Retail Payment Innovations and Cash Usage: Accounting for Attrition Using Refreshment Samples*

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Summary: We estimate a semiparametric panel data model that accounts for unobserved heterogeneity and general forms of non-random attrition to understand the impact of retail payment innovations on cash usage. Previous results from cross-sectional methods find a large impact of retail payment on cash usage (around 10 percent). We use annual data from the 2010-2012 Canadian Financial Monitor and find no significant impact for contactless credit cards and multiple stored-value cards; while single-purpose stored-value cards reduce the usage of cash by 2 percent in terms of volume. These results point to the uneven pace of diffusion of payment innovations.

Keywords: non-random attrition, cash usage, contactless credit and prepaid cards, missing-at-random, selection-on-unobservables, semiparametric panel data.

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1 Introduction

In the past 20 years, there has been a rapid transformation of retail payments systems and the share of cash has been decreasing; Amromin and Chakravorti (2009) document this trend in 13 developed countries for the period 1988-2003. However, a recent study by Bagnall, Bounie, Huynh, Kosse, Schmidt, Schuh, and Stix (2014) finds that cash still remains an important payment method across seven developed countries. The authors find that the cash share, in terms of volume, ranges from 40 percent for the United States to 80 percent for Austria. Also, cash still constitutes a non-trivial value share of payments at about 20 percent. One of the cited reasons for the continual use of cash is that it is used frequently for small-value transactions because of its speed, ease of use and wide acceptance; see Arango, Huynh, and Sabetti (2011) and Wakamori and Welte (2012), who confirm this result for Canada. However, Arango, Huynh, Fung, and Stuber (2012) discuss a number of innovations in the retail payment market that are designed to mimic these attractive features of cash.

One type of innovation is the contactless feature based on near-field communication (NFC) technology. In Canada, almost all credit cards now have a contactless feature and it has gained wider acceptance by merchants over recent years. These contactless credit card payments offer speed and convenience with *tap-and-go* and require no signature or personal identification number (PIN) verification for transactions below a certain value, typically $50. Another type of payment innovation is stored-value or prepaid cards. Such cards, where monetary value is stored, can be grouped into two categories: (1) multi-purpose/open-loop cards, which are mostly offered by the main credit card providers, and (2) single-purpose/closed loop, which are issued by specific retailers.

However, there are few empirical estimates of the effects of these retail payment innovations on the usage of cash. Fung, Huynh, and Sabetti (2012) use the 2009 Bank of Canada Method-of-Payments (MOP) survey and find that the use of contactless credit cards results in a decrease in cash usage of about 10 to 14 percent in terms of volume and value of transactions, respectively. These results are based on only one cross-section from 2009 and may be biased due to the presence of unobservable characteristics. For example, the diffusion and usage of innovations by both consumers and merchants are uneven, especially at the nascent stages. These patterns are known as S-curves: low rates of usage at the early stages of an innovation, a turning point and then almost universal usage. Usually, industries such as payment cards are described as two-sided markets where network externalities matter.[1] So, the reason for usage of payment innovations may be confounded by unobservables. One method to account for unobserved characteristics is to use longitudinal or panel data to model the households' payment decisions over time.[2]

A contribution of this paper is to use panel data from the Canadian Financial Monitor (CFM) to understand the impact of retail payment innovations on cash usage. We use the data from 2010, 2011 and 2012. However, one challenging feature of the data is that the attrition rate is about 50 percent. To correct for this attrition bias, we use a refreshment samples. These estimators allow for both unobserved heterogeneity and general non-random attrition. We find that single-purpose stored-value cards lower cash usage in volume by about 2 percent, while no significant effects are found for other payment innovations. Understanding the impact of retail payment innovations has important implications for central banks, since they are usually the sole issuers of bank notes.[3] Estimates of cash usage can help to inform the efficient handling and distribution of cash.

The rest of this paper is organized as follows. Section 2 provides a description of the CFM data used in the paper. Section 3 describes the challenges posed by non-random attrition. Section 4 discusses the correction method for non-random attrition via the refreshment samples methodology. The results are reported in Section 5. Section 6 concludes.

[1]Studies by Gowrisankaran and Stavins (2004) and Rysman (2007) have focused on the adoption and usage of an automated clearing house and credit cards.

[2]Wilshusen, Hunt, van Opstal, and Schneider (2012) utilize an anonymized data set of more than 280 million transactions for about three million prepaid cards issued by one issuer in the United States. However, due to privacy issues, their study does not link directly demographic details and does not contain a complete picture of payments in terms of cash, debit and credit.

[3]We use the terms cash and bank notes interchangeably but acknowledge that cash may also include coins.

2 The Canadian Financial Monitor

The CFM is an annual survey of Canadian households conducted by Ipsos Reid since 1999 that provides comprehensive information about household finances that includes demographics, banking habits, and household balance sheets (assets and liabilities). The survey is voluntary and respondents are not obliged to participate. About 1,000 households are surveyed on a monthly basis, so that the annual survey contains approximately 12,000 households.

A module concerning the method of payments and cash usage was introduced in the 2009 questionnaire on a trial basis. This module was revamped in 2010 and the questions were harmonized with the 2009 Bank of Canada MOP survey. Therefore, we use the 2010, 2011 and 2012 data, since the questions are consistent and comparable. For a detailed description of the variables used in our study, please refer to Appendix A.

2.1 Attrition and refreshment

The CFM survey has a sampling and weighting procedure to obtain annual representations of the Canadian population. Table 1 indicates an incidental panel dimension with an annual attrition rate of 50 percent. The CFM data are replenished annually with additional samples to maintain a constant yearly sample size and make each year's cross-section representative according to six main demographic and geographic categories. In contrast with the refreshment samples considered in Hirano, Imbens, Ridder, and Rubin (2001) and Bhattacharya (2008), where the new sampling units are randomly drawn from the second-period population hence themselves representative, the CFM refreshment samples are drawn to replace attritors so that the combination of the second-period panel stayers and these additional units is representative.[4]

Table 2 shows that among the households observed at least once over the 2010-12 period, 17 percent participated three years in a row (a household can receive only one CFM questionnaire in each 12-month period), while 23 percent participated twice. Of the

[4]We thank Pravin Trivedi for bringing to our attention the distinction between these two types of refreshment samples, the latter being sometimes called 'top-up' samples. The crucial feature of CFM is that a representative sample of each period is available.

11,695 households observed in 2010, 33 percent (3,853 households) participated again in the two following years, while 24 percent (2,852 households) of them participated again once, either in 2011 or 2012.

2.2 Retail payment innovations

We consider three payment innovations: (1) contactless credit cards (CTC), (2) multi-purpose stored-value cards (SVCm) and (3) single-purpose stored-value cards (SVCs). For each of these payment methods, a binary variable is used to denote whether a household has used it to make purchases in the past month. CTC were first introduced in Canada in 2006 (MasterCard *PayPass*) and 2007 (Visa *payWave*). Since NFC-enabled cards include a chip, the deployment of CTC and point-of-sale terminals is closely related to the rollout of chip credit cards, which replace previous cards with magnetic stripes. In Canada, the migration to chip technology began in the late 2000s and will culminate in 2015 with every credit card in Canada containing a chip; see Arango, Huynh, Fung, and Stuber (2012). Since cards are converted without the cardholders' request, the adoption process of the contactless feature can be considered passive.

Both SVCm and SVCs have been around since the early 2000s. The SVCm are usually branded Visa or MasterCard. SVCs are commonly referred to as gift cards and are usually issued by a retailer. The adoption of these cards can be either passive or active, since some consumers receive them as gifts or as rebates, while others actively seek them out.

Tables 3, 4 and 5 provide some descriptive statistics on who uses these retail payment innovations.[5] In general, households that use payment innovations tend to have a larger family size and younger family heads, and live in large cities. CTC and SVCs users are also more likely to be employed, earn higher household income and own their home relative to non-users. Conversely, SVCm users and non-users do not differ much in terms of income and employment status, and SVCm users are more likely to rent than are non-users.

[5] In Technical Appendix C, we also carry out a regression analysis to investigate the characteristics of payment innovations users. We estimate random-effects and fixed-effects panel logits on the three-year unbalanced and balanced panels.

Table 6 reports the usage patterns of payment innovations in the 2010-12 three-year balanced panel. Innovations have different penetration rates in the retail payment market. SVCm has a small presence in the market, since 87 percent of the households never used SVCm, while 74 percent never used CTC and only 49 percent never used SVCs. They differ also in terms of the persistence of usage, which is the ratio between the users to users (U-U) and the sum of U-U and users to non-users (U to N-U) in Table 6. CTC users are relatively more persistent, with about 70 percent of users in a given year continuing to use in the following year. This rate is about 30 percent and 50 percent for SVCm and SVCs, respectively. In other words, the rate of users who discontinue usage is high for SVCm. Finally, the users' switching rates can be measured by the proportion of households that either: (1) previously used but stop using or (2) did not use and start using in two following years (switchers). This rate is higher for SVCs with 33 percent, compared to 13 percent and 10 percent for CTC and SVCm, respectively.

2.3 Cash usage

We use two relative measures of cash usage based on volume and value constructed from the CFM data.[6] For each household, the cash ratio in volume is the ratio of the total number of cash purchases in the past month to the total number of all purchases in the past month. The second measure, the cash share in value, is the ratio of the total value of cash purchases in the past month to the total value of all transactions in the past month. Cash usage is more prevalent in terms of volume of purchases than in value, given that it is mainly used for small-value transactions. The typical cash transaction is about 20 dollars, while it is about 40, 50 and 20 dollars for CTC, SVCm, and SVCs, respectively.

Tables 7, 8 and 9 provide the average cash ratios for users and non-users of payment innovations across demographic categories. For all three innovations, the average non-user household pays around 37 percent of total volume purchases and 22 percent of total value purchases using cash. Those numbers are stable over the observation period.

Innovation users spend relatively less cash than non-users, both in terms of volume

[6] The CFM survey question regarding cash does not delineate between bank notes or coins, so we treat the term bank notes and cash interchangeably.

and value. This result is quite consistent across demographic groups (with a few exceptions for SVCm). For SVCs, the difference between user and non-user cash ratios is around 5 and 4 percentage points for volume and value, respectively. These differences are smaller and less stable over time for SVCm. We observe much larger user/non-user discrepancies for CTC, since the average user's volume and value cash ratios are about 11 percentage points smaller than the average non-user's. This relates to the fact that the cash shares of CTC users' purchases are much smaller than those of users of stored-value cards.

Cash ratios are also correlated with demographics. Urban and wealthy households with younger family heads or a larger household size tend to use relatively less cash. Cash usage is also relatively less predominant in the Western provinces than in the Eastern provinces.

3 Panel Data Estimation and Attrition

We utilize the panel dimension of the CFM survey over the years 2010 to 2012. An important advantage of panel data is that it enables us to account for individual unobserved heterogeneity. The standard panel data model with unobserved individual fixed-effects α_i is

$$CR_{it} = \alpha_i + \beta PI_{it} + X_{it}\gamma + u_{it}, \tag{1}$$

where CR denotes the cash ratio, PI is a binary variable denoting the use of a payment innovation and X contains demographic and other control variables. The parameter of interest, β, measures the effect of retail payment innovations on household cash usage. The presence of α_i can introduce an omitted variable bias in the cross-sectional estimation. Various methods can be used to account for this unobserved heterogeneity. One popular method is to assume a conditional distribution for α_i, such as normal, which is commonly known as the random-effects method. Alternatively, we can use the fixed-effects first-differencing estimator (1):[7]

$$\Delta CR_{it} = \beta \Delta PI_{it} + \Delta X_{it}\gamma + \Delta u_{it}. \tag{2}$$

[7] A Hausman test based on the balanced panel rejects the null hypothesis of the random-effects model. Therefore, all the panel estimates discussed here are from the fixed-effects panel regressions.

Equation (2) can only be estimated on units that remain in the sample during two consecutive periods. However, non-random attrition may generate another bias. Therefore, a useful exercise is to test whether attrition is random before proceeding with sophisticated attrition correction.

3.1 Is attrition really problematic?

Early work by Fitzgerald, Gottschalk, and Moffitt (1998) states that "the most potentially damaging threat [...] to the value of panel data is the presence of biasing attrition." Different forms of attrition would affect the estimate of β in our main equation (2). However, if the attrition mechanism does not depend on the outcome variable (CR), then attrition is deemed *missing-completely-at-random* (MCAR) and will only induce an efficiency loss but no bias. We complete a few procedures to check MCAR.

