sided markets or price discrimination use data from many firms or many (locally defined) markets. Unfortunately, our dataset is poor in regional information and the structure of the industry makes the use of the acquiring firm as cross-section unit excessively limiting. However, part of the information supplied by acquirers is disaggregated by client (merchant).

Acquirers were asked to define independently up to 20 market segments[27] in which they would sort merchants, according to their business line. For each market segment, individual data from the fifteen largest merchants in transacted value terms was reported. Merchants ranked among the 15 largest[28] of a segment at some point in time receive individual codes that

[26] The collection and manipulation of the data were conducted exclusively by the staff of the Central Bank of Brazil.

[27] A code is reserved for "Other".

[28] Although for the present study it would be ideal to possess data for all merchants, we believe this criterion does not generate selection bias, in the sense that presence in the sample results mainly from how a merchant's performance in his business ranks him inside his segment, which is not likely to be correlated with errors in the proposed equations for the discount rate. On the other hand, we should be cautious and restrict our conclusions to the group of the largest merchants of each segment.

allow us to observe them though time and any exits or returns to the sample. In total, 29 segments were defined by the two acquirers and their comparison between these two is not possible, given the independent definition.

For each of the merchants in the sample, at each point in time, we have many entries, containing average[29] discount rate, number of transactions and total transaction value. Each of these entries refers to a combination of four category sets: function (credit or debit); brand (for the data we use, Visa or MasterCard), number of installments and form of transaction capture technology. This last group includes categories: electronic card present transaction with magnetic stripe, electronic card present transaction with chip, card not present and not electronic (offline).

For the regression we estimate, we also need data on interchange fee. These are not reported by merchant, but by market segment. For each segment, at each point in time, the dataset features average interchange fee disaggregated into six category sets. Four of them are the same used for discount rate (function, brand, number of installments and capture technology). The other two, defined for credit cards only, are product and card modality. Product set includes, for example, categories such as international, gold or platinum. There are three possible card modalities: cobranded, hybrid and pure. A cobranded card is supplied by an issuer in partnership with a firm that is interested in promoting its brand, generally by offering some advantage to cardholders. A hybrid card is issued in partnership with a merchant and the cardholder gets two credit lines, one for general purchases and the other reserved for shopping in merchant partner stores. A pure credit card is supplied by the issuer alone.

We proxy merchant average interchange fee with the one calculated for the segment. How good a proxy this is depends on how similar is the merchant's transaction profile to segment profile, regarding product and modality. If these profiles were equal, the proxy would be a perfect measure. All other four category sets are preserved.

From the available data, we eliminate information regarding debit cards[30], since interchange fee was determined as 50% of the discount rate chosen by acquirers during a long period in our sample. In line with annex C of BCB, SEAE and SDE (2010), information about offline transactions was also ignored, because it is not representative of the industry, being mainly residual. We also discard data of pilot/trial transactions.

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[29] Averages of discount rates and interchange fees use transaction values as weights.

[30] To use debit card data we would need to outline another impact decomposition model, using a different optimization condition. The most import drawback would be the loss of our identification strategy, because the interchange fee is endogenous in that case. For this same reason, the pseudo control group model would also need a different specification.

With regard to the time span, we decided to restrict the data to the periods around the intervention that ended the exclusivity, effective from the third quarter of 2010. There are 12 quarters in the sample during the non-exclusive period, but each of them has about twice as many observations as quarters that had exclusivity, since each of the acquirers has data for both the brands, while before there was only one. Including data from the fourth quarter of 2004 generates a similar number of observations before and after the change.

The final sample size is 284.304 observations. Estimations conducted with other time spans did not significantly alter conclusions. Number of cards are expressed millions, while transacted values are in hundred millions and discount rate and interchange fee are in percent points. Monetary values were deflated by IPCA, the Brazilian official price index.

5. Specifications and Results

5.1. Pseudo control group model

We initially estimate two sets of preliminary regressions to find a pseudo control group, in which the market segments time series average discount rate of the 15 largest merchants were used as dependent variables[31]. In the first set, each time series was regressed against a constant, a time trend and a dummy variable which assumed value one for periods from the third quarter of 2010 on. In the second set, regressors are a constant and two time trends, one beginning at 2001:1 and the other at 2010:3. The objective is to select, for each acquirer, the market segment for which the break (either the dummy or the second time trend) was the least significant. For one of the acquirers both criterions pointed to the same market segment, which presented p-value of 0.002 for the first criterion and 0.012 for the second. All other segments presented p-values inferior to 0.0001 in both cases. For the other acquirer criterions diverged. Considering the lists for each criterion of the three segments with the highest p-values, only one of them appeared in both. It presented a p-value of 0.318 in the first criterion and 0.109 in the other, and was therefore selected as the control group.

Taking into account the structure of the data, g groups are defined as the combination of brand (b) with acquirer (a), form of capture (f) and number of installments (n). The cross-

[31] For these regressions we use observations from the first quarter of 2001 to the end of the sample.

section unit, i, combines these characteristics and the specific merchant (m). The variables that constitute vector $\boldsymbol{o}$ are total transaction value (v) and number of transactions (q), plus the set of dummy variables $dseg_s$, for $s \in S$, which indicate to which segment the merchant belongs. Making indexes explicit, equation (3.1) may be written as[32]:

$$d_{m,s,b,a,f,n,t} = \alpha_0 + \alpha_1 IF_{s,b,a,f,n,t} + \alpha_2 v_{m,s,b,a,f,n,t} + \alpha_3 q_{m,s,b,a,f,n,t} + \sum_S \beta_s dseg_{s(m)}$$

$$+ \sum_S \gamma_s dseg_{s(m)}\, dpost_t + u_{b,a,f,n,t} + \varepsilon_{i,t}$$

It is worth noting, still, that because the interchange fee does not vary between merchants belonging to the same s and g at a point in time, IF is indexed by them and not by m.

Using this form to rewrite equation (3.1'), we obtain:

$$d_{m,s,b,a,f,n,t} - \tilde{d}_{b,a,f,n,t} = \alpha_1\left(IF_{s,b,a,f,n,t} - \widetilde{IF}_{b,a,f,n,t}\right) + \alpha_2\left(v_{m,s,b,a,f,n,t} - \tilde{v}_{b,a,f,n,t}\right) + \alpha_3\left(q_{m,s,b,a,f,n,t} - \tilde{q}_{b,a,f,n,t}\right) + \textstyle\sum_s(\beta_s - \tilde{\beta}_c)dseg_{s(m)} + \gamma dpost_t + \check{\varepsilon}_{i,t} \quad (5.1)$$

Equation (5.1) was estimated using pooled OLS, random effects (RE) and fixed effects (FE)[33]. In the latter, segment dummies were excluded. For the panel estimators, each combination of merchant, brand, form of capture and number of installments was treated as a unit of cross-section. The number of observations is 235.367 and all estimators we use are robust to heteroscedasticity.

