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Abstract

Many predict that innovations in retail payment may render cash obsolete. We investigate this possibility in the context of recent payment innovations such as contactless-credit and stored-value cards. We apply causal inference methods on the 2009 Bank of Canada Method of Payment survey, a representative sample of adult Canadians' shopping behaviour for retail consumption over a three-day period. We find that using contactless credit cards and stored-value cards lead to a reduction in average cash usage for transactions both in terms of value and volume. Sensitivity analysis is undertaken and our estimates are robust to hidden bias.

JEL classification: E41, C35, C83
Bank classification: Econometric and statistical methods; Financial services; Payment, clearing, and settlement services

Résumé

L'idée que les nouveautés dans le domaine des paiements de détail pourraient rendre l'argent comptant obsolescent est de plus en plus répandue. Nous étudions cette possibilité dans le contexte de récentes innovations comme la carte de crédit sans contact et la carte prépayée. À l'aide de méthodes d'inférence causale appliquées à l'enquête sur les modes de paiement menée par la Banque du Canada en 2009, nous étudions le comportement d'un échantillon représentatif d'adultes canadiens en matière de paiement de détail sur une période de trois jours. Nous montrons que le recours à la carte de crédit sans contact et à la carte prépayée se solde par une diminution de l'utilisation moyenne des espèces pour le règlement des transactions, à la fois en valeur et en volume. Une analyse de sensibilité confirme la robustesse de nos estimations à la présence éventuelle de biais cachés.

Classification JEL : E41, C35, C83
Classification de la Banque : Méthodes économétriques et statistiques; Services financiers; Services de paiement, de compensation et de règlement

1 Introduction

Prior to past innovations in retail payment instruments such as cheques, credit cards and debit cards, the overwhelming majority of transactions were conducted with cash. Significant declines in cash usage for retail payments have prompted some observers to point to the dismal prospects for cash in light of future payment innovations. This paper investigates the impact of recent retail payments innovations, such as stored-value and contactless-credit cards, on household cash usage. These payment innovations are often described and marketed as substitutes for cash, promising fast, convenient and secure payment services at the point-of-sale.[1] Understanding the possible substitution away from cash to electronic payments is important for central banks, such as the Bank of Canada, as they are the sole issuers of cash.

To put things in context we provide a brief overview regarding the evolution of the payments landscape in Canada. Figure 1 shows that the notes in circulation as a ratio of GDP peaked at about five percent in 1961 and declined to a trough of just below three percent in 1981, where it has remained fairly stable over the past 30 years. However, the trend by denominations offers a different perspective. Bank notes of 20 dollars or less, which are considered principally for retail transactions, have declined steadily since 1961 from roughly 3.5 to 1.2 percent. Meanwhile, bank notes of denominations of 50 dollars and above, often held for store-of-value or precautionary purposes, have seen an increase from 1.4 to 2.5 percent over this period. Over the last 40 years, there has been a considerable decline in the use of bank notes for retail transactions. Part of the explanation of this decline is due to inflation. However, alternative explanations are due changing payment landscape. The study by Amromin and Chakravorti (2009) finds that the decline in small value notes is consistent for many countries. They conduct a survey of cash usage in 13 countries (including Canada). They segment bank notes into low, medium and high denominations and conduct panel data estimates. They conclude that small value denominations are falling for transaction purposes, while larger denominations are increasing to serve as a store of value function.

[1]Examples of stored-value cards are merchant gift cards, pre-paid credit cards, etc. They were introduced in Canada around 2000. Contactless-credit cards were first introduced in 2006 and consist of chip embedded on the credit card. It promises convenience and speed as customers need only tap their card on a payment terminal instead of swiping the card and providing a signature for verification. For more information on the Canadian Payments landscape see the following report:
http://paymentsystemreview.ca/wp-content/uploads/Payments-Landscape-Full-Report-e3.pdf

In terms of the relative usage of cash and other means of payment, Figure 2 shows how the usage of credit cards and debits cards has increased rapidly while cash withdrawals from automated teller machine (ATM) have fallen over the past 20 years. Table 1 provides estimates of cash usage in terms of value and volume based on aggregate network data. During this 20 year period, the share of cash has fallen. Debit and credit cards account for a large portion of the value substitution while debit has captured a major portion of the cash volume share. However, despite the widespread diffusion of debit and credit cards the cash volume share illustrates that there is still a role for cash in retail payments.