First, we consider the two-year panels 2010-11 and 2011-12 and examine the distributions of outcome and control variables in the initial period, conditional on the attrition status in the following period. In Table 10, we consider the seven basic demographics.[8] This cross-tabulation reveals some significant differences between attritors and stayers. Attritor households tend to have younger family heads, live in an urban area and are more likely to rent. They are also more likely to be employed and live in a larger household with higher household income. Table 11 shows that attritors and stayers frequently differ in their banking and payment characteristics, but not in their cash ratios.

Second, we test the MCAR hypothesis: whether the attrition status is related to either lagged (MAR) or contemporaneous (HW) cash ratio variables following Moffit, Fitzgerald, and Gottschalk (1999) and Fitzgerald, Gottschalk, and Moffitt (1998). To test for MCAR versus HW, we exploit the fact that units in the refreshment (or top-up) samples are very similar to attritors. For brevity, we confirm that these parametric tests reject the MCAR hypothesis and details are provided in Technical Appendix C.

[8] Demographics have low missing rates. However, other variables suffer from item non-response, hence there are smaller sample sizes in the other tables.

4 Correcting for Non-random Attrition

If attrition is not MCAR, balanced panel estimators (i.e., based on the stayers only) are potentially biased. To see this, consider estimating β using both lagged variables $z_{t-1} \equiv (x_{t-1}, y_{t-1})$ and contemporaneous variables $z_t \equiv (x_t, y_t)$ in the following structural model, where the function $\phi(\cdot)$ is known:

$$E\left[\phi\left(z_{t-1}, z_t, \beta\right)|x_{t-1}, x_t\right] = 0. \tag{3}$$

For the first-differencing (FD) equation (2), $\phi(\cdot) = \Delta CR_{it} - \beta\Delta PI_{it} - \Delta X_{it}\gamma$. Define the conditional probability of attrition as

$$\Pr(S_t = 0|\ z_{t-1}, z_t) \equiv 1 - g\left(z_{t-1}, z_t\right), \tag{4}$$

where $S_t = 0$ for attritors and $S_t = 1$ for stayers.

By the law of iterated expectations, the FD equation (3) and attrition probability (4) imply that

$$E\left[\left.\frac{\phi\left(\cdot\right)}{g\left(\cdot\right)}\right|\ S_t = 1, x_{t-1}, x_t\right] = 0 \tag{5}$$

if $E\left(S_t|\ x_{t-1}, x_t\right) > 0$ for all x_{t-1}, x_t. Note that MCAR implies $E\left[\phi\left(\cdot\right)|S_t = 1, x_{t-1}, x_t\right] = 0$, but $E\left[\phi\left(\cdot\right)|S_t = 1, x_{t-1}, x_t\right] \neq 0$ for the other types of attrition.[9] This suggests that using the balanced panel (i.e., conditioning on $S_t = 1$) when attrition is non-random requires that we identify the survival function $g\left(\cdot\right)$ in the moment condition (5).

In our panel setting, we distinguish between two main types of non-random attrition.[10] One, attrition that is termed *missing-at-random* (MAR) or *selection-on-observables* implies that the "missing" status is correlated with lagged observable characteristics; see Rubin (1976) or Little and Rubin (1987). Two, the attrition processes related to contemporaneous variables that are not observed for attritors are essentially *selection-on-unobservables*. Under selection-on-unobservables, we distinguish between an attrition mechanism that depends on contemporaneous observations only (HW), as discussed in Hausman and Wise (1979), and a more general attrition mechanism that depends on both lagged and contemporaneous variables.

[9] Cheng and Trivedi (2014) extend Heckman's two-step estimator to the panel data by directly modelling $E\left[\phi\left(\cdot\right)|S_t = 1, x_{t-1}, x_t\right]$.

[10] We assume away both initial non-responses and population attrition; see Kim (2012).

4.1 Identification of attrition function without refreshment

Provided one is ready to make rather restrictive assumptions on the form of the attrition process, the attrition function could be non-parametrically identified based on the unbalanced panel alone. More precisely, without a refreshment sample, the survival function $g(\cdot)$ can be specified either with lagged variables (MAR) or with contemporaneous variables (HW), but not both. If we specify $g(\cdot)$ as the single-index model $g(k(\cdot))$ where $g : \mathbb{R} \to [0, 1]$ is known (i.e., logit or probit), then the identifying conditions for the index function $k(\cdot)$ are

$$\textbf{MAR}: \qquad E\left[\frac{S_2}{g(k(z_1))} - 1 \middle| z_1\right] = 0, \tag{6}$$

$$\textbf{HW}: \qquad E\left[\frac{S_2}{g(k(z_2))} - 1 \middle| z_1\right] = 0, \tag{7}$$

where z_1 and z_2 are the lagged (first) and contemporaneous (second) variables for a two-period panel.

Notice that although we do not need the refreshment sample to identify the index function $k(\cdot)$, we could use it to differentiate between the MAR and HW attrition processes, as in Hirano, Imbens, Ridder, and Rubin (2001). But, most importantly, the extra information provided by the refreshment sample can also be exploited to identify a more general survival function $g(\cdot)$.

4.2 Identification of attrition function with refreshment

In the context of a simple two-period panel, Hirano, Imbens, Ridder, and Rubin (2001) show that the refreshment data can help identify a class of models that generalizes MAR and HW by allowing the survival function, $g(k(z_1, z_2))$, depending both on lagged (first) and contemporaneous (second) variables. They show that an attrition probability explained by both lagged (first) and contemporaneous (second) period variables is non-parametrically identified, but this identification excludes any interaction between the lagged and contemporaneous variables, $k(z_1, z_2) = k_1(z_1) + k_2(z_2)$. In the remainder of the paper, we follow Hirano, Imbens, Ridder, and Rubin (2001), who refer to this class of models as *additive non-ignorable* (AN), to reflect the additivity between the lagged

$k_1(z_1)$ and contemporaneous $k_2(z_2)$ variables in the attrition function. The AN model nests the MAR and HW models as special cases.

Our data consist of three years, so we will discuss the case of a three-period attrition function that depends on the first z_1, second z_2 and third z_3 period variables.[11] Following Hirano, Imbens, Ridder, and Rubin (2001), we show that the attrition function is non-parametrically identified with the help of the second and third periods' refreshment samples. Applying their constrained functional optimization to the three-period panel, we obtain the more flexible attrition function as $1 - g(k_1(z_1) + k_2(z_2) + k_3(z_3))$.[12]

Define $S_2S_3 = 1$ if a unit observed in the initial sample (period 1) survives in both periods 2 and 3; that is, the stayers of the three-period balanced panel. Under the additive non-ignorable assumption, the survival function $\Pr(S_2S_3 = 1|\ z_1, z_2, z_3) \equiv g(k_1(z_1) + k_2(z_2) + k_3(z_3))$ is non-parametrically identified by the following integral equations, where the function $g(\cdot)$ is known and functions $k_1(\cdot)$, $k_2(\cdot)$ and $k_3(\cdot)$ are non-parametrically identified up to a location normalization:

$$\iint \frac{f(z_1, z_2, z_3|S_2S_3 = 1)\Pr(S_2S_3 = 1)}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} dz_2 dz_3 = f_1(z_1), \tag{8}$$

$$\iint \frac{f(z_1, z_2, z_3|S_2S_3 = 1)\Pr(S_2S_3 = 1)}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} dz_1 dz_3 = f_2(z_2), \tag{9}$$

$$\iint \frac{f(z_1, z_2, z_3|S_2S_3 = 1)\Pr(S_2S_3 = 1)}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} dz_1 dz_2 = f_3(z_3), \tag{10}$$

with f being the joint density of z_1, z_2 and z_3 conditional on $S_2S_3 = 1$, and f_t being the marginal density of z_t for $t = 1, 2, 3$. The innovation of Bhattacharya (2008) is to write the integral equations as the equivalent moment conditions. For our three-period set-up, the moment conditions are

$$E\left[\frac{S_2S_3}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} - 1|R_1 = 1, z_1\right] = 0, \tag{11}$$

$$E\left[\frac{S_2S_3}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} - 1|R_2 = 1, z_2\right] = 0, \tag{12}$$

$$E\left[\frac{S_2S_3}{g\left(k_1(z_1) + k_2(z_2) + k_3(z_3)\right)} - 1|R_3 = 1, z_3\right] = 0, \tag{13}$$

[11] Technical Appendix C provides a detailed discussion of the two-period attrition function.

[12] We could use the approach by Bhattacharya (2008), though it might be difficult to justify the *just*-identification under the non-parametric set-up.

where the indicator variable R_t denotes whether a unit belongs to the refreshment sample in period t, for $t = 1, 2, 3$. Here for $t = 2, 3$, the refreshment sample in period t is constructed by the survey company to replace the attritors with respondents that have similar characteristics. Therefore, the refreshment sample in period t plus the stayers are a representative cross-section in period t.

Notice that only conditional moment (11) is identifiable from the unbalanced panel. The conditional moments (12) and (13) require that the refreshment sample and stayers be drawn from the second and third periods. Moreover, the refreshment plus stayer sample, R_t, can be thought of as an exclusion restriction, since it is independent of the survival process S_2S_3.

4.3 Estimation

Bhattacharya (2008) employs a sieve minimum distance (SMD) method proposed in Ai and Chen (2003) to jointly estimate β and the survival function $g(\cdot)$. Since different conditioning variables are used in the different conditional moments, we use the methodology of Ai and Chen (2007).[13] Denote by n the total number of households in the three-period panel, n_t the number of units in each period t for $t = 1, 2, 3$, and n_{123} the number of stayers in the three-period balanced panel. The simultaneous conditional moments with $\delta \equiv (\beta, k_1, k_2, k_3)$ are

$$m_0(x_2, x_3, \delta) \equiv E\left\{\frac{\phi(z_2,z_3,\beta)}{g(k_1(z_1)+k_2(z_2)+k_3(z_3))} \mid S_2S_3 = 1, x_2, x_3\right\} = 0, \tag{14}$$
$$m_1(z_1, \delta) \equiv E\left\{\frac{S_2S_3}{g(k_1(z_1)+k_2(z_2)+k_3(z_3))} - 1 | R_1 = 1, z_1\right\} = 0, \tag{15}$$
$$m_2(z_2, \delta) \equiv E\left\{\frac{S_2S_3}{g(k_1(z_1)+k_2(z_2)+k_3(z_3))} - 1 | R_2 = 1, z_2\right\} = 0, \tag{16}$$
$$m_3(z_3, \delta) \equiv E\left\{\frac{S_2S_3}{g(k_1(z_1)+k_2(z_2)+k_3(z_3))} - 1 | R_3 = 1, z_3\right\} = 0. \tag{17}$$

The set of conditional moments (14)-(17) implies that the true parameter δ uniquely minimizes the positive semi-definite quadratic form:

$$\begin{aligned} Q(\delta) \equiv \quad & E_{x_2,x_3}\left[m_0(x_2, x_3, \delta)^2 \,|S_2S_3 = 1\right] + E_{z_1}\left[m_1(z_1, \delta)^2 \,|R_1 = 1\right] \\ & + E_{z_2}\left[m_2(z_2, \delta)^2 | R_2 = 1\right] + E_{z_3}\left[m_3(z_3, \delta)^2 | R_3 = 1\right]. \end{aligned} \tag{18}$$

[13] As with Ai and Chen (2007), we do not discuss the efficiency issue.

The estimation strategy is to minimize the sample analog of $Q(\delta)$. The SMD estimator $\widehat{\delta} \equiv (\widehat{\beta}, \widehat{k}_1, \widehat{k}_2, \widehat{k}_3)$ is obtained by minimizing

$$\widehat{Q}(\delta_n) = \frac{1}{n}\sum_{i=1}^{n} \Big\{\frac{n}{n_{123}} S_{2i}S_{3i}\widehat{m}_0(x_{2i}, x_{3i}, \delta_n)^2 + \frac{n}{n_1} R_{1i}\widehat{m}_1(z_{1i}, \delta_n)^2 + \frac{n}{n_2} R_{2i}\widehat{m}_2(z_{2i}, \delta_n)^2 + \frac{n}{n_3} R_{3i}\widehat{m}_3(z_{3i}, \delta_n)^2\Big\}, \tag{19}$$

where $\delta_n \equiv (\beta, k_{1n}, k_{2n}, k_{3n})$, k_{1n}, k_{2n} and k_{3n} are linear sieve approximations of k_t for $t = 1, 2, 3$, and $\widehat{m}_0(\cdot), \widehat{m}_1(\cdot), \widehat{m}_2(\cdot), \widehat{m}_3(\cdot)$ are the least-squares sieve estimators of the conditional moments. A detailed implementation of the SMD estimator is provided in Technical Appendix C, using R optimization routines suggested by Tierney, Rossini, Li, and Sevcikova (2013).