[32] The identification of α_0, in case this equation was to be estimated in this form, would require the exclusion of a dummy $dseg_s$ for some s.

[33] For these estimation we excluded entries for number of installments higher than 10. This decision was taken because in several cases these transactions are not observed. Since the occurrence of transactions in the pseudo control group of a given g is necessary for the transformed observations to be computed, absence or presence of such observations might generate some bias (for example, selecting only one brand, acquirer and form of capture combination for these long operations). For OLS and RE pseudo control segment dummies plus one were excluded, enabling the identification of a constant.

Table 5.1 – Results of equation (5.1) estimation

Variável	Coeficiente	OLS	RE	FE
$dpost_t$	γ	-0.19401***	-0.16740***	-0.15904***
		(0.00219)	(0.00240)	(0.00628)
$IF_{s,b,a,f,n,t} - \widetilde{IF}_{b,a,f,n,t}$	α_1	0.13004***	0.13276***	0.14662***
		(0.00613)	(0.00604)	(0.01185)
$v_{i,s,b,a,f,n,t} - \tilde{v}_{b,a,f,n,t}$	α_2	-0.23774***	-0.04807***	-0.03341
		(0.01381)	(0.01303)	(0.02554)

The three estimators employed agree qualitatively about the diagnostic that in fact there is a break in the discount rate series, even after purging the element common to the control group, as is verified by the negative and significant coefficients related to $dpost_t$, the dummy that indicates the period after the intervention in the industry[34]. Estimated coefficients are displayed in Table 5.1. Full regression results are shown in the appendix.

We may attempt an economic interpretation of the other results taking as given the values for the control groups. Thus, in first place we observe that higher interchange fees are associated with higher discount rates, as expected. It does not seem adequate to interpret these coefficients as markups, since there is no economic model underlying these estimations to justify that.

Secondly, higher transaction values are related to lower discount rates, what probably captures the higher bargain power of larger merchants, but also may reflect a smaller cost by each Real transacted.

Thirdly, a higher number of transactions results in a higher discount rate. Keeping in mind that this result is obtained given transaction value, an increase in the number of transactions probably raises acquirers' costs. When we exclude $v_{i,s,b,a,f,n,t} - \tilde{v}_{b,a,f,n,t}$ from the equation, coefficients obtained for $q_{i,s,b,a,f,n,t} - \tilde{q}_{b,a,f,n,t}$ become negative, corroborating this interpretation, since in that context the number of transactions becomes the merchant size measure.

Finally, coefficients of dummy variables were not included in the table, because we are not directly interested in them. We made estimations with a constant and, therefore, excluding

[34] Before the intervention, average difference of the discount rates with pseudo control groups was -0.29387. In absolute terms, the impact of the end of exclusivity corresponds to an increase of 66% in this measure.

one of the segment dummies, automatically selected by the software in RE estimation. Using results of OLS and RE, we performed equality tests for the segment dummies coefficients, without even imposing that these values would all be zero[35]. They rejected the null hypothesis at all usual confidence levels. This reflects the price dispersion between segments.

5.2. Impact decomposition model

We estimate equation (3.2) with nonlinear least squares, using a covariance matrix robust to heteroscedasticity. Data are the same as in the previous section, with the only difference that they were not transformed and all segments were directly included[36].

On the cost side, the main identifying assumption is that there are no marginal costs omitted terms that, even after we control for market segment dummies and the number and value of transactions, are correlated with the interaction of interchange fee with the intervention dummy. On the demand side, analogously, we assume the absence of omitted elements correlated with the intervention, given the controls we propose.

The impact of the end of exclusivity on markup, measured by the estimated parameter φ, is -0.142, with a 95% confidence interval between -0.139 and -0.145.

That indicates that the end of exclusivity was effective in the reduction of estimated markups. We build a measure of average markup using the average value of the number of transactions and of active cards and taking the simple average of markup intercept along segments. We find a factor of 1.62, that means, a margin of 62% over marginal cost and a reduction of almost 23% of that measure. This result is consistent with the increase in competition.

As for the impact on marginal cost, the estimated measure for ω is not significantly different from zero. That result is not surprising if we keep in mind that in the production side, the end of exclusivity actually allowed acquirers to add a product (a new brand) to their acquiring infrastructure. That way, possible gains, mainly related to fixed cost[37], may leave the cost of having one extra merchant acquired unchanged. Furthermore, notice that the marginal

[35] We did not analyze the possibility of subgroups of segments having equal coefficients, given that the information of what kind of merchant they contain is difficult to use to obtain some kind of pattern.

[36] Full results for the nonlinear regression and a summary of them including all variables for the other regressions are shown in the appendix.

[37] In addition, such gains would be expected from an increase in cooperation at the infrastructure level, which did not materialize.

costs we work with are net from merchant's network value, so that a drop in marginal cost may have been compensated by a reduction of part of the network captured by the acquirer once he ceases to be the only one for a card brand.

As robustness tests, we perform linear estimations. If we multiply markup and marginal cost terms in equation (3.2), we obtain an equation like the following:

$$d_{kt} = \sum_s \alpha_{1,s} b_s IF_{kt} + \alpha_2 t_{kt} IF_{kt} + \alpha_3 c_t IF_{kt} + \alpha_4 dpost_t IF_{kt} + \sum_s \alpha_{5,s} \frac{b_s}{v_{kt}} + \sum_s \alpha_{6,s} \frac{b_s}{v_{kt}} c_t + \sum_s \alpha_{7,s} \frac{b_s}{v_{kt}} t_{kt} + \sum_s \alpha_{8,s} \frac{b_s}{v_{kt}} dpost_t + \alpha_9 \frac{t_{kt}^2}{v_{kt}} + \alpha_{10} \frac{t_{kt}}{v_{kt}} dpost_t + \alpha_{11} \frac{t_{kt}}{v_{kt}} c_t + \alpha_{12} \frac{dpost_t}{v_{kt}} c_t + \alpha_{13} \frac{dpost_t}{v_{kt}} \qquad (5.2)$$

This equation does not explicitly consider restrictions over parameters imposed by the original one, making it more flexible[38]. In this form, the main variable of interest is $dpost_t IF_{kt}$, the interaction between the intervention dummy and the interchange fee. Therefore, we use the fact that the coefficient of interchange fee in the marginal cost is known to be equal to 1 to capture the impact of the intervention on markup through the coefficient α_4. Additionally, we are interested in the effect on marginal cost, which can be computed from α_{12} and α_3 or from α_{13} and α_4, as we will describe.