To understand the use of cash and other means of payment, the Bank of Canada conducted the 2009 Method of Payments Survey which offers a clear picture of payment choice at the micro level. Table 2 illustrates that cash is dominant in volume and value for *micro payment* transactions i.e. less than 10 dollars. As transaction value rises, there is a shift towards debit card in terms of volume and credit cards for value. The main determinants of debit and credit card usage are safety, record keeping, the ability to delay payment and credit card rewards. Research by Arango, Huynh, and Sabetti (2011) show that consumer preference for cash is correlated with speed or convenience, merchant acceptance and low costs. Therefore, for card payments to compete with cash they must mimic the desirable features of cash.

Stored-value cards and contactless-credit cards were introduced to fill this convenience niche. The attractiveness of these cards for micro payments is the speed of use (e.g. contactless cards entail tapping your card at a POS terminal instead of swiping or entering a PIN code) and relative low costs for consumers. Currently, these payment innovations have minimal market share, see Table 2. Despite the relatively low market share there is a large potential for this market.[2] Figure 3 shows that the payment profile of stored-value cards is similar to cash as they are predominately used for low value transactions. For contactless-credit cards, see Figure 3, the profile is similar for debit at intermediate transaction values (20-50 dollars).

Previous studies have attempted to study the impact of payment innovations on the use of cash.[3] Our paper contributes to this literature in two major aspects. First, the novelty of our

[2]For example, Borzekowski and Kiser (2008) predict that *contactless-debit* in the U.S. will increase substantially in the next 10 years.

[3]See Lippi and Secchi (2009) for a brief discussion of the related literature. See Stuber (1996) for a discussion of the electronic purse.

study is to assess the impact of the most recent payment innovations such as contactless-credit or stored-value cards, which compete directly with cash in terms of convenience and ease of use. Second, we use the program evaluation methodology (propensity score matching) to study the impact of payment innovation on the cash ratio, defined as the ratio of the value of cash purchases to the value of total expenditures in the survey diary. This method allows researchers to correct for selection bias that is inherent in non-experimental data without imposing too many assumptions. For example, instrumental variable (IV) or parametric selection models require that an instrument (exclusion restriction) exists and a specific functional form exists between the cash ratio and innovation equations. In many cases, it is hard to think of a variable that affects payment innovation without a direct affect on the cash ratio. Also, solely relying on functional forms is not considered a convincing identification strategy. In contrast, propensity score matching (PSM) only requires some assumptions on the probability of payment innovation and that the selection effect is driven by observable factors.

In this paper, we use data from the 2009 Bank of Canada Method of Payment (MOP) survey to estimate the effect of retail payment innovations on the cash ratio at the individual level. Using causal inference methods we find that: first, the average treatment effect of contactless-credit card results in a decrease of 14 per cent in the cash ratio in terms of value and 13 per cent for volume; second, the average treatment effect of stored-value cards suggests a decrease of roughly 12 per cent in the cash ratio in terms of value and 15 per cent for volume; third, sensitivity analysis suggests the findings are robust to varying degrees of unobserved heterogeneity.

The rest of this paper will proceed as follows: Section 2 will describe the micro data used in detail while Section 3 describes the empirical methodology. Section 4 highlights the results of the paper and Section 5 offers concluding remarks.

2 2009 Method of Payment (MOP) Survey

In order to provide a better understanding of the retail payment landscape, the Bank of Canada conducted an extensive micro survey of Canadians. The Bank of Canada 2009 MOP survey was conducted in November of 2009. Stratified random samples of adult Canadians aged 18 to 75 years old were drawn from access panels to obtain a national representative sample.

The inclusion of an offline panel ensured coverage of the segment of the population without internet access. Survey respondents completed a survey questionnaire (SQ) and a three-day shopping diary (DSI), which was optional for participants from the online panel. The SQ included questions on demographics, banking and card information, perceptions on method of payment attributes and cash management or spending habits. The DSI collected records of payment behavior such as type of good purchased, value of transaction, payment method used, and whether any cash was obtained during the transaction. The survey comprised roughly 6,800 SQ respondents, and 3,200 DSI respondents which generated over 17,000 transactions. Finally, sample weights were designed to combine both online and offline samples using the Statistics Canada 2009 Canadian Internet Use Survey (CIUS) and a random digital dialing telephone survey.