4.4 Inference

We follow the approach by Ai and Chen (2007) and Bhattacharya (2008) to derive the standard errors of the finite dimensional parameter estimates $\widehat{\beta}$. Although estimating the analytical asymptotic variance is not straightforward, it is preferred to the bootstrap approach proposed by Tunali, Ekinci, and Yavuzoglu (2012). Those authors do not provide an asymptotic justification for their bootstrap approach. Please refer to Technical Appendix C to calculate the analytical standard errors.

5 Impact of Retail Payment Innovations

In this section, we report two main findings: one, the cross-sectional estimates of the payment innovations ($\hat{\beta}$) are larger in absolute magnitude for CTC in relation to the panel estimates. This difference justifies the importance of controlling for unobserved heterogeneity. Two, $\hat{\beta}$ are larger in absolute magnitude for SVCm and SVCs (in the case of cash ratio in volume) if we do not account for non-random attrition. This shows that failing to correct for unobserved heterogeneity and non-random attrition will lead to downward-biased estimates or overestimation of the impact of retail payment innovations on cash usage. We will discuss the sources and mechanisms behind these biases in this section.

5.1 Cross-sectional and panel data analysis

There are two outcome variables (cash ratio in terms of value or volume) and there are three types of payment innovations (CTC, SVCm and SVCs) considered in this study. Therefore, six different sets of parameters are estimated. To understand the importance of controlling for unobserved heterogeneity, the estimates obtained on cross-sectional or pooled data can be compared with the FD estimates obtained on the three-year balanced panel without correcting for attrition. Results for the estimated parameters are summarized in Table 12.

For CTC, estimates obtained on cross-sectional or pooled data are all highly significant. The estimated negative impacts of CTC on cash usage range between 8 and 10 per cent for both volume and value in our 2010-12 CFM study. These results are comparable to Fung, Huynh, and Sabetti's (2012) estimates of 13 and 14 percent obtained on the 2009 cross-section MOP survey.

The balanced panel data FD estimate of CTC is insignificant, which indicates that unobserved heterogeneity drives the results obtained on cross-sectional data. Therefore, ignoring it will lead to overstatement in the impact of CTC on cash usage. However, for SVCm and SVCs, we observe that panel coefficients are in general larger in absolute value than cross-sectional or pooled coefficients, and the values of test statistics increase. However, the consequences of controlling for unobserved heterogeneity for SVCm and SVCs are smaller than for CTC. Once controlling for unobserved heterogeneity, we estimate an SVCm impact on cash in volume close to 4 percent. The SVCs estimates decrease to 2.6 and 1.8 percent for cash usage in volume and value, respectively.

5.2 Effects of correcting for attrition

The panel coefficient estimates are obtained for each model with and without correcting for attrition, and are summarized in Table 13. There are many potential channels through which attrition correction might influence the estimation. In what follows, we put forward three main mechanisms that seem to explain our results. First, identification of β relies on switchers ($\Delta PI \neq 0$) in the panel, and the accuracy of $\hat{\beta}$ is positively related to the number of switchers. The attrition correction mechanism can compensate for the small proportion of switchers. If switchers receive larger weights than non-switchers, the impact of switchers is further augmented by the attrition correction. Second, within the switchers, new-users ($\Delta PI = 1$) tend to be associated with the negative cash ratios ($\Delta CR < 0$), while stop-users ($\Delta PI = -1$) are more likely to have a positive cash ratio ($\Delta CR > 0$). Hence the magnitude and sign of β are also driven by the size of new-users and their range for ΔCR. Attrition correction might then impact the estimation by changing the relative importance of new-users and stop-users in the switchers sample. Finally, the beta estimates are obtained using two different subsamples, the 2010-11 two-years balanced panel (used for $M^{01}_{(1,2)}$) and the three-years balanced panel (used for $M^{02}_{(2,3)}$). Attrition correction can influence the results by weighting the two subsamples differently. Figures 1 to 6 illustrate these three mechanisms for all six cases.

5.2.1 Effects on CTC

Panel coefficient estimates for CTC are not significant, whether with or without attrition correction. It is clear from Figures 1 and 2 that this result is mainly driven by a relatively small number of switchers (either new-users or stop-users), associated with small changes in cash ratios. In the case of CTC, we observe both a small extensive margin with only 13 percent of households being switchers, and a relatively small intensive margin or the support of ΔCR is narrow and centered around zero. As a result, the inverse probability-weighting offered by the attrition correction, $1/g(\cdot)$, does not affect $\hat{\beta}$.

5.2.2 Effects on SVCm

The estimates of the impact of SVCm obtained without correcting for attrition are negative and significant for cash in volume. For the cash ratio in value, only the parametric estimate is significant at the usual confidence levels. The switchers with large ΔCR are driving the result (see Figures 3 and 4). While the panel estimation without correction assigns equal weights to both 2010-11 and 2010-12 balanced panels, attrition correction weights relatively more toward the latter. Since we observe small changes in cash ratios for the 2010-12 switchers compared to the 2010-11 ones, especially for cash in value, the SVCm estimates are dampened by the attrition correction.

5.2.3 Effects on SVCs

For SVCs, estimates obtained without correcting for attrition are negative and significant with a 2 percent reduction in the cash ratio in volume, but insignificant for the cash ratio in value. As mentioned previously, single-purpose stored-value cards are characterized by higher switching rates than other payment innovations (CTC and SVCm). The negative sign of our volume estimate is mainly due to the decreased cash usage by new-users, who account for more than half of the switchers. In the value case, the impact of new-users is offset by the stop-users who are associated with a negatively centered intensive margin (see Figures 5 and 6).

Attrition correction comes into play by weighting stop-users relatively more than new-users. The resulting estimate for cash in value is reduced, while that for volume is still around 2 percent. In brief, after controlling for unobserved heterogeneity and attrition, only SVCs are found to have a significant impact on cash volume usage: on average, the use of single-purpose stored-value cards by at least one person in the household decreases the number of purchases paid in cash by approximately 2 percent.

5.3 Time-varying effects of innovations

In order to capture the rapidly changing retail payment landscape from the year 2010 to 2012, we also estimate two separate two-year panels (the 2010-11 and 2011-12 panels), which allows for time-varying β.[14] Here we highlight some important aspects and summarize the various cross-sectional and panel estimates in Figures 7-12. The estimated impacts of CTC on the cash ratio in value and SVCs on the cash ratio in volume are not significant in the first panel, but become significant in the second panel. A possible interpretation is that in 2010-11, CTC users did not use the innovation heavily because it was not yet widely accepted by merchants. However, the turning point seems to occur around the 2011-12 panel, when almost all credit cards had a contactless functionality and acceptance was more widespread across merchants. As for SVCs, the trend is also clear.

The estimated effect of SVCm on cash usage is significant in the 2010-11 panel for

[14]Please refer to Technical Appendix C for details.

both volume and value, and is also significant in the 2011-12 panel. This continuing large impact of SVCm is that they are used in a manner quite similar to traditional credit cards, so that no adaptation is required by the merchant, and no learning or adjusting is needed for the consumer. For example, SVCm still use a magnetic stripe and do not have PIN and chip authentication.

6 Conclusions

Gauging the impact of retail payment innovations on cash usage is an important public policy question. Central banks as the sole issuer of cash must understand the potential substitution from cash to retail payment innovations in order to plan for the design, production and distribution of cash. Market infrastructure participants such as card processors and merchants need to understand whether there is a demand for terminals.

In this study, we utilize panel data to estimate the impact of these payment innovations. However, econometric issues arise from non-random attrition. We take advantage of the availability of refreshment samples to account for attrition without relying on rather restrictive assumptions. We find that accounting for unobserved heterogeneity and non-random attrition is crucial for correctly assessing the impact of retail payment innovations on the relative cash usage of Canadian households. Except for the single-purpose stored-value cards, we estimate impacts that are either non-significant or small, which differs from the findings of previous studies based on cross-sectional data. An explanation for this finding is that CTC and SVCm are bundled products (i.e., a payment method with a credit and/or liquidity function). To use these products requires both that consumers have the card and that merchants have the necessary physical infrastructure, whereas the SVCs is a specialized product that consumers know exactly where to use (e.g., coffee shops) for convenience. It is therefore not surprising that a SVCs leads to a reduction in cash usage.

There are several caveats to this study. First, payment innovations such as contactless credit cards are still in the nascent stage, so these estimates should be taken with caution. Second, we focus only on consumer outcomes and are silent on merchants' adoption of contactless terminals, due to the lack of available information. It would be interesting to combine merchant information to estimate a two-sided market model that would account for network externalities. Third, we consider the impacts only on cash. Future research will examine simultaneous implications for the use of credit cards and debit cards.

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Table 1: Attrition and refreshment samples: Two-year panels

Panels	2010-11	2011-12
Beginning sample size:	11,695	12,241
Stayers	5,699	6,079
- Attritors	5,996	6,162
+ Refreshment sample	6,542	4,944
End sample size	12,241	11,023

Note: A household can receive and answer only one CFM questionnaire in a 12-month period.

Table 2: Participation patterns: Three-year panel

Pattern	Counts	Frequency	Cumulative
1..	4,990	0.23	
.1.	4,316	0.19	
..1	3,938	0.18	0.60
11.	1,846	0.08	
1.1	1,006	0.05	
.11	2,226	0.10	0.23
111	3,853	0.17	0.17
Total	22,175	1.00	1.00

Note: Counts give the number of households; for example, [1..] means participation in 2010 only.

Table 3: Demographic characteristics of CTC users and non-users

	2010		2011		2012	
	U	N-U	U	N-U	U	N-U
City size:						
<10K	0.139	0.187	0.146	0.186	0.122	0.190
10-100K	0.131	0.138	0.120	0.144	0.133	0.142
100K-1M	0.240	0.250	0.251	0.248	0.257	0.247
1M+	0.490	0.424	0.484	0.422	0.488	0.421
HH size:						
1	0.222	0.276	0.226	0.277	0.228	0.277
2	0.325	0.338	0.344	0.333	0.334	0.335
3	0.186	0.155	0.169	0.158	0.166	0.157
4+	0.267	0.231	0.261	0.232	0.271	0.230
Age of Head:						
18-34	0.229	0.192	0.244	0.190	0.222	0.187
35-49	0.339	0.301	0.321	0.302	0.327	0.290
50-64	0.251	0.280	0.265	0.278	0.261	0.296
65+	0.180	0.227	0.170	0.231	0.189	0.228
Income:						
<25K	0.092	0.190	0.106	0.192	0.091	0.197
25-34K	0.088	0.107	0.083	0.106	0.087	0.103
35-44K	0.086	0.105	0.087	0.105	0.089	0.104
45-59K	0.135	0.134	0.128	0.129	0.122	0.130
60-69K	0.093	0.077	0.090	0.076	0.086	0.077
70+K	0.507	0.387	0.506	0.392	0.526	0.389
Home Ownership	0.765	0.673	0.758	0.670	0.757	0.669
Rent	0.235	0.327	0.242	0.330	0.243	0.331
Unemployed	0.338	0.410	0.360	0.411	0.347	0.413
Employed	0.662	0.590	0.640	0.589	0.653	0.587
BC	0.089	0.141	0.110	0.137	0.111	0.140
AB	0.086	0.100	0.083	0.104	0.085	0.102
MB/SK	0.060	0.072	0.054	0.073	0.057	0.072
ON	0.433	0.356	0.432	0.352	0.443	0.350
QC	0.256	0.253	0.250	0.255	0.241	0.255
Maritimes	0.077	0.079	0.071	0.080	0.063	0.081
Observations	1,597	9,748	2,149	9,770	1,996	8,728

Notes: Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Numbers are in proportions. Sample weights are used in these computations.