Equation (5.2) was estimated using ordinary least squares as in the original formulation (we call that version NOC, for "no constant") and with intercept (OLS). It was also estimated taking into account the panel structure, with random (RE) and fixed effects (FE), using the combination of merchants, brand, number of installments and form of capture as the cross-section unit. All estimations use covariance matrices robust to heteroscedasticity.

These robustness tests confirm the conclusion we have presented in this section. In particular, the impact of the end of exclusivity on markup, α_4, has a point estimate between -0.132 and -0.141. Confidence intervals are displayed in Table 5.2.

Table 5.2 – Robustness tests: α_4

Estimator	Coefficient	Std. Dev.	95% confidence interval	
NOC	-0.13653	0.00230	-0.14105	-0.13202
OLS	-0.13233	0.00172	-0.13570	-0.12896
RE	-0.13812	0.00132	-0.14070	-0.13554

38 Later on, we test these restrictions.

As for the impact on marginal costs, represented by ω in equation (3.2), there is no parameter in (5.2) that corresponds directly to it. Although it is also part of other coefficients of this equation, implicit values of ω may be estimated dividing $\hat{\alpha}_{12}$ by $\hat{\alpha}_3$or $\hat{\alpha}_{13}$ by $\hat{\alpha}_4$, where "^" indicated estimates. We call the first value $\widehat{\omega}_1$ and the second $\widehat{\omega}_2$. Standard deviations for each of them and for the statistic $\widehat{\omega}_2 - \widehat{\omega}_1$ were obtained by the delta method.

Table 5.3 - Robustness tests: ω

Estimator	$\widehat{\omega}_1$	Std.Dev.	$\widehat{\omega}_2$	Std.Dev.	$\widehat{\omega}_2 - \widehat{\omega}_1$	Std.Dev.	p-value
NOC	-2.69E-06	5.71e-07	1.29E-05	3.06E-06	1.56E-05	3.05-E-06	8.72E-06
OLS	-2.18E-06	1.14E-06	5.82E-06	2.16E-06	8.01E-06	2.96E-06	6.89E-03

Results may be analyzed in Table 5.3, where we show that the restriction $\widehat{\omega}_1 = \widehat{\omega}_2$ is strongly rejected in each of the estimations. Furthermore, considering $\widehat{\omega}_1$ or $\widehat{\omega}_2$ individually, there is no robustness between such estimators.

In order to grasp the general performance of the model, we compute the forecasts it generates for the discount rate in the sample period. For each quarter, we take the weighted average of the forecasts, using observed cross-section transaction values as weights. This measure is compared to the analogous one, calculated using observed data. Both these measures are displayed in Graph 6, in two panels. Panel A shows the result considering a version of the model we call "No-Break", which excludes the intervention dummy. Panel B shows the original model ("Break").

The estimator we employ for the forecasts calculations is the OLS without a constant (NOC), The reason for this choice is that it is just a little more flexible than the original model, but much more economic in terms of computational capacity. That is a very convenient feature, because we need to use bootstrapping to compute confidence intervals. The number of requested replications was 100, but there were 21 fails in the "Break" case. Anyway, results are very similar to the ones obtained requesting only 50 replications. The resulting confidence intervals seem reasonably small, varying between 0.081 and 0.191 percent point above and below average forecasts.

As we verify in the graph, the "No-Break" version produces practically one sole decreasing tendency through all the sample period and leaves many observations immediately preceding the intervention and others in 2008 and 2012 outside the confidence intervals. The "Break" version performs much better, although it overestimates (in 0.036 percent point, considering the upper limit of the confidence interval) the immediate reduction of the average discount rate at the time of the break.

Graph 6 – Average Discount Rates: Observed X Forecasted
Data Source of Observed Values: Banco Central do Brasil

Other Results

It is worthwhile to look briefly at the results for the issues of price discrimination and network effects that we discussed in the article.

Concerning the first issue, markups vary significantly across market segments and with merchant size. Estimated α_s were significantly larger than one in estimations which are closer to the theoretical model, i.e. Nonlinear and NOC. In OLS estimation all of them were significantly larger than zero, what also happened in RE estimation, but for one segment, for which the estimated coefficient was negative but not significant[39]. Furthermore, the hypothesis of equal α_s for all segments was rejected[40].

As for coefficient β, representing the impact on markup of the number of transactions, the estimated value is -0.105 in the nonlinear model, meaning a sizeable reduction if, *coeteris paribus*, a cross-section unit has an increase of a million transactions[41]. Specifications estimated as robustness tests confirm that larger merchants get smaller markups. Estimated β's vary between -0.190 and -0.065, all of them significant at 0.1%, as is shown in table 5.4.

Table 5.4 - β

Estimator	**Coefficient**	**Std.Dev.**	**Confidence Interval 95%**	
Nonlinear	-0.10523	0.01185	-0.12844	-0.08201
NOC	-0.06529	0.01430	-0.09332	-0.03726
OLS	-0.18992	0.01837	-0.22592	-0.15392

As for the hypothesis of different marginal costs as an explanation for price dispersion, it may be more directly analyzed in the nonlinear specification. Estimates of θ_s are quite heterogeneous. We do not report them in the main text, since there is no direct interest in them, but likelihood ratio tests for the estimated model and for its homoscedastic version reject equality of these coefficients through segments at all usual significance levels.

[39] When we say simply "significant", without stating the confidence level, we mean "significant at all usual confidence levels".

[40] In the Nonlinear specification, we use a likelihood ratio test. In linear regressions, equality of $\alpha_{1,s}$ was rejected by Wald tests.

[41] We may use the same procedure we employed for the fall in markup brought about by the end of exclusivity. The estimated value for β implies a reduction of 17% of the margin accompanies an increase of a million transactions.

Also, parameter μ, which seeks to capture the impact of a merchant size increase in the cost of adding him to the scheme, was estimated to be 0.137 and significant in the nonlinear regression, which implies, given transacted value, an increase of R$ 0.00137 in the cost of acquiring one extra merchant, if, *coeteris paribus*, he had a million transactions more. Therefore, although statistically significant, this effect is quantitatively small. Furthermore, the coefficient was not robust trough different specifications and the equality of the parameters obtained from (4.2) computing $\mu_1 = \alpha_9/\alpha_2$ and $\mu_2 = \alpha_{11}/\alpha_3$ was rejected in three of them. In the FE estimation, in which this equality was not rejected, one of the estimated parameters was positive and not significant while the other was negative and significant, as may be verified in Table 5.5.