The survey specifically asks respondents whether their main credit card was embedded with the contactless feature and whether the feature was used for transaction purposes. Questions about stored-value cards also appear in the survey. Table 2 shows the market shares in volume and value for each retail payment instrument used by individuals in the 2009 MOP Survey. It shows that cash still accounts for about half of all consumer spending in terms of volume but for only about 21 percent in terms of value. Credit cards and debit cards account for about the remaining half in terms of volume, and 76 percent in terms of value. However, cash dominates in low value transactions. Further, the shares of contactless-credit and stored-value cards are both small. In 2009, the share of contactless-credit card transactions was 1.2 and 0.9 percent in volume and value, respectively. Stored-value card purchases represented 1.6 and 1.1 percent in volume and value, respectively.

To estimate the impact on cash usage, we construct two measures of cash usage based on value and volume. For each individual in the DSI, we compute the cash ratio in terms of value, is the ratio of total value of cash purchases to total value of all purchases. The second measure, the cash share in terms of volume, is the ratio of total number of cash purchases to total number of all transactions. We suspect the effect on volume is important as the use of payment innovation is more greatly concentrated at the lower transaction value spectrum. We use these measures as opposed to a measure of cash holding, whether at the start of the diary or some average, due to the endogeneity between cash holding and spending. A large cash holding may be partly motivated by the anticipation of incurring a large purchase or may be due to precautionary motives. Another issue is that cash holdings are strongly linked to economic transactions above and beyond retail locations. As a result, we exclusively focus on cash spending at retail locations as a proportion of total spending, and abstract from cash holdings. There are some diaries which have no transactions or just a a few (less than three). These respondents may have underreported or did not have many shopping opportunities.[4] Therefore, in the analysis only respondents who conducted at least three transactions in the DSI are used in our estimation sample. Conditioning on this sample, the average respondent conducts about six transactions, or roughly two per day. We find that excluding those individuals with fewer than three transactions does not affect the results, but reduces noise in our outcome variable. Although a diary of longer duration may have resulted in richer payment histories, the costs of collecting such information as well as the limitations of survey completion rates and fatigue effects, made three days the most practical length. For a practical suggestion on diary length see Jonker and Kosse (2009).

Table 3 distinguishes users of contactless-credit and stored-value cards (innovators) from individuals who do not (non-innovators) use them. The sample of innovators is more skewed towards the higher income and education brackets, and also spends more on average in the DSI and carries higher average bank account balances. Users of contactless-credit begin the diary with a slightly smaller amount of cash in their wallets on average as to non-users. However, the initial average cash holding for stored-value card users is roughly 64 dollars, which is less than the average of 77 dollars for non-users. Table 4 highlights the cash value and volume shares across innovators and non-innovators. The average non-user of contactless, with access to a credit card, spends roughly 32 percent of total value of purchases using cash while this number falls to 13 percent for contactless-users. The average stored-value card user spends 17 percent of total value using cash compared to 37 percent for the average non-user. In terms of volume, the average non-innovator conducts roughly half of all purchases in cash. The ratio of number of cash purchases to the total number of purchases in the DSI falls to 34 percent for the average contactless-user and to 29 percent for the average stored-value card user. We

[4] A statistical analysis was completed to compare demographic characteristics of these households. There was no marked statistical significance in the characteristics.

find that both cash ratios, in terms of value and volume, are lower for payment innovators than for non-innovators and this finding is consistent across demographic groups, such as income levels. Table 4 also highlights a correlation between cash ratios in value and volume and some observable variables. For instance, the cash ratios are declining as income rises, and as debit and credit cards are more often accepted during one's shopping history. Furthermore, higher rankings of cash in terms of perceptions such as record keeping are associated with higher cash ratios in value and volume. The correlation across age seems to exhibit a U-shaped pattern, with higher cash usage seen across young adults under 25 and the elder over 55. An exception is contactless-credit users whose cash ratio increases with age. The results are generally in line with previous studies such as Stavins (2001), inter alia.

From the DSI we can observe some interesting empirical facts about the use of contactless-credit and stored-value cards in relation to the traditional payment methods, cash, debit and credit. For example, Table 5 shows that the use of stored-value cards varies across types of purchases but that the bulk of purchases, roughly 43 percent, fall in the category of entertainment or meals, which also includes popular coffee outlets. Contactless-credit card purchases are overwhelmingly used for groceries, 56 percent, and at gasoline stations, 24 percent. Interestingly, the share of contactless-credit purchases in the retail goods category falls to roughly three percent, compared to 22 percent for credit cards. The lower use of contactless-credit feature relative to the traditional swipe-method for this class of purchases which are larger on average and more time-intensive suggests both reduced availability from the merchant side and less demand for facilitating the speed of the transaction from the consumer side.