Table 4: Demographic characteristics of SVCm users and non-users

	2010		2011		2012	
	U	N-U	U	N-U	U	N-U
City size:						
<10K	0.167	0.181	0.141	0.183	0.168	0.179
10-100K	0.129	0.139	0.136	0.140	0.122	0.142
100K-1M	0.216	0.253	0.228	0.251	0.225	0.253
1M+	0.488	0.427	0.495	0.426	0.484	0.427
HH size:						
1	0.227	0.271	0.239	0.269	0.220	0.273
2	0.320	0.338	0.290	0.343	0.323	0.337
3	0.173	0.159	0.202	0.155	0.179	0.157
4+	0.281	0.232	0.269	0.233	0.278	0.233
Age of Head:						
18-34	0.220	0.196	0.245	0.195	0.249	0.185
35-49	0.319	0.305	0.338	0.301	0.337	0.292
50-64	0.241	0.280	0.243	0.279	0.238	0.297
65+	0.220	0.218	0.174	0.225	0.176	0.226
Income:						
<25K	0.175	0.174	0.166	0.177	0.177	0.175
25-34K	0.102	0.105	0.104	0.100	0.115	0.097
35-44K	0.103	0.102	0.091	0.103	0.092	0.103
45-59K	0.145	0.134	0.121	0.130	0.126	0.128
60-69K	0.074	0.080	0.071	0.080	0.084	0.078
70+K	0.401	0.405	0.446	0.411	0.405	0.418
Home Ownership	0.637	0.692	0.661	0.692	0.644	0.694
Rent	0.363	0.308	0.339	0.308	0.356	0.306
Unemployed	0.395	0.398	0.359	0.406	0.353	0.405
Employed	0.605	0.602	0.641	0.594	0.647	0.595
BC	0.124	0.133	0.141	0.132	0.142	0.133
AB	0.111	0.097	0.096	0.100	0.119	0.096
MB/SK	0.059	0.070	0.048	0.072	0.060	0.071
ON	0.359	0.369	0.372	0.366	0.367	0.368
QC	0.273	0.253	0.282	0.250	0.244	0.253
Maritimes	0.074	0.078	0.062	0.080	0.068	0.079
Observations	1,076	10,188	1,176	10,672	1,107	9,531

Notes: Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Numbers are in proportions. Sample weights are used in these computations.

Table 5: Demographic characteristics of SVCs users and non-users

	2010		2011		2012	
	U	N-U	U	N-U	U	N-U
City size						
<10K	0.141	0.204	0.132	0.205	0.149	0.195
10-100K	0.138	0.137	0.144	0.137	0.133	0.143
100K-1M	0.274	0.233	0.268	0.234	0.263	0.238
1M+	0.447	0.426	0.456	0.423	0.455	0.424
HH size						
1	0.210	0.299	0.203	0.312	0.211	0.302
2	0.323	0.345	0.317	0.350	0.332	0.337
3	0.181	0.151	0.187	0.143	0.182	0.149
4+	0.287	0.205	0.293	0.196	0.275	0.213
Age of Head:						
18-34	0.229	0.180	0.234	0.179	0.215	0.181
35-49	0.342	0.282	0.353	0.272	0.336	0.272
50-64	0.269	0.281	0.259	0.285	0.279	0.297
65+	0.159	0.257	0.155	0.264	0.169	0.251
Income						
<25K	0.129	0.203	0.125	0.212	0.129	0.204
25-34K	0.085	0.117	0.081	0.113	0.079	0.112
35-44K	0.094	0.106	0.092	0.110	0.097	0.106
45-59K	0.140	0.132	0.121	0.133	0.121	0.132
60-69K	0.080	0.079	0.084	0.076	0.085	0.074
70+K	0.471	0.363	0.498	0.357	0.489	0.372
Home Ownership	0.716	0.670	0.727	0.658	0.738	0.658
Rent	0.284	0.330	0.273	0.342	0.262	0.342
Unemployed	0.330	0.442	0.330	0.445	0.328	0.445
Employed	0.670	0.558	0.670	0.555	0.672	0.555
BC	0.138	0.130	0.148	0.124	0.144	0.129
AB	0.115	0.088	0.127	0.082	0.118	0.085
MB/SK	0.067	0.070	0.064	0.071	0.069	0.069
ON	0.437	0.325	0.420	0.331	0.422	0.335
QC	0.160	0.313	0.167	0.314	0.166	0.308
Maritimes	0.083	0.074	0.074	0.078	0.081	0.074
Observations	4,059	6,950	4,510	7,125	3,911	6,562

Notes: Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Numbers are in proportions. Sample weights are used in these computations.

Table 6: Usage patterns of payment innovations

CTC	N-U	U	Total
N-U	0.74	0.08	0.82
U	0.05	0.13	0.18
Total	0.79	0.21	1.00

SVCm	N-U	U	Total
N-U	0.87	0.05	0.92
U	0.05	0.02	0.08
Total	0.92	0.08	1.00

SVCs	N-U	U	Total
N-U	0.49	0.17	0.66
U	0.16	0.18	0.34
Total	0.65	0.35	1.00

Notes: Let U and N-U denote the user and non-user of the payment innovation in the past month, respectively. Numbers are obtained on the 2010-12 three-year balanced panel. Sample weights are used in these computations.

Table 7: Cash ratios of CTC users and non-users

	Volume						Value					
	2010		2011		2012		2010		2011		2012	
	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U
Overall	0.27	0.38	0.26	0.37	0.25	0.37	0.13	0.23	0.12	0.23	0.12	0.23
City Size:												
<10K	0.28	0.38	0.29	0.37	0.23	0.40	0.15	0.24	0.15	0.24	0.12	0.26
10-100K	0.27	0.38	0.30	0.38	0.26	0.38	0.14	0.25	0.15	0.25	0.13	0.25
100K-1M	0.27	0.38	0.26	0.37	0.24	0.36	0.13	0.24	0.11	0.23	0.11	0.23
1M+	0.27	0.38	0.23	0.37	0.26	0.35	0.12	0.22	0.10	0.21	0.12	0.21
HH Size:												
1	0.32	0.43	0.28	0.43	0.28	0.43	0.15	0.25	0.13	0.25	0.12	0.27
2	0.29	0.36	0.26	0.35	0.26	0.35	0.13	0.22	0.11	0.21	0.12	0.21
3	0.26	0.38	0.23	0.36	0.19	0.35	0.13	0.24	0.11	0.24	0.11	0.22
4+	0.24	0.35	0.25	0.34	0.25	0.33	0.11	0.22	0.12	0.22	0.12	0.21
Age of Head:												
18-34	0.24	0.36	0.23	0.34	0.22	0.34	0.12	0.24	0.12	0.22	0.11	0.23
35-49	0.26	0.38	0.25	0.36	0.23	0.35	0.12	0.23	0.11	0.22	0.10	0.22
50-64	0.29	0.38	0.28	0.39	0.29	0.38	0.13	0.22	0.13	0.23	0.13	0.23
65+	0.31	0.41	0.29	0.40	0.28	0.40	0.14	0.24	0.12	0.23	0.13	0.24
Income:												
<25K	0.35	0.49	0.32	0.50	0.37	0.47	0.21	0.35	0.18	0.37	0.20	0.36
25-34K	0.34	0.45	0.31	0.41	0.27	0.42	0.19	0.30	0.15	0.28	0.19	0.28
35-44K	0.29	0.40	0.33	0.39	0.30	0.40	0.15	0.25	0.18	0.24	0.12	0.26
45-59K	0.31	0.37	0.27	0.36	0.25	0.35	0.15	0.23	0.14	0.22	0.13	0.21
60-69K	0.29	0.33	0.26	0.32	0.26	0.31	0.13	0.20	0.10	0.21	0.13	0.19
70+K	0.23	0.33	0.22	0.31	0.22	0.31	0.09	0.16	0.09	0.15	0.09	0.16
Homeowner	0.26	0.35	0.24	0.33	0.23	0.33	0.12	0.19	0.10	0.19	0.10	0.19
Rent	0.30	0.44	0.30	0.44	0.30	0.43	0.16	0.30	0.16	0.31	0.17	0.30
Unemployed	0.32	0.41	0.28	0.40	0.27	0.41	0.17	0.26	0.13	0.26	0.13	0.27
Employed	0.25	0.36	0.25	0.35	0.24	0.34	0.11	0.22	0.11	0.21	0.11	0.20
BC	0.25	0.33	0.21	0.34	0.21	0.33	0.13	0.19	0.10	0.20	0.09	0.19
AB	0.22	0.31	0.22	0.31	0.20	0.29	0.10	0.17	0.10	0.18	0.09	0.16
MB/SK	0.19	0.36	0.26	0.33	0.20	0.32	0.08	0.23	0.11	0.19	0.10	0.18
ON	0.28	0.40	0.25	0.39	0.25	0.38	0.12	0.24	0.10	0.24	0.12	0.23
QC	0.32	0.41	0.29	0.38	0.29	0.40	0.16	0.26	0.15	0.25	0.15	0.27
Maritimes	0.25	0.43	0.27	0.40	0.25	0.41	0.10	0.29	0.12	0.28	0.11	0.28
Observations	1169	6944	1553	6776	1471	6248	1035	6171	1378	5992	1329	5590

Notes: The cash ratio is measured in terms of volume (number of cash to total purchases) and value (cash value to total value of purchases). Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Sample weights are used in these computations.

Table 8: Cash ratios of SVCm users and non-users

	Volume						Value					
	2010		2011		2012		2010		2011		2012	
	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U
Overall	0.34	0.37	0.30	0.35	0.32	0.35	0.21	0.22	0.18	0.21	0.19	0.21
City Size:												
<10K	0.37	0.37	0.29	0.36	0.35	0.38	0.23	0.23	0.18	0.23	0.23	0.24
10-100K	0.36	0.37	0.33	0.37	0.33	0.36	0.23	0.23	0.21	0.23	0.22	0.23
100K-1M	0.38	0.37	0.31	0.36	0.31	0.34	0.23	0.22	0.18	0.21	0.19	0.20
1M+	0.30	0.37	0.30	0.34	0.31	0.33	0.18	0.21	0.17	0.19	0.16	0.19
HH Size:												
1	0.38	0.42	0.32	0.41	0.36	0.41	0.23	0.24	0.19	0.24	0.22	0.25
2	0.31	0.36	0.30	0.34	0.31	0.33	0.19	0.21	0.19	0.19	0.17	0.19
3	0.33	0.36	0.31	0.34	0.32	0.32	0.22	0.23	0.17	0.22	0.16	0.20
4+	0.35	0.33	0.28	0.32	0.29	0.31	0.21	0.20	0.17	0.20	0.19	0.19
Age of Head:												
18-34	0.32	0.35	0.30	0.32	0.33	0.31	0.21	0.23	0.19	0.20	0.21	0.20
35-49	0.36	0.36	0.29	0.35	0.29	0.33	0.24	0.21	0.17	0.21	0.17	0.20
50-64	0.33	0.37	0.32	0.37	0.34	0.37	0.18	0.21	0.19	0.22	0.19	0.21
65+	0.34	0.41	0.34	0.38	0.32	0.38	0.17	0.23	0.19	0.22	0.18	0.23
Income:												
<25K	0.39	0.49	0.41	0.49	0.39	0.47	0.26	0.35	0.29	0.35	0.27	0.35
25-34K	0.39	0.43	0.39	0.40	0.37	0.40	0.29	0.29	0.23	0.27	0.25	0.27
35-44K	0.40	0.39	0.31	0.39	0.37	0.38	0.29	0.23	0.15	0.24	0.22	0.24
45-59K	0.33	0.37	0.30	0.35	0.33	0.33	0.20	0.22	0.18	0.21	0.17	0.19
60-69K	0.32	0.32	0.24	0.32	0.27	0.31	0.17	0.19	0.16	0.19	0.16	0.18
70+K	0.30	0.31	0.25	0.29	0.27	0.29	0.16	0.15	0.13	0.14	0.13	0.14
Homeowner	0.33	0.34	0.27	0.32	0.27	0.32	0.19	0.18	0.14	0.17	0.15	0.17
Rent	0.35	0.44	0.36	0.43	0.40	0.41	0.24	0.30	0.25	0.29	0.25	0.28
Unemployed	0.36	0.40	0.35	0.38	0.33	0.39	0.23	0.25	0.22	0.24	0.21	0.25
Employed	0.33	0.35	0.28	0.34	0.31	0.32	0.20	0.20	0.16	0.19	0.18	0.18
BC	0.35	0.32	0.28	0.33	0.27	0.31	0.19	0.18	0.16	0.18	0.13	0.18
AB	0.24	0.31	0.25	0.30	0.29	0.28	0.14	0.17	0.16	0.17	0.12	0.15
MB/SK	0.31	0.35	0.29	0.33	0.28	0.30	0.26	0.21	0.16	0.18	0.19	0.16
ON	0.36	0.38	0.32	0.36	0.35	0.35	0.23	0.22	0.18	0.21	0.22	0.20
QC	0.33	0.40	0.32	0.38	0.31	0.39	0.19	0.25	0.19	0.24	0.18	0.25
Maritimes	0.43	0.40	0.32	0.39	0.37	0.38	0.24	0.27	0.23	0.26	0.21	0.26
Observations	749	7441	832	7578	806	6988	652	6608	713	6719	708	6261

Notes: The cash ratio is measured in terms of volume (number of cash to total purchases) and value (cash value to total value of purchases). Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Sample weights are used in these computations.