Table 5.5 Robustness tests:μ

Estimator	$\widehat{\mu}_1$	Std.Dev.	$\widehat{\mu}_2$	Std.Dev.	$\widehat{\mu}_2 - \widehat{\mu}_1$	Std.Dev.	p-value
NOC	1.02720	0.36168	-0.38976	0.04919	-1.41697	0.36162	0.00009
OLS	0.23948	0.07845	-0.90220	0.11440	-1.14168	0.13648	0.00000

As for network effects, apart from what is indistinguishable from marginal costs in our formulation, the regressor available (number of active cards nationwide in each scheme) does not perform well to capture them. The estimated parameter is always negative, significant and superior to -0.015, as may be checked from Table 5.6. Probably this indicates the negative correlation between the active number of cards, which always presented an increasing tendency, and discount rates. The inadequacy of the regressor is likely to be related to it only presenting two possible values at each point in time, being unable to reflect the number of cardholders that really is relevant for merchant choice of participation[42].

Table 5.6 - γ

Estimator	Coefficient	Std.Dev.	Confidence Interval 95%	
Não Linear	-0.01329	0.00149	-0.14503	-0.13922
NOC	-0.01425	0.00017	-0.01458	-0.01392
OLS	-0.00375	0.00013	-0.00400	-0.00349

[42] There is also the argument that, when a two-sided market becomes mature, marginal network externalities may disappear. That is to say, given that there is a very large mass of participants on one side, its increase does not generate additional interest for participation on the other side. In large Brazilian cities it may be possible to think that additional cardholders do not affect merchant choice, but considering less developed regions that idea is much less appealing. This highlights the importance of having regional data for this kind of analysis.

6. Conclusion

In this paper we develop two empirical models to evaluate the effects of the break of exclusivity on the acquiring side of Visa and MasterCard credit card schemes in Brazil. In the first model, we try to identify a pseudo control group, less sensitive to the intervention, to purge common effects between merchants that might mislead our conclusions. In the second model, we decompose the main price formed in the industry, the merchant discount rate, into marginal cost and markup. We base our specification in an acquirers profit maximization equation and we use information on the interchange fee (an observable part of marginal cost that has a known coefficient) to identify these components.

Our main conclusion is that the intervention produced a price reduction mainly explained by a markup decrease, which we interpret as an increase in competition. We find a reduction of 14.2 percent points on an average margin of 62% over marginal cost, representing a reduction of almost 23% of that measure. Although the composition of the sample (the largest merchants of each market segment) restricts the reach of the results, they still remain a strong indication of the success of the intervention.

Estimations did not allow the isolation of network effects, which is not surprising, given the limitations in our dataset. Indeed, the recent literature about network effects in the credit card industry, as Carbó-Valverde, Liñares-Zegarra and Rodríguez-Fernández (2012) and Rysman (2007) employ data with variation in the geographic dimension, which is not the case of our dataset.

On the other hand, results strongly reflect another characteristic of acquirers operation in Brazil: price discrimination. We find that markups vary between market segments and are smaller for larger merchants. This characteristic had already been detected, with another approach, in BCB, SEAE & SDE (2010), Annex C.

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Appendix

In this appendix, we report the full econometric results we obtained. In order to help interpretation, we present once more the equations introduced in the main text.

Results – Control group Model

$$d_{m,s,b,a,f,n,t} - \tilde{d}_{b,a,f,n,t} = \alpha_1\left(IF_{s,b,a,f,n,t} - \widetilde{IF}_{b,a,f,n,t}\right) + \alpha_2\left(v_{m,s,b,a,f,n,t} - \tilde{v}_{b,a,f,n,t}\right) + \alpha_3\left(q_{m,s,b,a,f,n,t} - \tilde{q}_{b,a,f,n,t}\right) + \Sigma_s(\beta_s - \tilde{\beta}_c)dseg_{s(m)} + \gamma dpost_t + \check{\varepsilon}_{i,t} \quad (5.1)$$

Table A.1- Control group model – Estimated coefficients:

		OLS	RE	FE
$IF_{s,b,a,f,n,t} - \widetilde{IF}_{b,a,f,n,t}$	α_1	.13003599***	.13276092***	.14661752***
$v_{m,s,b,a,f,n,t} - \tilde{v}_{b,a,f,n,t}$	α_2	-.23773761***	-.04806773***	-0.03341029
$q_{m,s,b,a,f,n,t} - \tilde{q}_{b,a,f,n,t}$	α_3	.05477802***	0.01796552	0.01584841
$dpost_t$	γ	-.19401241***	-.16739639***	-.15903532***
Segment Dummies:	$(\beta_{01} - \tilde{\beta}_c)$	-.10971518***	-.15997976***	
	$(\beta_{03} - \tilde{\beta}_c)$	.07236604***	-.1566945***	
	$(\beta_{04} - \tilde{\beta}_c)$	.51561182***	.37485214***	
	$(\beta_{05} - \tilde{\beta}_c)$	-.06854851***	-.15229179***	
	$(\beta_{06} - \tilde{\beta}_c)$	.50161604***	.47419221***	
	$(\beta_{07} - \tilde{\beta}_c)$	.17288063***	0.04112005	
	$(\beta_{08} - \tilde{\beta}_c)$	.26616834***	.21088602***	
	$(\beta_{09} - \tilde{\beta}_c)$	-0.00092428	-.2115453***	
	$(\beta_{10} - \tilde{\beta}_c)$	-.31958371***	-.52698731***	
	$(\beta_{11} - \tilde{\beta}_c)$	-.24117237***	-.31448119***	
	$(\beta_{12} - \tilde{\beta}_c)$	.05181055***	-0.04180042	
	$(\beta_{14} - \tilde{\beta}_c)$	.52351903***	.18710223***	
	$(\beta_{15} - \tilde{\beta}_c)$	-.44794395***	-.62954085***	
	$(\beta_{16} - \tilde{\beta}_c)$	.54224521***	.51461218***	
	$(\beta_{17} - \tilde{\beta}_c)$	-.27608382***	-.42895636***	
	$(\beta_{18} - \tilde{\beta}_c)$	-.14897293***	-.18280011***	
	$(\beta_{19} - \tilde{\beta}_c)$	.36111827***	.1871275***	
	$(\beta_{20} - \tilde{\beta}_c)$	1.2399698***	1.1956409***	
	$(\beta_{21} - \tilde{\beta}_c)$	-.27077966***	-.46866955***	
	$(\beta_{22} - \tilde{\beta}_c)$	.25441072***	0.00707271	
	$(\beta_{23} - \tilde{\beta}_c)$	-.21039582***	-.39723705***	