Table 6 computes the proportion of transactions by payment method at different time intervals in terms of value and volume. It compares both weekday and weekend, and morning (AM) and afternoon or evening (PM). The table reveals that the majority of transactions are on weekday PM for all payment choices. However, both contactless-credit and stored-value cards have a larger proportion relative to other payment methods in terms of value. For both cash and stored-value cards the weekday AM transactions are larger in terms of volume than value pointing to small value transactions undertaken (i.e. buying a coffee). The patterns for contactless-credit, relative to debit and credit, indicate that it is used mostly in the PM weekday where time may be a constraint. On weekend PM the shares are slanted towards debit and credit cards.

The descriptive statistics offer preliminary suggestive evidence that payment innovation, defined by usage of contactless-credit and stored of value cards, is leading to a reduction of cash usage. However, we also observe that payment innovators are not a random sample from the broader population and the decision to use payment innovation may not be exogenous to cash usage. In the next section we discuss how empirically we can conduct a more appropriate assessment.

3 Empirical Methodology

From our descriptive statistics in Table 3 we find that innovators tend to use less cash than non-innovators. To link observable information with cash ratio we can estimate the relationship using an ordinary least squares (OLS) regression:

$$CR_i = \mathbf{X_i}\beta + \delta PI_i + u_i, \tag{1}$$

where CR_i is cash ratio, PI_i takes a value of one if the individual uses innovation and zero otherwise, and $\mathbf{X_i}$ is the vector of observables. In order to obtain an unbiased estimate of $\hat{\delta}$, the causal parameter, we require that PI is strictly exogenous. However, the direction of causation could run in the reverse direction i.e. people who use less cash are more likely to use innovative payment choices. This raises the endogeneity issues of whether innovation drives cash usage or vice-versa. Also, there maybe a selection issue whereby a third, unobserved factor, causes an individual both to select an innovative feature and simultaneously to use less cash.[5] An example could be an individual's preference for technology. Individuals who prefer technology may also tend to hold less cash and high propensity to use payment innovations. Under a scenario of selection bias, the causal effect of payment innovation on cash usage may be confounded.

The advantage of the 2009 MOP Survey is that beyond pertinent observable characteristics for each individual, whether demographics, banking profile or shopping behaviour, the inclu-

[5]For payment card choice it is exacerbated by the issue of two-sided markets. That is the users of card payments and the merchants who offer these payment choices via terminals. Therefore, the usage of payment innovation may exhibit feedback effects. For more details on the empirics of two-sided markets see Rysman (2007).

sion of perceptions on payment attributes helps capture what otherwise would be unobserved heterogeneity. Therefore, the usage of payment innovation is non-random, so we need to control for selection. A common approach, suggested by Duca and Whitesell (1995), is to estimate a two-system equation which models the outcome or cash ratio and the selection or payment innovation:

$$\begin{aligned} CR_i &= \mathbf{X_i}\beta_1 + \delta PI_i + u_i, \\ PI_i^* &= \mathbf{X_i}\beta_2 + \rho \mathbf{W_i} + \epsilon_i, \end{aligned} \tag{2}$$

where PI_i^* represents the latent utility from using payment innovation or

$$PI_i = \begin{cases} 1, & \text{if } PI_i^* > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

However, this methodology requires the variable, $\mathbf{W_i}$, to be correlated with the probability of payment innovation but not to directly affect cash usage. In the econometric literature this shifter is known as an exclusion restriction. The robustness of the results will hinge on the quality of these exclusion restrictions which can be difficult to ascertain.[6] Without exclusion restrictions, identification depends on strong assumptions of normality and functional forms, which may not be tenable.[7] Our attempt to implement this procedure resulted in implausible estimates, due to the lack of instruments and the parametric specification that the error terms follows a bivariate normal distribution.

Panel data methods are an alternative way to account for unobserved heterogeneity. For example, Hsiao (2002) discusses how to either parametrize the unobserved heterogeneity using the random-effects approach or to *difference* it via fixed-effects. Empirical implementation of such methods have been used by Lippi and Secchi (2009) or Fujiki and Tanaka (2009). These authors use the panel structure of the Italian and Japanese household data, respectively, to control for unobserved heterogeneity. Unfortunately, our study does not contain panel data and so this feature cannot be exploited.