Table 9: Cash ratios of SVCs users and non-users

	Volume						Value					
	2010		2011		2012		2010		2011		2012	
	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U	U	N-U
Overall	0.34	0.38	0.32	0.37	0.31	0.36	0.19	0.23	0.18	0.22	0.18	0.22
City Size:												
<10K	0.34	0.39	0.33	0.37	0.32	0.40	0.19	0.24	0.18	0.25	0.19	0.27
10-100K	0.35	0.38	0.34	0.39	0.31	0.38	0.21	0.25	0.21	0.24	0.19	0.25
100K-1M	0.34	0.38	0.32	0.38	0.31	0.35	0.20	0.24	0.19	0.23	0.18	0.22
1M+	0.34	0.37	0.31	0.36	0.31	0.35	0.19	0.21	0.17	0.20	0.17	0.20
HH Size:												
1	0.39	0.43	0.36	0.42	0.34	0.43	0.22	0.25	0.21	0.24	0.20	0.27
2	0.34	0.36	0.31	0.35	0.30	0.35	0.19	0.21	0.17	0.21	0.17	0.21
3	0.34	0.37	0.32	0.35	0.31	0.33	0.21	0.24	0.21	0.21	0.19	0.20
4+	0.32	0.35	0.31	0.33	0.30	0.32	0.18	0.22	0.17	0.23	0.18	0.20
Age of Head:												
18-34	0.33	0.35	0.28	0.34	0.28	0.33	0.20	0.24	0.18	0.22	0.19	0.22
35-49	0.33	0.38	0.31	0.36	0.29	0.35	0.19	0.24	0.18	0.22	0.16	0.22
50-64	0.35	0.37	0.35	0.38	0.34	0.38	0.19	0.22	0.20	0.22	0.19	0.22
65+	0.38	0.41	0.37	0.39	0.35	0.39	0.21	0.23	0.18	0.23	0.19	0.23
Income:												
<25K	0.43	0.50	0.43	0.50	0.39	0.49	0.29	0.36	0.30	0.37	0.29	0.36
25-34K	0.41	0.44	0.36	0.42	0.33	0.42	0.28	0.29	0.23	0.28	0.23	0.29
35-44K	0.39	0.39	0.38	0.38	0.37	0.39	0.25	0.23	0.24	0.23	0.25	0.23
45-59K	0.34	0.38	0.34	0.35	0.32	0.34	0.21	0.23	0.21	0.20	0.18	0.20
60-69K	0.31	0.32	0.30	0.32	0.28	0.31	0.18	0.19	0.18	0.19	0.16	0.19
70+K	0.31	0.31	0.28	0.29	0.27	0.29	0.15	0.15	0.13	0.14	0.13	0.14
Homeowner	0.32	0.35	0.30	0.33	0.29	0.33	0.16	0.19	0.15	0.18	0.16	0.18
Rent	0.40	0.44	0.38	0.44	0.37	0.43	0.27	0.30	0.26	0.30	0.25	0.29
Unemployed	0.37	0.41	0.35	0.39	0.35	0.40	0.22	0.26	0.21	0.25	0.22	0.25
Employed	0.33	0.35	0.31	0.35	0.29	0.34	0.18	0.21	0.17	0.20	0.16	0.20
BC	0.31	0.33	0.28	0.35	0.26	0.35	0.17	0.19	0.16	0.21	0.14	0.19
AB	0.29	0.31	0.29	0.30	0.25	0.30	0.14	0.19	0.16	0.17	0.12	0.17
MB/SK	0.32	0.36	0.28	0.35	0.28	0.31	0.18	0.23	0.14	0.20	0.15	0.17
ON	0.35	0.39	0.34	0.38	0.33	0.37	0.20	0.23	0.19	0.22	0.19	0.22
QC	0.37	0.40	0.35	0.38	0.35	0.39	0.23	0.25	0.21	0.24	0.22	0.25
Maritimes	0.38	0.42	0.36	0.40	0.34	0.41	0.22	0.29	0.20	0.29	0.21	0.28
Observations	3055	5135	3298	5112	2940	4854	2648	4595	2916	4502	2617	4346

Notes: The cash ratio is measured in terms of volume (number of cash to total purchases) and value (cash value to total value of purchases). Let U denote users of the payment innovations while N-U are the non-users. HH denotes household. Sample weights are used in these computations.

Table 10: First-year demographic characteristics: attritors vs. stayers

	2010-11 panel			2011-12 panel		
	2010	Attritors	Stayers	2011	Attritors	Stayers
City Size: <10K	0.179	0.169	0.191*	0.178	0.169	0.189*
10-100K	0.139	0.135	0.144	0.140	0.138	0.141
100K-1M	0.248	0.248	0.248	0.248	0.244	0.253
1M+	0.434	0.448	0.417*	0.434	0.449	0.417*
HH Size: 1	0.267	0.231	0.311*	0.268	0.236	0.305*
2	0.336	0.314	0.363*	0.336	0.315	0.360*
3	0.160	0.180	0.136*	0.159	0.177	0.138*
4+	0.237	0.275	0.190*	0.237	0.272	0.196*
Age of Head: 18-34	0.198	0.255	0.131*	0.199	0.263	0.125*
35-49	0.304	0.352	0.247*	0.304	0.347	0.255*
50-64	0.276	0.240	0.319*	0.276	0.248	0.308*
65+	0.221	0.153	0.303*	0.221	0.142	0.312*
Income: <25K	0.178	0.158	0.201*	0.177	0.171	0.184
25-34K	0.104	0.103	0.106	0.102	0.095	0.110*
35-44K	0.102	0.098	0.107	0.101	0.096	0.107
45-59K	0.133	0.135	0.132	0.129	0.120	0.139*
60-69K	0.079	0.087	0.069*	0.078	0.078	0.079
70+ K	0.404	0.419	0.385*	0.412	0.439	0.382*
Home Ownership	0.686	0.661	0.716*	0.685	0.652	0.723*
Rent	0.314	0.339	0.284*	0.315	0.348	0.277*
Unemployed	0.400	0.355	0.454*	0.402	0.355	0.456*
Employed	0.600	0.645	0.546*	0.598	0.645	0.544*
BC	0.132	0.129	0.136	0.133	0.133	0.133
AB	0.099	0.097	0.100	0.098	0.104	0.092
MB/SK	0.069	0.061	0.078*	0.069	0.061	0.078*
ON	0.367	0.374	0.359	0.367	0.376	0.356*
QC	0.255	0.264	0.245	0.255	0.257	0.254
NB/NF/NS/PEI	0.078	0.075	0.082	0.078	0.069	0.088*
Observations	11,695	5,996	5,699	12,241	6,162	6,079

Notes: HH denotes household. Numbers are in proportions. Characteristics are measured in 2010 for the 2010-11 panel, and in 2011 for the 2011-12 panel. Sample weights were used in these computations. $*$ denotes significant difference between stayers and attritors at 5 percent level.

Table 11: First-year banking and payment characteristics: attritors vs. stayers

	2010-11 panel			2011-12 panel		
	2010	Attritors	Stayers	2011	Attritors	Stayers
Cash Ratio: Value	0.219	0.219	0.220	0.209	0.211	0.206
Volume	0.361	0.359	0.368	0.352	0.349	0.357
CC balance	3,153	3,409	2,547	2,828	2,970	2,532
Bank account balance	11,610	10,249	14,832*	12,078	10,623	15,121*
CC revolver (proportion)	0.366	0.395	0.298*	0.372	0.406	0.300*
Number of CC	1.91	1.89	1.95	1.90	1.86	1.98*
Number of bank accounts	2.26	2.26	2.24	2.28	2.27	2.28
Number of DC	2.31	2.38	2.14*	2.35	2.41	2.21*
HH that paid with:						
Cash past week	0.912	0.915	0.906	0.899	0.900	0.897
CC past month	0.785	0.779	0.800	0.807	0.797	0.828*
DC past month	0.801	0.840	0.708*	0.800	0.843	0.711*
CTC past month	0.135	0.133	0.141	0.181	0.171	0.202*
SVCm past month	0.098	0.112	0.066*	0.112	0.117	0.100
SVCs past month	0.391	0.410	0.345*	0.409	0.430	0.364*
Cheque past month	0.564	0.551	0.596*	0.544	0.536	0.561
Relative Expenditure Share:						
Groceries	1.042	1.072	0.968*	1.034	1.057	0.984*
Food at restaurants/takeout	1.025	1.058	0.948*	1.003	1.027	0.953
Food from convenience stores	1.051	1.110	0.912*	1.023	1.096	0.871*
Recreation	1.015	1.102	0.810*	1.011	1.012	1.007
Automobile/gas	0.999	1.032	0.922*	1.036	1.066	0.973
Observations	4,161	2,834	1,327	4,235	2,751	1,484

Notes: CC: credit card, DC: debit card, HH: household. Balances are in dollars. Payment method users are in proportions. Relative expenditure shares are ratios relative to the average within the household head's demographic stratum. Characteristics are measured in 2010 for the 2010-11 panel, and in 2011 for the 2011-12 panel. Sample weights are used in these computations. $*$ denotes significant difference between stayers and attritors at 5 percent level.

Table 12: Cash ratio regressions without attrition correction

	2010 OLS	2011 OLS	2012 OLS	Pooled OLS	Balanced panel OLS	Balanced panel FD
CTC						
$\hat{\beta}$ for cash volume	-0.082	-0.093	-0.106	-0.096	-0.105	0.000
s.e.	0.0089	0.0081	0.0081	0.0055	0.0129	0.0151
t-stat	-9.21	-11.48	-13.09	-17.45	-8.14	0.00
$\hat{\beta}$ for cash value	-0.083	-0.084	-0.097	-0.089	-0.091	-0.006
s.e.	0.0072	0.0066	0.0068	0.0051	0.0119	0.0151
t-stat	-11.53	-12.73	-14.26	-17.45	-7.65	-0.40
SVCm						
$\hat{\beta}$ for cash volume	-0.018	-0.023	-0.018	-0.021	-0.031	-0.037
s.e.	0.0121	0.0105	0.0112	0.0069	0.0193	0.0170
t-stat	-1.49	-2.19	-1.61	-3.04	-1.61	-2.18
$\hat{\beta}$ for cash value	0.005	-0.005	-0.017	-0.006	-0.014	-0.023
s.e.	0.0114	0.0095	0.0098	0.0064	0.0178	0.0170
t-stat	0.44	-0.53	-1.73	-0.94	-0.79	-1.35
SVCs						
$\hat{\beta}$ for cash volume	-0.015	-0.02	-0.033	-0.022	-0.018	-0.026
s.e.	0.007	0.007	0.0073	0.0043	0.0109	0.0097
t-stat	-2.14	-2.86	-4.52	-5.12	-1.65	-2.68
$\hat{\beta}$ for cash value	-0.01	-0.013	-0.016	-0.013	-0.006	-0.018
s.e.	0.0066	0.0065	0.0069	0.004	0.01	0.0097
t-stat	-1.52	-2.00	-2.32	-3.25	-0.60	-1.86
Observations	4,759	4,511	4,331	13,601	2,286	2,286
Households	4,759	4,511	4,331	10,397	762	762

Notes: OLS is the ordinary least-squares estimator. Pooled OLS is the pooled OLS estimator obtained on the unbalanced panel. Balanced panel denotes households who participated in all three years. $\hat{\beta}$ are the point estimates, while s.e. are standard errors. Balanced panel OLS is the pooled OLS estimator obtained on the balanced panel. FD is the first-difference estimator.