(continues)

(end)

	OLS	RE	FE
$(\beta_{24} - \tilde{\beta}_c)$	.12542952***	-0.042274	
$(\beta_{26} - \tilde{\beta}_c)$	.15061181***	-0.05800768	
$(\beta_{27} - \tilde{\beta}_c)$	.35412846***	.21249754***	
$(\beta_{28} - \tilde{\beta}_c)$	.37330676***	.34933283***	
$(\beta_{29} - \tilde{\beta}_c)$	.13255518***	-.11212723**	
constant	-.32245912***	-.15518429***	-.27864338***

Segments with excluded dummies: 2, 13, 25

Legend: * p<0.05, ** p<0.01, *** p<0.001

Results – Impact Decomposition Model

Nonlinear estimation:

$$d_{kt} = \left(\sum_{s \in S} \alpha_s b_s + \beta t_{kt} + \gamma c_t + \varphi dpost_t\right)\left[IF_{kt} + \sum_{s \in S} \theta_s \frac{b_s}{v_{kt}} + \mu \frac{t_{kt}}{v_{kt}} + \omega \frac{dpost_t}{v_{kt}}\right] \quad (3.2)$$

Number of observations: 284,304

R^2:0.9564

Adjusted R^2: 0.9564

Root MSE: 0.5666312

Table A.2- Nonlinear Estimation – Markup Components

		Coefficient	Robust Std. Dev.	t	P-value	[Conf. Interv.	
Segment Dummies:	α_{01}	1.888726	0.005391	350.37	0.000	1.878161	1.
	α_{02}	2.205033	0.006173	357.23	0.000	2.192935	2.
	α_{03}	1.986331	0.006017	330.11	0.000	1.974538	1.
	α_{04}	2.391295	0.00777	307.76	0.000	2.376066	2.
	α_{05}	2.054165	0.011959	171.77	0.000	2.030726	2.
	α_{06}	2.380607	0.007421	320.81	0.000	2.366063	2.
	α_{07}	2.093431	0.00582	359.67	0.000	2.082023	2.
	α_{08}	2.14471	0.006516	329.17	0.000	2.13194	[illegible]
	α_{09}	2.071278	0.005761	359.51	0.000	2.059986	2.
	α_{10}	1.835721	0.006519	281.61	0.000	1.822945	1.
	α_{11}	1.937016	0.005983	323.77	0.000	1.92529	1.
	α_{12}	2.198761	0.01517	144.94	0.000	2.169029	2.
	α_{13}	2.004025	0.019014	105.4	0.000	1.966758	2.
	α_{14}	2.445115	0.012516	195.35	0.000	2.420583	2.
	α_{15}	1.811259	0.007402	244.7	0.000	1.796751	1.
	α_{16}	2.25618	0.010066	224.15	0.000	2.236452	2.
	α_{17}	1.883229	0.007325	257.11	0.000	1.868873	1.
	α_{18}	1.949991	0.007404	263.39	0.000	1.93548	1.
	α_{19}	2.12119	0.006094	348.06	0.000	2.109245	2.
	α_{20}	2.256095	0.180382	12.51	0.000	1.902552	2.
	α_{21}	1.718635	0.006706	256.29	0.000	1.705492	1.
	α_{22}	1.928431	0.0076	253.74	0.000	1.913536	1.
	α_{23}	1.71946	0.005341	321.94	0.000	1.708992	1.
	α_{24}	1.836013	0.009975	184.07	0.000	1.816463	1.
	α_{25}	2.059463	0.009333	220.67	0.000	2.041171	2.
	α_{26}	1.925091	0.005775	333.33	0.000	1.913772	1.
	α_{27}	1.973374	0.007145	276.18	0.000	1.95937	1.
	α_{28}	2.09874	0.008249	254.42	0.000	2.082572	2.
	α_{29}	1.84639	0.006636	278.25	0.000	1.833384	1.
Transaction number([illegible]):	β	-0.10523	0.011846	-8.88	0.000	-0.12844	-(
Active card quant.([illegible]):	γ	-0.01329	0.000131	-101.69	0.000	-0.01355	-(
Break Dummy ([illegible]):	φ	-0.14213	0.001485	-95.74	0.000	-0.14503	-(

Table A.3- Nonlinear Estimation – Marginal Cost Components

(variables are divided by transacted value)

		Coefficient	Robust Std. Dev.	t	P-value	[Conf. Interv.	
Segment Dummies:	θ_{01}	-1.33E-07	1.39E-08	-9.61	0.000	-1.61E-07	-1.06
	θ_{02}	-1.21E-07	1.90E-08	-6.36	0.000	-1.58E-07	-8.36
	θ_{03}	-1.27E-07	1.24E-08	-10.19	0.000	-1.51E-07	-1.02
	θ_{04}	-1.52E-07	2.16E-08	-7.02	0.000	-1.94E-07	-1.09
	θ_{05}	-4.34E-08	2.43E-08	-1.79	0.074	-9.10E-08	4.15
	θ_{06}	-1.01E-07	4.33E-08	-2.32	0.020	-1.86E-07	-1.58
	θ_{07}	4.36E-08	6.54E-08	0.67	0.505	-8.45E-08	1.72
	θ_{08}	-1.35E-07	1.20E-08	-11.24	0.000	-1.58E-07	-1.11
	θ_{09}	-1.12E-07	2.00E-08	-5.62	0.000	-1.51E-07	-7.30
	θ_{10}	-1.56E-07	2.78E-08	-5.63	0.000	-2.11E-07	-1.02
	θ_{11}	-6.58E-08	2.86E-08	-2.3	0.021	-1.22E-07	-9.80
	θ_{12}	-1.26E-07	1.43E-08	-8.77	0.000	-1.54E-07	-9.75
	θ_{13}	-6.89E-08	2.16E-08	-3.2	0.001	-1.11E-07	-2.66
	θ_{14}	-3.71E-07	1.33E-07	-2.79	0.005	-6.31E-07	-1.10
	θ_{15}	-1.00E-07	1.98E-08	-5.06	0.000	-1.39E-07	-6.13
	θ_{16}	-1.35E-07	1.18E-08	-11.48	0.000	-1.58E-07	-1.12
	θ_{17}	-1.41E-07	3.20E-08	-4.41	0.000	-2.04E-07	-7.84
	θ_{18}	-2.13E-07	9.44E-08	-2.25	0.024	-3.98E-07	-2.77
	θ_{19}	-1.30E-07	1.87E-08	-6.94	0.000	-1.66E-07	-9.30
	θ_{20}	-1.41E-07	1.33E-08	-10.59	0.000	-1.67E-07	-1.15
	θ_{21}	-3.91E-07	3.87E-08	-10.11	0.000	-4.67E-07	-3.15
	θ_{22}	-1.42E-07	1.70E-08	-8.38	0.000	-1.76E-07	-1.09
	θ_{23}	-1.37E-07	1.22E-08	-11.25	0.000	-1.61E-07	-1.13
	θ_{24}	-2.18E-07	2.24E-08	-9.72	0.000	-2.62E-07	-1.74
	θ_{25}	-2.16E-07	2.63E-08	-8.2	0.000	-2.68E-07	-1.64
	θ_{26}	-1.51E-07	1.32E-08	-11.41	0.000	-1.77E-07	-1.25
	θ_{27}	-1.03E-07	2.47E-08	-4.18	0.000	-1.52E-07	-5.48
	θ_{28}	-1.30E-07	3.72E-08	-3.48	0.000	-2.03E-07	-5.67
	θ_{29}	-1.28E-07	3.13E-08	-4.1	0.000	-1.90E-07	-6.69
Transaction number([illegible]):	μ	0.137762	0.011804	11.67	0.000	0.114627	0.16
Break Dummy ([illegible]):	ω	-1.03E-08	1.19E-08	-0.87	0.384	-3.36E-08	1.30