Our analysis is undertaken in the spirit of Mulligan and Sala-i-Martin (2000) who model

[6] Attanasio, Guiso, and Jappelli (2002) in their study of Italian household data use provincial variation in the number of bank branches and ATMs as an exclusion restriction. They argue that the geographical variation in banking should affect adoption but not money demand.

[7] Other empirical examples are Stix (2004), Schuh and Stavins (2010), inter alia.

the extensive and intensive margins of money demand. They explicitly model the decision to adopt a bank account (extensive margin) and find that it affects one-half of the interest elasticity (intensive margin) especially at low interest rates. The intensive margins are important if there are large variations in the interest rates. However, at low interest rates the extensive margins dominates since there is a lot of heterogeneity or variation across households.

3.1 Program Evaluation Approach

Here we briefly discuss how we use the program evaluation approach to estimate the impact of innovations on cash usage. With respect to both measures of cash usage in terms of value and volume, we can define $CR_i(PI_i)$ as the cash ratio for individual i, which can take on either of two values, $CR_i(1)$ for innovators ($PI_i = 1$) and $CR_i(0)$ for non-innovators ($PI_i = 0$). We are interested in the difference between cash ratios for individual i as a payment innovator and as non-innovator or $CR_i(1) - CR_i(0)$. However, we can only observe either $CR_i(1)$ or $CR_i(0)$. Instead, we compare the cash ratio, for a payment innovator and a non-innovator who has comparable characteristics.

The group of innovators is referred to as the treatment group, whereas the non-innovators are the control group. The average difference in cash ratios is computed by taking the expectation of the difference in cash ratios between innovators and non-innovators, conditional on a set of observables. This quantity is known as the average treatment effect (ATE) and the average treatment effect on the treated (ATT):

$$\tau_{ATE|\mathbf{X}} = E[CR_i(1) - CR_i(0)|\mathbf{X_i}], \tag{4}$$

$$\tau_{ATT|\mathbf{X}} = E[CR_i(1) - CR_i(0)|\mathbf{X_i}, PI = 1]. \tag{5}$$

The ATE ($\tau_{ATE|X}$) represents the expected treatment on a randomly drawn individual across the entire sample whereas the the ATT ($\tau_{ATT|X}$) measures the mean effect for the sample of innovators. From a policy perspective, the latter quantity may be more relevant for individuals in the sample who are more likely to become payment innovators.

Thus, we estimate the $\tau_{ATE|X}$ and $\tau_{ATT|X}$ by comparing innovators and non-innovators with the same propensity score, $p(PI_i = 1|\mathbf{X_i})$, which denotes the probability that individual i uses payment innovation conditional on observable characteristics. This technique, known as propensity-score matching (PSM), allows for simple estimation of the desired causal impact because it reduces the matching problem from a vector of observable characteristics to a simple unit-dimensional measure. In the first stage, the propensity score denoted by $\hat{p}(X_i)$ is estimated. The propensity scores can then be compared using some distance metric. In our implementation we use both nearest-neighbour matching (NN) and kernel matching (KM). Therefore, we can write the PSM estimators for $\tau_{ATE|X}$ and $\tau_{ATT|X}$ as,

$$\widehat{ATE} = \hat{\tau}_{ATE|X} = \frac{1}{N}\sum_{i=1}^{N}\frac{[PI_i - \hat{p}(X_i)]\,CR_i(PI_i)}{\hat{p}(X_i)[1 - \hat{p}(X_i)]}, \tag{6}$$

$$\widehat{ATT} = \hat{\tau}_{ATT|X} = \frac{1}{N_1}\sum_{i=1}^{N_1}\frac{[PI_i - \hat{p}(X_i)]\,CR_i(PI_i)}{1 - \hat{p}(X_i)}, \tag{7}$$

where N_1 is the number of individuals who are payment innovators while N_2 are the non-innovators. By definition, the total sample is $N = N_1 + N_2$ individuals. Intuitively these estimators can be interpreted as an average of cash ratios weighted by propensities to use payment innovations.

A technical assumption required is the overlap assumption — individuals with the same characteristics must be capable of both participating and non-participating in payment innovations, or $0 < p(PI_i = 1|\mathbf{X_i}) < 1$. Otherwise, we would not have a comparison group for this subset of the sample. This assumption is verified by comparing the propensity scores of the two groups.