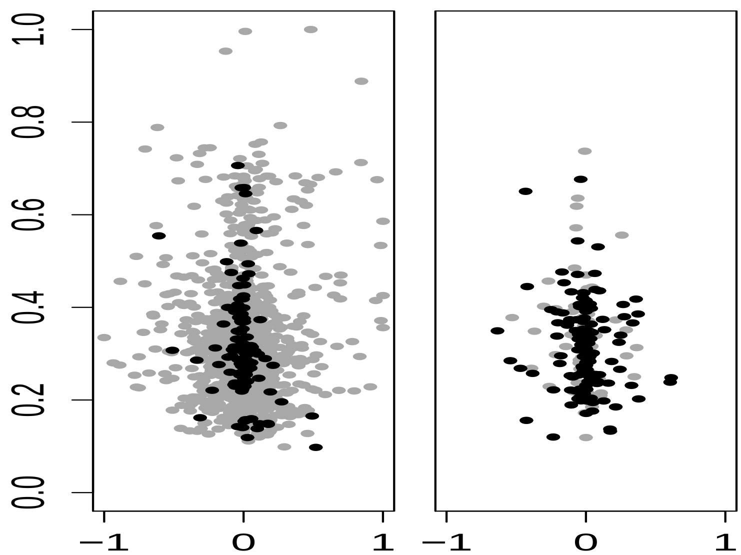
Table 13: Cash ratio regressions with attrition correction

	No correction		Correction
	FD	$\mathcal{M}^2_{NC}$	$\mathcal{M}^2_{AN}$
CTC			
$\hat{\beta}$ for cash volume	0.001	0.006	0.015
s.e.	0.0127	0.0108	0.0137
t-stat	0.08	0.52	1.12
$\hat{\beta}$ for cash value	0.005	0.006	0.002
s.e.	0.0126	0.0106	0.0125
t-stat	0.40	0.61	0.14
SVCm			
$\hat{\beta}$ for cash volume	-0.025	-0.023	-0.024
s.e.	0.0145	0.0155	0.0227
t-stat	-1.72	-1.50	-1.08
$\hat{\beta}$ for cash value	-0.022	-0.017	-0.002
s.e.	0.0144	0.0143	0.0194
t-stat	-1.53	-1.16	-0.12
SVCs			
$\hat{\beta}$ for cash volume	-0.018	-0.020	-0.022
s.e.	0.0085	0.0091	0.0099
t-stat	-2.12	-2.22	-2.19
$\hat{\beta}$ for cash value	-0.008	-0.009	-0.001
s.e.	0.0084	0.0085	0.0098
t-stat	-0.95	-1.08	-0.08
Observations	2,113	2,113	13,601
Households	1,351	1,351	10,397

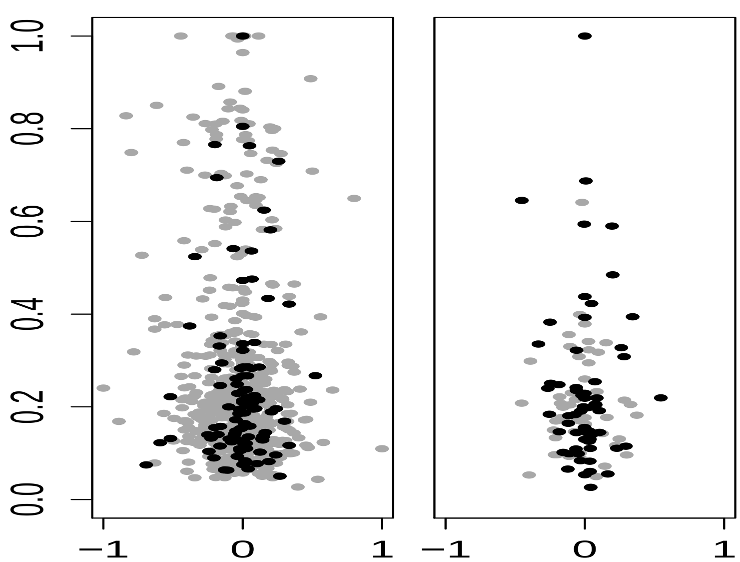
Notes: $\hat{\beta}$ are the point estimates, while s.e. are standard errors. FD is the parametric first-difference estimator. $\mathcal{M}^2_{NC}$ and $\mathcal{M}^2_{AN}$ are sieve minimum distance estimators, with and without attrition correction. In all cases, the two first-differencing equations are estimated on the 2010-11 balanced panel and the three-year balanced panel. Details are provided in Appendix B.

Figure 1: CTC, attrition probability versus the cash ratio in volume

$$M^{01}_{(1,2)}:\ E\left[\frac{\Delta CR_2 - \hat{\beta}\Delta PI_2 - \Delta X_2 \hat{\gamma}}{\hat{g}(X_1, CR_1, X_2, CR_2)}\,\middle|\, S_2 = 1, X_1, X_2\right]$$



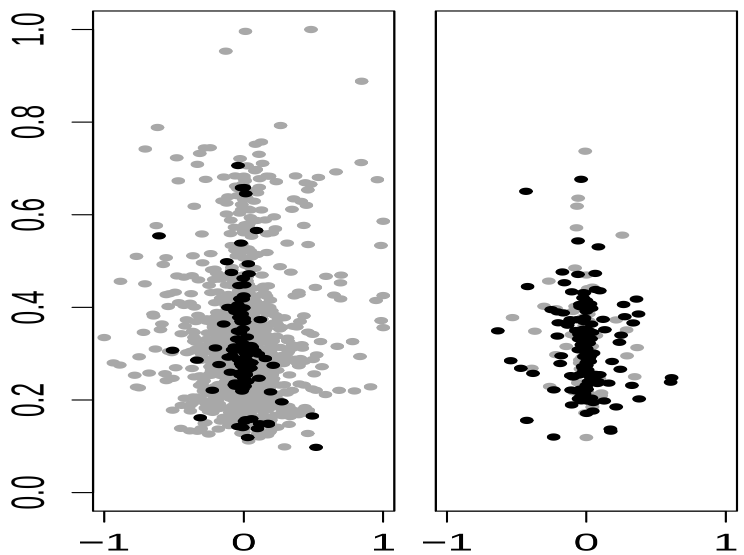
$$M^{02}_{(2,3)}:\ E\left[\frac{\Delta CR_3 - \hat{\beta}\Delta PI_3 - \Delta X_3 \hat{\gamma}}{\hat{g}(X_1, CR_1, X_2, CR_2, X_3, CR_3)}\,\middle|\, S_2 S_3 = 1, X_2, X_3\right]$$



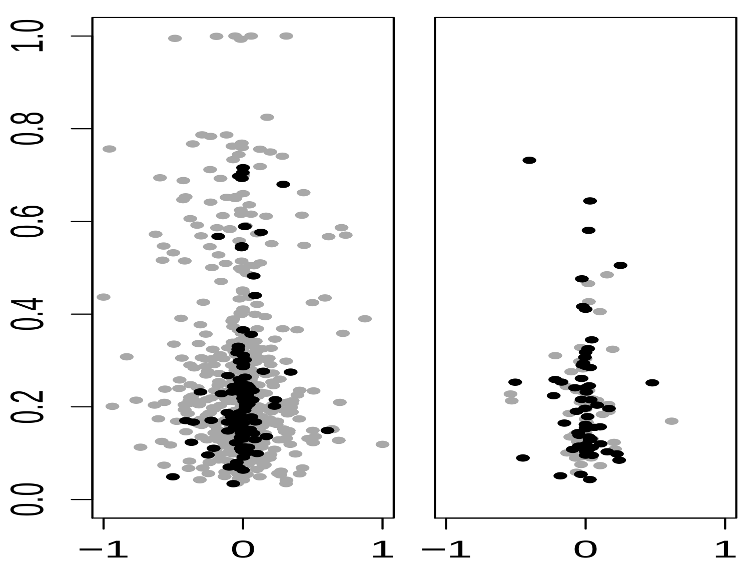
Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 2: CTC, attrition probability versus the cash ratio in value

$$M^{01}_{(1,2)}:\ E\left[\frac{\Delta CR_2-\hat{\beta}\Delta PI_2-\Delta X_2\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2)}\middle| S_2=1,X_1,X_2\right]$$



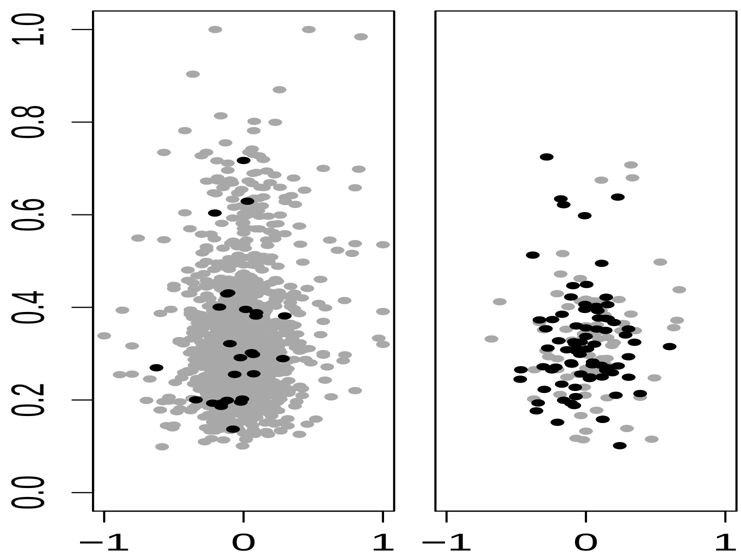
$$M^{02}_{(2,3)}:\ E\left[\frac{\Delta CR_3-\hat{\beta}\Delta PI_3-\Delta X_3\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2,X_3,CR_3)}\middle| S_2S_3=1,X_2,X_3\right]$$



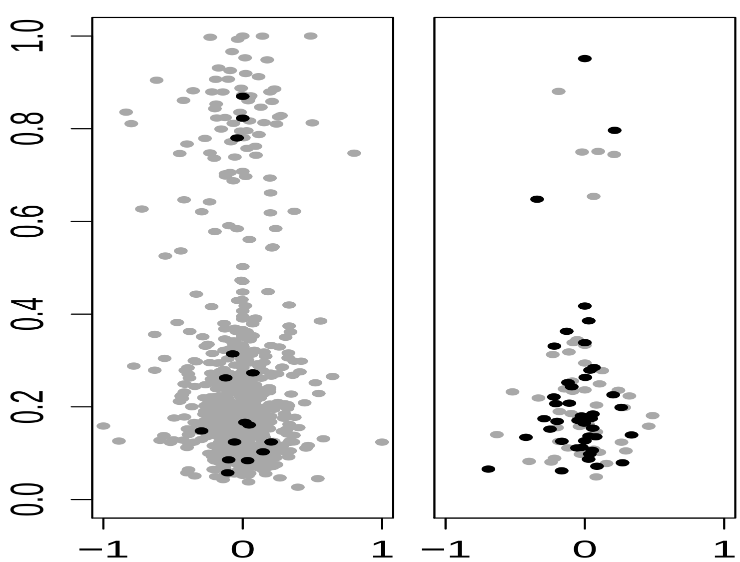
Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 3: SVCm, attrition probability versus the cash ratio in volume

$$M^{01}_{(1,2)}\colon\ E\left[\frac{\Delta CR_2-\hat{\beta}\Delta PI_2-\Delta X_2\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2)}\middle| S_2=1,X_1,X_2\right]$$



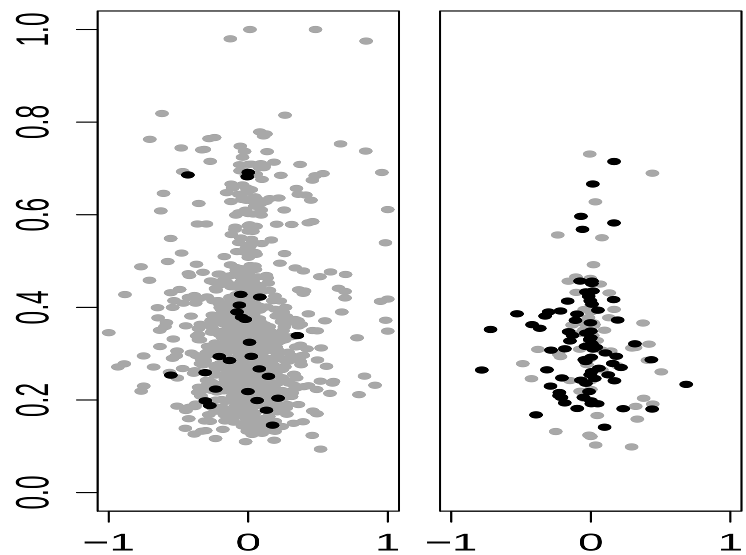
$$M^{02}_{(2,3)}\colon\ E\left[\frac{\Delta CR_3-\hat{\beta}\Delta PI_3-\Delta X_3\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2,X_3,CR_3)}\middle| S_2S_3=1,X_2,X_3\right]$$



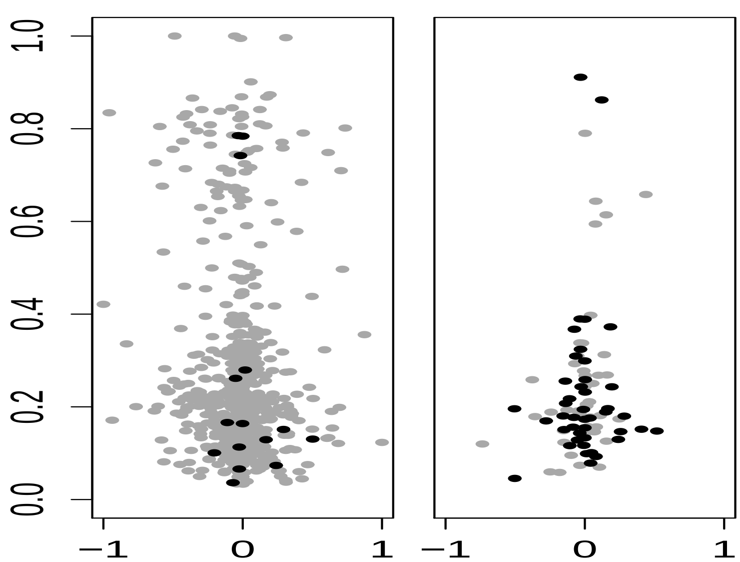
Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 4: SVCm, attrition probability versus the cash ratio in value

$$M^{01}_{(1,2)}:\ E\left[\frac{\Delta CR_2-\hat{\beta}\Delta PI_2-\Delta X_2\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2)}\middle| S_2=1,X_1,X_2\right]$$