Linear Estimations

$$d_{kt} = \sum_s \alpha_{1,s} b_s IF_{kt} + \alpha_2 t_{kt} IF_{kt} + \alpha_3 c_t IF_{kt} + \alpha_4 dpost_t IF_{kt} + \sum_s \alpha_{5,s} \frac{b_s}{v_{kt}} + \sum_s \alpha_{6,s} \frac{b_s}{v_{kt}} c_t + \sum_s \alpha_{7,s} \frac{b_s}{v_{kt}} t_{kt} + \sum_s \alpha_{8,s} \frac{b_s}{v_{kt}} dpost_t + \alpha_9 \frac{t_{kt}^2}{v_{kt}} + \alpha_{10} \frac{t_{kt}}{v_{kt}} dpost_t + \alpha_{11} \frac{t_{kt}}{v_{kt}} c_t + \alpha_{12} \frac{dpost_t}{v_{kt}} c_t + \alpha_{13} \frac{dpost_t}{v_{kt}} \tag{5.2}$$

Table A.4- Linear Estimations

		NOC	OLS	RE	FE
$b_s IF_{kt}$:	$\alpha_{1,01}$	1.909309***	.55350438***	.28267492***	.32730183***
	$\alpha_{1,02}$	2.177344***	.85224592***	.436829***	.16033399***
	$\alpha_{1,03}$	1.9972772***	.68360426***	.22718724***	-0.00885772
	$\alpha_{1,04}$	2.4109419***	.98985066***	.51355668***	-0.11802937
	$\alpha_{1,05}$	2.1196514***	.65325748***	.21573197***	-.34146665**
	$\alpha_{1,06}$	2.4009743***	.9670918***	.57421589***	.20910565***
	$\alpha_{1,07}$	2.1336579***	.76284014***	.31471828***	.21418675***
	$\alpha_{1,08}$	2.0646324***	.71814256***	.37840119***	.0523319**
	$\alpha_{1,09}$	2.0786087***	.62208281***	.10255499***	-.05934492*
	$\alpha_{1,10}$	1.8241626***	.46352645***	.04248205***	.25697114***
	$\alpha_{1,11}$	1.9092123***	.51696925***	.1937515***	.27003616***
	$\alpha_{1,12}$	2.3051991***	.81405476***	.28739925***	0.06842023
	$\alpha_{1,13}$	2.2575413***	.60080878***	.255178***	.27971987***
	$\alpha_{1,14}$	2.3604034***	.87197158***	.34454406***	.14743259***
	$\alpha_{1,15}$	1.8104045***	.45050723***	-0.0159441	0.11748077
	$\alpha_{1,16}$	2.2883805***	.92135478***	.44328041***	.12566587**
	$\alpha_{1,17}$	1.913713***	.49632812***	.0757381***	.28657461***
	$\alpha_{1,18}$	2.0086222***	.57977407***	.2165272***	.07800907**
	$\alpha_{1,19}$	2.1094488***	.82371126***	.33191628***	-.12815961***
	$\alpha_{1,20}$	2.8217823***	1.258859***	.69336579***	.05245434**
	$\alpha_{1,21}$	1.7509513***	.36965116***	-.02808943**	.45703974***
	$\alpha_{1,22}$	1.9537458***	.63378335***	.17454968***	-.20318786***
	$\alpha_{1,23}$	1.7477497***	.45565695***	.10248335***	.57364129***
	$\alpha_{1,24}$	1.8881243***	.54732319***	.16415578***	.42117894***
	$\alpha_{1,25}$	2.1547306***	.8013648***	.3306422***	.52426673***
	$\alpha_{1,26}$	1.9702427***	.56695163***	.12323472***	-0.08233804
	$\alpha_{1,27}$	1.9882175***	.6762323***	.26125599***	.32448286***
	$\alpha_{1,28}$	2.1257927***	.73296876***	.30187336***	.20945694***
	$\alpha_{1,29}$	1.8589585***	.55910998***	.17632543***	.12775854**
$t_{kt} IF_{kt}$	α_2	-.0652863***	-.18991786***	-.10066301***	-.07576451***
$c_t IF_{kt}$	α_3	-.01425168***	-.00374861***	-.00177317***	-.00077785***
$dpost_t IF_{kt}$	α_4	-.13653442***	-.13232961***	-.13812077***	-.14061584***
b_s/v_{kt}	$\alpha_{5,01}$	1.749e-06*	8.259e-07**	1.52E-07	5.691e-07*
	$\alpha_{5,02}$	1.793e-06**	8.66E-07	5.797e-07*	8.509e-07***
	$\alpha_{5,03}$	-1.893e-07***	2.818e-07***	1.120e-07***	2.239e-07*
	$\alpha_{5,04}$	-1.24E-07	-6.63E-09	1.354e-07*	-5.28E-08
	$\alpha_{5,05}$	2.03E-07	3.241e-07*	9.44E-08	-4.90E-08

(continues)