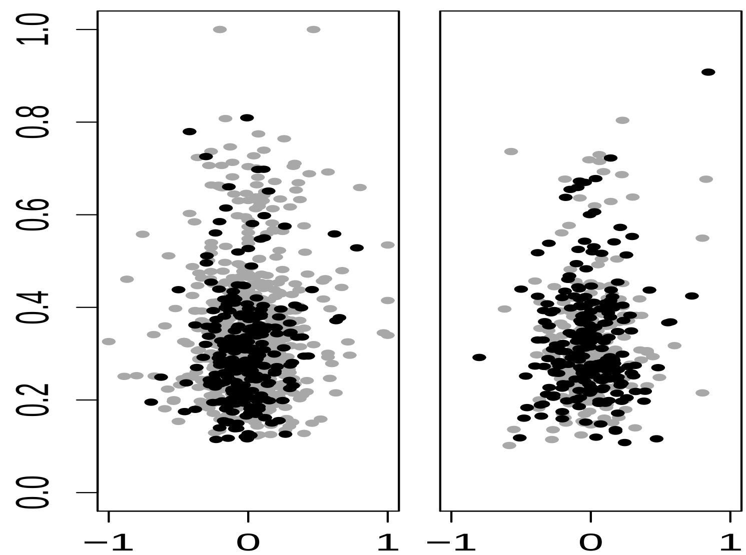
$$M^{02}_{(2,3)}:\ E\left[\frac{\Delta CR_3-\hat{\beta}\Delta PI_3-\Delta X_3\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2,X_3,CR_3)}\middle| S_2S_3=1,X_2,X_3\right]$$



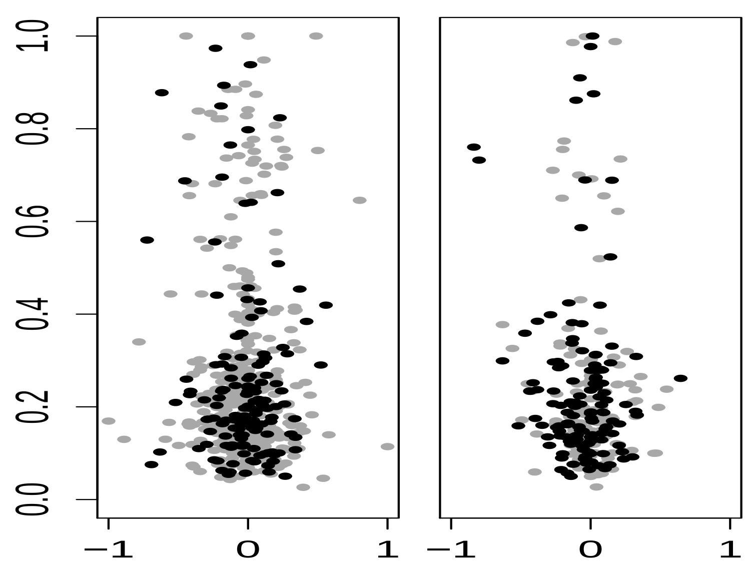
Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 5: SVCs, attrition probability versus the cash ratio in volume

$$M^{01}_{(1,2)}:\ E\left[\frac{\Delta CR_2-\hat{\beta}\Delta PI_2-\Delta X_2\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2)}\middle| S_2=1,X_1,X_2\right]$$



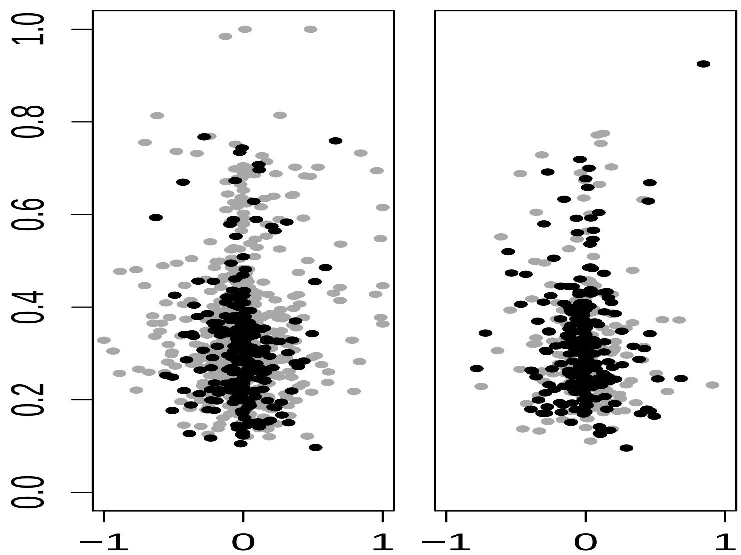
$$M^{02}_{(2,3)}:\ E\left[\frac{\Delta CR_3-\hat{\beta}\Delta PI_3-\Delta X_3\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2,X_3,CR_3)}\middle| S_2S_3=1,X_2,X_3\right]$$



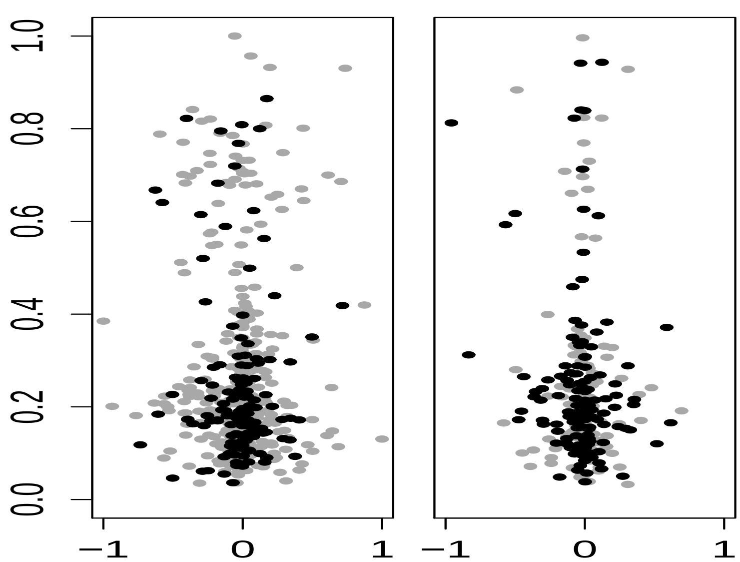
Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 6: SVCs, attrition probability versus the cash ratio in value

$$M^{01}_{(1,2)}:\ E\left[\frac{\Delta CR_2-\hat{\beta}\Delta PI_2-\Delta X_2\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2)}\middle| S_2=1,X_1,X_2\right]$$



$$M^{02}_{(2,3)}:\ E\left[\frac{\Delta CR_3-\hat{\beta}\Delta PI_3-\Delta X_3\hat{\gamma}}{\hat{g}(X_1,CR_1,X_2,CR_2,X_3,CR_3)}\middle| S_2S_3=1,X_2,X_3\right]$$



Notes: The estimated survival function, $\hat{g}(\cdot)$, is on the y-axis while the change in the cash ratio is on the x-axis. The functions $\hat{g}_{1,2}$ (from $M^{01}_{(1,2)}$) and $\hat{g}_{1,2,3}$ (from $M^{02}_{(2,3)}$) are depicted in the top and bottom panes, respectively. The left-side pane depicts: the never-users (0,0) in grey and the always-users (1,1) in black; the right-side pane contains: the stop-users (1,0) in grey and the new-users (0,1) in black.

Figure 7: Comparison of CTC Estimates (Volume)

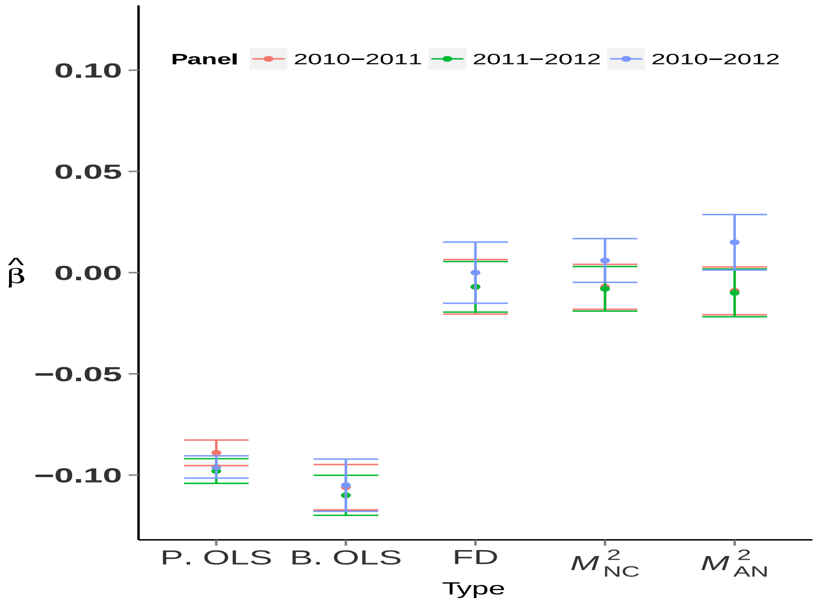
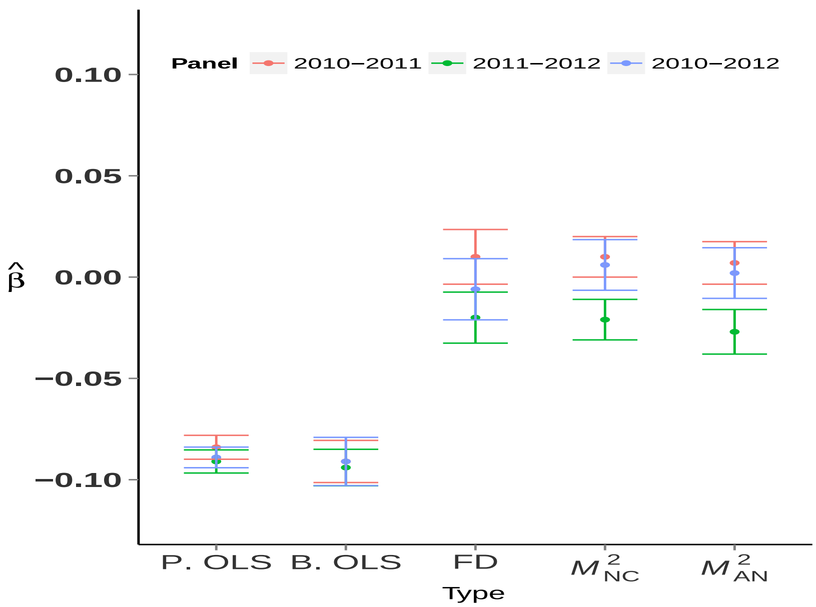


Figure 8: Comparison of CTC Estimates (Value)



Notes: These box-plots depict estimates of β with their 95 percent confidence intervals. Estimates are obtained on the two-year and three-year panels. P. OLS is the pooled OLS estimator obtained on unbalanced panels. B. OLS is the pooled OLS estimator obtained on balanced panels. FD is the panel first-difference estimator. Models $\mathcal{M}^2_{NC}$ and $\mathcal{M}^2_{AN}$ are for estimating β according to Appendix B.