		NOC	OLS	RE	FE
b_s/v_{kt}	$\alpha_{5,06}$	-6.493e-07*	-5.147e-07*	6.24E-08	-7.44E-08
	$\alpha_{5,07}$	2.666e-06***	1.284e-06**	-1.68E-07	-2.77E-07
	$\alpha_{5,08}$	5.50E-08	-5.92E-07	-1.07E-07	-1.45E-07
	$\alpha_{5,09}$	1.639e-06***	7.596e-07***	9.84E-08	-4.59E-11
	$\alpha_{5,10}$	1.335e-07**	1.262e-07***	-7.75E-09	-1.45E-08
	$\alpha_{5,11}$	-4.05E-07	3.46E-07	1.16E-07	2.03E-07
	$\alpha_{5,12}$	1.616e-07*	4.88E-08	6.764e-08*	5.39E-08
	$\alpha_{5,13}$	2.288e-06***	6.008e-07*	-1.31E-07	-7.84E-08
	$\alpha_{5,14}$	-1.66E-06	-8.15E-07	1.436e-06**	1.600e-06***
	$\alpha_{5,15}$	-5.89E-08	3.628e-07***	5.58E-08	1.08E-08
	$\alpha_{5,16}$	-8.17E-08	4.184e-08*	-5.350e-08***	-4.36E-08
	$\alpha_{5,17}$	-1.15E-08	1.807e-06***	2.58E-07	2.42E-07
	$\alpha_{5,18}$	-1.06E-07	-5.191e-07***	-1.650e-07**	-1.148e-07*
	$\alpha_{5,19}$	7.439e-07**	5.291e-07***	-5.70E-08	-1.822e-07**
	$\alpha_{5,20}$	2.526e-07***	1.512e-07***	1.39E-09	-1.66E-08
	$\alpha_{5,21}$	-8.591e-07*	-1.93E-07	-2.34E-07	-1.05E-07
	$\alpha_{5,22}$	-3.58E-07	-2.50E-07	7.02E-08	-2.28E-08
	$\alpha_{5,23}$	1.74E-08	2.904e-07***	1.163e-07***	1.60E-08
	$\alpha_{5,24}$	-1.40E-10	1.59E-07	-1.04E-07	-7.96E-08
	$\alpha_{5,25}$	-2.40E-08	1.67E-07	-1.42E-07	-1.89E-07
	$\alpha_{5,26}$	-4.66E-08	-1.58E-07	-1.53E-07	-1.26E-07
	$\alpha_{5,27}$	-8.273e-07*	-2.41E-07	4.663e-07**	6.214e-07***
	$\alpha_{5,28}$	-7.340e-07*	1.11E-07	1.99E-07	2.36E-07
	$\alpha_{5,29}$	2.70E-07	4.66E-07	-2.32E-08	-1.07E-07
$b_s c_t/v_{kt}$	$\alpha_{6,01}$	-6.855e-08**	-2.596e-08***	-4.35E-09	-1.491e-08**
	$\alpha_{6,02}$	-7.473e-08**	-3.044e-08*	-2.029e-08*	-3.372e-08***
	$\alpha_{6,03}$	-5.937e-09***	-3.749e-09***	-2.87E-10	-4.72E-09
	$\alpha_{6,04}$	-5.72E-09	2.92E-09	-1.14E-09	2.13E-09
	$\alpha_{6,05}$	-3.50E-10	-1.85E-09	-1.46E-09	1.02E-09
	$\alpha_{6,06}$	1.64E-08	2.081e-08*	3.32E-09	5.46E-09
	$\alpha_{6,07}$	-6.691e-08**	4.37E-09	6.89E-09	2.35E-09
	$\alpha_{6,08}$	-4.791e-08***	-1.43E-08	-2.99E-09	2.71E-09
	$\alpha_{6,09}$	-6.313e-08***	-2.010e-08***	2.71E-09	7.52E-09
	$\alpha_{6,10}$	-2.563e-08***	-3.471e-09***	8.79E-10	-7.21E-10
	$\alpha_{6,11}$	-9.77E-09	-7.62E-09	-1.51E-09	-7.22E-09
	$\alpha_{6,12}$	-8.207e-09***	1.71E-09	-2.42E-10	-1.20E-09
	$\alpha_{6,13}$	-6.290e-08***	-1.39E-08	4.44E-09	1.10E-09
	$\alpha_{6,14}$	4.48E-08	2.27E-08	-3.470e-08*	-3.836e-08**
	$\alpha_{6,15}$	-7.268e-09***	-5.777e-09***	-6.26E-10	-1.49E-09
	$\alpha_{6,16}$	-5.587e-09***	-3.750e-09***	-1.70E-10	-2.84E-11
	$\alpha_{6,17}$	-2.50E-09	-5.269e-08***	-9.635e-09*	-8.62E-09
	$\alpha_{6,18}$	3.45E-09	1.614e-08***	3.913e-09*	2.39E-09
	$\alpha_{6,19}$	-4.321e-08***	-1.274e-08**	1.82E-09	5.270e-09**
	$\alpha_{6,20}$	-6.154e-09***	-3.435e-09***	4.01E-10	7.26E-10
	$\alpha_{6,21}$	1.45E-08	1.52E-08	5.82E-09	9.68E-10
	$\alpha_{6,22}$	3.01E-09	1.08E-08	3.96E-09	7.38E-09
	$\alpha_{6,23}$	-7.011e-09***	-4.127e-09***	-5.88E-11	-1.48E-10
	$\alpha_{6,24}$	-1.34E-08	-1.039e-08*	2.09E-09	1.20E-09
	$\alpha_{6,25}$	-1.14E-08	-4.61E-09	3.24E-09	3.19E-09
	$\alpha_{6,26}$	-1.91E-09	6.55E-09	7.187e-09*	6.37E-09

(continues)

		NOC	OLS	RE	FE
$b_s c_t/v_{kt}$	$\alpha_{6,27}$	1.93E-08	1.36E-08	-1.828e-08**	-2.583e-08***
	$\alpha_{6,28}$	1.07E-08	-3.35E-09	-8.845e-09*	-9.76E-09
	$\alpha_{6,29}$	-2.19E-08	-1.979e-08*	-5.74E-10	1.85E-09
$b_s t_{tk}/v_{kt}$	$\alpha_{7,01}$	.47371318**	-0.03205233	0.00325041	-0.00051916
	$\alpha_{7,02}$	.74463272***	-0.01794986	0.02112623	-0.06273752
	$\alpha_{7,03}$	.21885995***	-.26289325***	-.08961856***	-0.03019677
	$\alpha_{7,04}$	.18847293***	-.19701127***	-.11840593***	-0.00600196
	$\alpha_{7,05}$	-0.01181459	-.13797707***	-0.02590678	0.03226957
	$\alpha_{7,06}$	.19531761***	-.1074035***	-.13506462***	-0.06290032
	$\alpha_{7,07}$	-.10861662*	-1.2679536***	-.32735096***	-0.09961993
	$\alpha_{7,08}$	1.6220264***	1.0251583***	.240995***	0.05921978
	$\alpha_{7,09}$	.42474133***	-.14001154***	-0.05775876	-0.08749484
	$\alpha_{7,10}$	.25065044***	-.13218098***	-0.00637254	0.03517239
	$\alpha_{7,11}$	.63901372***	-.15932263***	-.08283787***	0.03543938
	$\alpha_{7,12}$	-0.0477638	-.26635697***	-.05215324**	0.00685995
	$\alpha_{7,13}$	-.1803912***	-.15524265***	-0.02904356	0.04874713
	$\alpha_{7,14}$	.44927942***	.32395682***	0.02159677	-0.03871015
	$\alpha_{7,15}$	.13972274***	-.30210895***	-0.04195817	0.0380932
	$\alpha_{7,16}$	0.0899226	-0.02894454	.06653338***	.05640381*
	$\alpha_{7,17}$	0.03273141	-.18188061***	.05178581***	.06122161*
	$\alpha_{7,18}$	-0.07663197	-.09276438***	.07225995***	.07417551***
	$\alpha_{7,19}$	.54383043***	-.14355731***	0.0433431	0.04898973
	$\alpha_{7,20}$	-.23395107***	-.15101705***	-0.00298913	0.00996593
	$\alpha_{7,21}$	-0.00801477	-.18331739***	.02581694**	0.03326115
	$\alpha_{7,22}$	.06175186**	-.13104234***	-.10607593***	-0.10568148
	$\alpha_{7,23}$	0.01790865	-.2806264***	-.11050696***	-0.00123968
	$\alpha_{7,24}$	-0.01155553	-.13550853***	-0.00283254	0.02342948
	$\alpha_{7,25}$	-.14838776***	-.43762735***	-0.02935346	0.04908524
	$\alpha_{7,26}$	-.08282882***	-.15125833***	-.05652823**	-0.05224609
	$\alpha_{7,27}$	.12393717***	-.20267551***	.10999515***	.18732868***
	$\alpha_{7,28}$	.08012748***	-.13543032***	0.02457116	0.01762803
	$\alpha_{7,29}$	.14251654***	.06244633**	.02775924*	0.02972312
$b_s dpost_t/v_{kt}$	$\alpha_{8,01}$	6.004e-07*	6.256e-07**	-1.46E-07	-2.23E-07
	$\alpha_{8,02}$	4.36E-07	6.936e-07*	-2.56E-08	3.13E-07
	$\alpha_{8,03}$	4.57E-07	5.376e-07*	-1.95E-07	-3.03E-07
	$\alpha_{8,04}$	8.38E-08	3.45E-07	-1.93E-07	-3.16E-07
	$\alpha_{8,05}$	-2.69E-08	2.58E-07	-1.88E-07	-2.74E-07
	$\alpha_{8,06}$	-1.46E-07	4.16E-07	-7.97E-08	-1.91E-07
	$\alpha_{8,07}$	0	0		0
	$\alpha_{8,08}$	3.47E-07	6.683e-07**	-1.35E-07	-2.89E-07
	$\alpha_{8,09}$	5.48E-07	5.717e-07*	-2.97E-07	-4.447e-07*
	$\alpha_{8,10}$	8.385e-07**	5.843e-07*	-1.12E-07	-1.57E-07
	$\alpha_{8,11}$	4.40E-07	5.861e-07*	-1.02E-07	-7.51E-08
	$\alpha_{8,12}$	3.81E-07	5.317e-07*	-1.47E-07	-2.37E-07
	$\alpha_{8,13}$	4.91E-07	4.968e-07*	-1.86E-07	-2.69E-07
	$\alpha_{8,14}$	-1.368e-06**	-7.44E-07	-2.33E-07	-1.52E-07
	$\alpha_{8,15}$	4.39E-07	5.974e-07*	-8.45E-08	-1.62E-07
	$\alpha_{8,16}$	2.73E-07	5.261e-07*	-1.67E-07	-2.56E-07
	$\alpha_{8,17}$	1.57E-07	8.728e-07***	-8.84E-08	-2.06E-07
	$\alpha_{8,18}$	1.02E-07	4.37E-07	-2.25E-07	-3.05E-07
	$\alpha_{8,19}$	5.16E-07	4.935e-07*	-2.26E-07	-3.27E-07

(continues)

(end)

		NOC	OLS	RE	FE
$b_s dpost_t/v_{kt}$	$\alpha_{8,20}$	5.82E-08	9.02E-07	1.41E-06	2.183e-06***
	$\alpha_{8,21}$	6.234e-07*	2.15E-07	-1.31E-07	-1.58E-07
	$\alpha_{8,22}$	4.90E-07	4.77E-07	-2.94E-07	-4.375e-07*
	$\alpha_{8,23}$	5.696e-07*	6.205e-07**	-1.82E-07	-2.61E-07
	$\alpha_{8,24}$	6.407e-07*	7.054e-07**	-1.48E-07	-2.52E-07
	$\alpha_{8,25}$	7.292e-07*	7.453e-07**	-1.29E-07	-2.29E-07
	$\alpha_{8,26}$	2.89E-07	3.94E-07	-2.53E-07	-3.12E-07
	$\alpha_{8,27}$	4.01E-07	4.15E-07	3.89E-08	1.25E-08
	$\alpha_{8,28}$	9.083e-07*	7.448e-07**	3.43E-08	-6.03E-08
	$\alpha_{8,29}$	6.510e-07*	6.108e-07*	-1.97E-07	-2.83E-07
t_{kt}^2/v_{kt}	α_9	-.06706232***	-.04548069***	.03723521***	.0333354***
$t_{kt} dpost_t/v_{kt}$	α_{10}	-.07698177***	-.07420459***	-.06647224***	-.05963289***
$t_{kt} c_t/v_{kt}$	α_{11}	.00555477***	.00338201***	-0.00021382	-0.00034767
$dpost_t c_t/v_{kt}$	α_{12}	3.834e-08***	8.19E-09	-2.31E-09	-5.087e-09**
$dpost_t/v_{kt}$	α_{13}	-1.758e-06***	-7.703e-07**	3.331e-07*	5.269e-07*
constant			1.8849956***	2.5645269***	2.5738617***

Legend: * p<0.05, ** p<0.01, *** p<0.001