Figure 9: Comparison of SVCm Estimates (Volume)

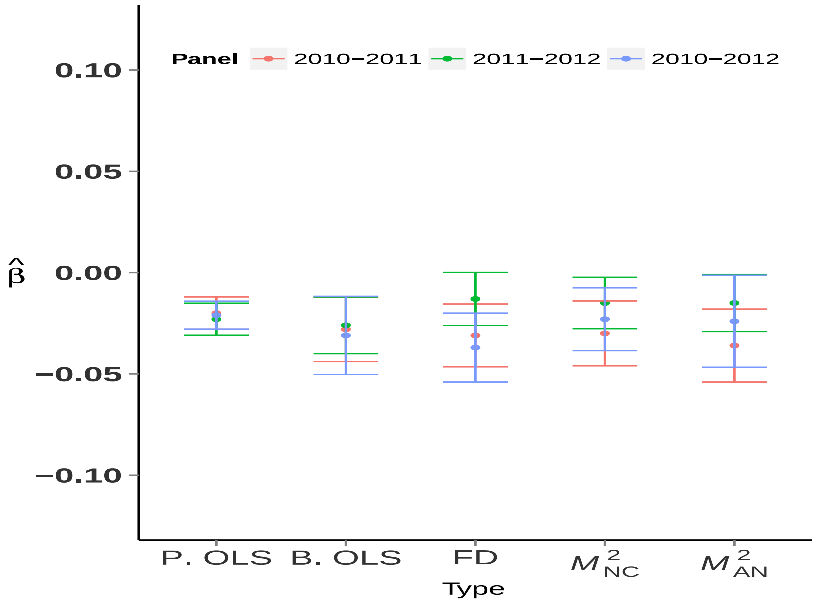
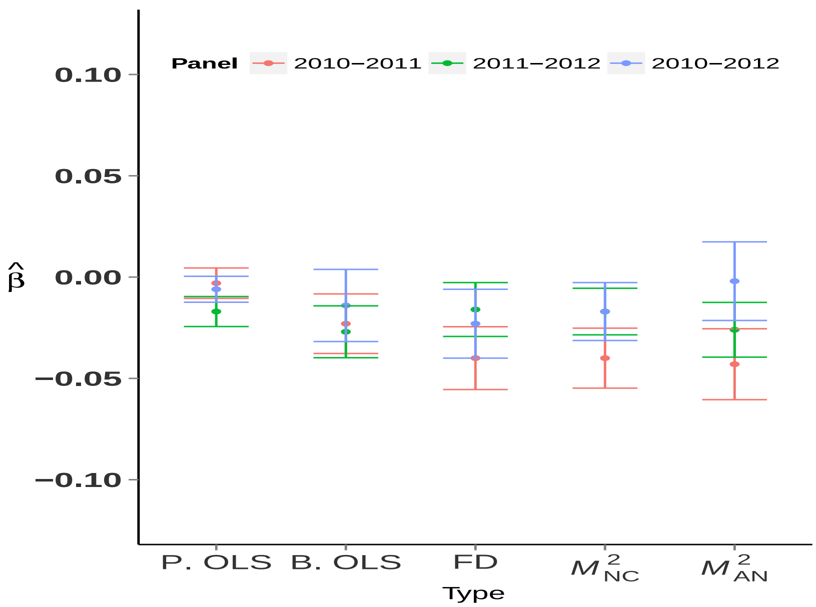


Figure 10: Comparison of SVCm Estimates (Value)



Notes: These box-plots depict estimates of β with their 95 percent confidence intervals. Estimates are obtained on the two-year and three-year panels. P. OLS is the pooled OLS estimator obtained on unbalanced panels. B. OLS is the pooled OLS estimator obtained on balanced panels. FD is the panel first-difference estimator. Models $\mathcal{M}^2_{NC}$ and $\mathcal{M}^2_{AN}$ are for estimating β according to Appendix B.

Figure 11: Comparison of SVCs Estimates (Volume)

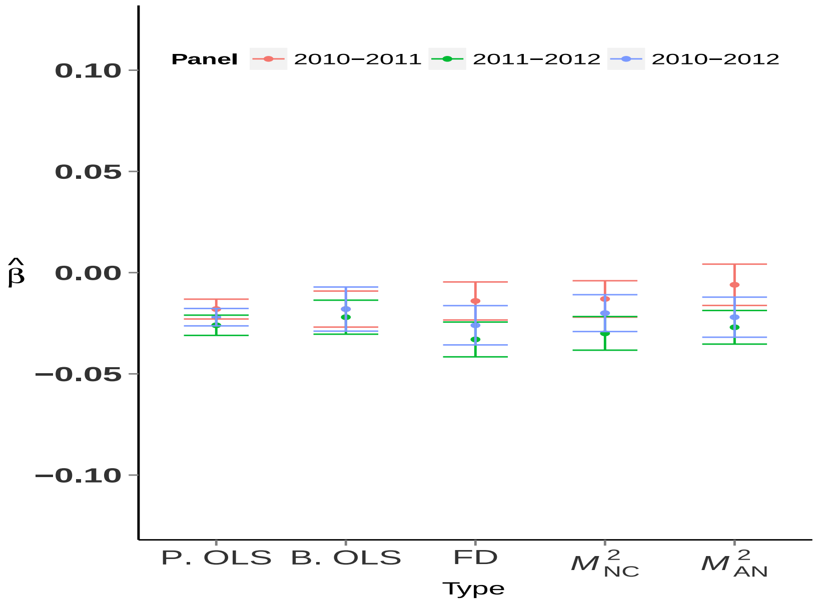
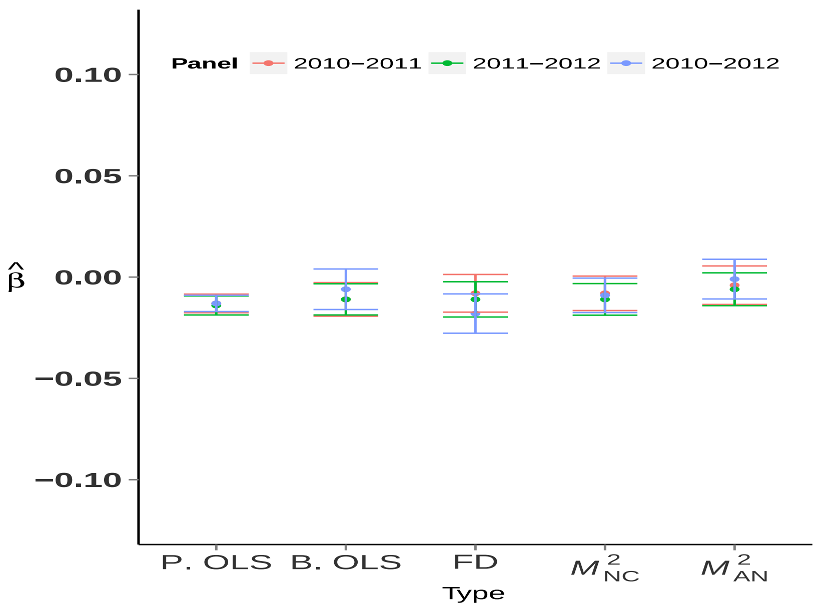


Figure 12: Comparison of SVCs Estimates (Value)



Notes: These box-plots depict estimates of β with their 95 percent confidence intervals. Estimates are obtained on the two-year and three-year panels. P. OLS is the pooled OLS estimator obtained on unbalanced panels. B. OLS is the pooled OLS estimator obtained on balanced panels. FD is the panel first-difference estimator. Models $\mathcal{M}^2_{NC}$ and $\mathcal{M}^2_{AN}$ are for estimating β according to Appendix B.

A Variables description

This section describes the variables from the Canadian Financial Monitor used in our analysis. Explanatory variables included in the first-differencing equation (2):[15]

1. Demographics:
   - Log of head age and Log of head age squared: logarithm and square of logarithm of age of the household head in years.
   - Income: household income for the past year before taxes, a categorical variable the base category of which is under 30K.
   - Internet user: a dummy variable indicating whether any member of the household uses the Internet.
   - CC revolver: a dummy variable indicating whether any member of the household revolved on their credit card balance in the past month.
2. Types of expenditure:

   To avoid potential endogeneity issues, we measure household expenditures in various categories as a ratio relative to the average within the individual's demographic stratum (defined according to age and income group), following Stango (2000). Expenditure categories considered are: groceries, including beverages; food and beverages at restaurants/clubs/bars; snacks and beverages from convenience stores; recreation; automobile maintenance/gas. For each household, we calculate the share of expenditures made in each category in the past month relative to the total value of purchases made in the past month.
3. Payment innovation variables such as CTC/SVCm/SVCs user: a dummy variable indicating whether any member of the household used a given payment innovation to make purchases in the past month.

[15]Besides the use of the payment innovation variable, the same variables are used to specify the attrition function.

B Attrition Function and Moment Conditions

Table B.1: Description of the estimated models

Model	EF	SF	Moments	Panels
$\mathcal{M}^1_{NC}$	ϕ_t	1	$M^{01}_{(t-1,t)}$	t=2011,2012
$\mathcal{M}^1_{MAR}$	ϕ_t	g_{t-1}	$M^{01}_{(t-1,t)}, M^{11}_{t-1}$	t=2011,2012
$\mathcal{M}^1_{HW}$	ϕ_t	g_t	$M^{01}_{(t-1,t)}, M^{11}_{t-1}$	t=2011,2012
$\mathcal{M}^1_{AN1}$	ϕ_t	$g_{(t-1,t)}$	$M^{01}_{(t-1,t)}, M^{11}_{t-1}, M^{21}_t$	t=2011,2012
$\mathcal{M}^1_{AN2}$	ϕ_t	$g_{(t-2,t-1,t)}$	$M^{02}_{(t-1,t)}, M^{12}_{t-2}, M^{22}_{t-1}, M^{32}_t$	t=2012
$\mathcal{M}^2_{NC}$	$\{\phi_{t-1},\ \phi_t\}$	$\{1,1\}$	$\{M^{01}_{(t-2,t-1)}, M^{02}_{(t-1,t)}\}$	t=2012
$\mathcal{M}^2_{AN}$	$\begin{cases}\phi_{t-1}\\ \phi_t\end{cases}$	$\begin{cases}g_{(t-2,t-1)}\\ g_{(t-2,t-1,t)}\end{cases}$	$\begin{cases}M^{01}_{(t-2,t-1)}, M^{11}_{t-2}, M^{21}_{t-1}\\ M^{02}_{(t-1,t)}, M^{12}_{t-2}, M^{22}_{t-1}, M^{32}_t\end{cases}$	t=2012

The estimation function (EF) is defined as

$$\phi_t: \ \ \phi(z_{t-1}, z_t, \beta) \ = \ \Delta CR_{it} = \beta \Delta PI_{it} + \Delta X_{it}\gamma + \Delta u_{it}.$$

The survival function (SF) is defined as

$$\begin{aligned}
g_{t-1}: & \quad \Pr(S_t = 1) & \equiv \ & g\left(k(z_{t-1})\right), & [MAR]\\
g_t: & \quad \Pr(S_t = 1) & \equiv \ & g\left(k(z_t)\right), & [HW]\\
g_{(t-1,t)}: & \quad \Pr(S_t = 1) & \equiv \ & g\left(k_1(z_{t-1}) + k_2(z_t)\right), & [AN1]\\
g_{(t-2,t-1,t)}: & \quad \Pr(S_{t-1}S_t = 1) & \equiv \ & g\left(k_1(z_{t-2}) + k_2(z_{t-1}) + k_3(z_t)\right). & [AN2]
\end{aligned}$$

The moments are defined as

$$\begin{aligned}
M^{01}_{(t-1,t)}: & \quad m_{01}(x_{t-1}, x_t, \delta) & \equiv \ & E\left\{\tfrac{\phi(z_{t-1}, z_t, \beta)}{\Pr(S_t=1)} \middle| \ S_t = 1, x_{t-1}, x_t\right\} = 0,\\
M^{11}_{t-1}: & \quad m_{11}(z_{t-1}, \delta) & \equiv \ & E\left\{\tfrac{S_t}{\Pr(S_t=1)} - 1 \middle| R_{t-1} = 1, z_{t-1}\right\} = 0,\\
M^{21}_t: & \quad m_{21}(z_t, \delta) & \equiv \ & E\left\{\tfrac{S_t}{\Pr(S_t=1)} - 1 \middle| R_t = 1, z_t\right\} = 0,\\
M^{02}_{(t-1,t)}: & \quad m_{02}(x_{t-1}, x_t, \delta) & \equiv \ & E\left\{\tfrac{\phi(z_{t-1}, z_t, \beta)}{\Pr(S_{t-1}S_t=1)} \middle| \ S_{t-1}S_t = 1, x_{t-1}, x_t\right\} = 0,\\
M^{12}_{t-2}: & \quad m_{12}(z_{t-2}, \delta) & \equiv \ & E\left\{\tfrac{S_{t-1}S_t}{\Pr(S_{t-1}S_t=1)} - 1 \middle| R_{t-2} = 1, z_{t-2}\right\} = 0,\\
M^{22}_{t-1}: & \quad m_{22}(z_{t-1}, \delta) & \equiv \ & E\left\{\tfrac{S_{t-1}S_t}{\Pr(S_{t-1}S_t=1)} - 1 \middle| R_{t-1} = 1, z_{t-1}\right\} = 0,\\
M^{32}_t: & \quad m_{32}(z_t, \delta) & \equiv \ & E\left\{\tfrac{S_{t-1}S_t}{\Pr(S_{t-1}S_t=1)} - 1 \middle| R_t = 1, z_t\right\} = 0.
\end{aligned}$$