The second and more crucial assumption is commonly known in the literature as ignorability of treatment. That is conditional on observables $\mathbf{X}$, the decision to use payment innovation is random, or in other words, it is exogenous to the cash ratio decision. This assumption, also known as unconfoundedness or selection on observables, requires that two individuals with the same observable characteristics will both be just as likely to participate in innovation. In order for this assumption to hold, there must not exist any remaining factor beyond our current set of control variables that systematically causes two identically observed individuals to differ in their odds of using payment innovation, referred to as hidden bias. In practice, we cannot directly test the unconfoundedness assumption. However, we can offer some guidance on how much of an impact on the decision to use payment innovation some unobserved factor must have in order to render our results insignificant.

3.2 Sensitivity Analysis: Rosenbaum Bounds

To quantify how sensitive our PSM estimates are to unobserved factors we compute the Rosenbaum bounds (RB), as described in Rosenbaum (2002). The RB are framed in terms of ratio of propensities to use innovation for two matched individuals, a payment innovator and a non-innovator, with the same observed characteristics. The probability of payment innovation can be written as:

$$p(PI_i|\mathbf{X_i}) = F(\mathbf{X_i}\beta + \gamma u_i), \tag{8}$$

where u denotes an unobserved variable, γ is a scalar and F denotes a cumulative density function. Assuming there is no hidden bias, $\gamma = 0$, then the log-odds ratio $p(PI_i|\mathbf{X_i})/p(PI_j|\mathbf{X_j}) = 1$ for individuals with the exact same characteristics $\mathbf{X_i} = \mathbf{X_j}$. If hidden bias exists then $\gamma > 0$ so that the log-odds ratio $p(PI_i|\mathbf{X_i})/p(PI_j|\mathbf{X_j}) \neq 1$. Sensitivity analysis evaluates the impact of unobserved heterogeneity on the log-odds ratio of propensities between two matched individuals reduces the statistical significance of the treatment effect. The RB is the upper bound on how much hidden bias can be tolerated.

4 Results

We consider two payment innovations: contactless-credit and stored-value cards. The treatment group is defined as the users of these payment innovations during the DSI. Both cases have as control group non-users of payment innovation, however, the control group for contactless-credit users excludes individuals without access to credit cards. For each case, we estimate two models: a simple model controlling for demographics only (DEMO) and a full model (FULL) which controls additionally for shopping characteristics from the DSI, and perceptions on payment method attributes. We use perceptions on cash attributes relative to credit and debit. To avoid potential endogeneity issues, we measure each respondent's shopping characteristic, such as initial cash holdings, as a ratio relative to the average within the individual's demographic stratum, following Stango (2000). The appendix contains a more complete description of the variables.

For contactless-credit, the marginal effects of the propensity score estimates for the first stage are displayed in Table 7. Overall, we observe that the coefficients in DEMO are robust to the more complete (FULL) specification. We observe that family size, whether an individual revolves on her credit card are significant factors in explaining usage of contactless-credit feature, along with certain perceptions and shopping characteristics. Individuals in larger households, likely with children, may be under more time constraints and may be attracted to the added convenience of the contactless feature. Revolvers on credit cards are roughly six percent less likely to use the contactless-credit feature, as they may prefer using the credit card for its credit facility rather than for its transactional services and they may also be individuals with lower incomes on average. We find that as fear of fraud of cash relative to cards increases, individuals are less likely to use contactless-credit, perhaps due to the lack of merchant verification associated with the contactless-credit feature. Individuals are also more likely to use contactless-credit when they view cash as more expensive than credit and debit cards.

For stored-value card users, there is a significant positive income effect. In contrast to the effect of perceptions on the propensity to use contactless-credit, as the fear of fraud of cash relative to cards increases, individuals tend to be more likely to revert to stored-value cards which have limited liability. Lastly, as the perception of cost of cash increases relative to cards, individuals tend to be less likely to use stored-value cards, which may suggest some complementarity between cash and prepaid cards. Figures 4 and 5 display the propensity scores for innovator and non-innovators for contactless credit and stored-value card, respectively. These figures confirm visually that the overlap assumption is met. Further, Figures 6 and 7 illustrate the cash ratio versus propensity score for non-innovator and innovators of contactless-credit and stored-value cards, in terms of value and volume. These figures show innovators tend to have a lower cash ratio as their propensity score increases while for non-innovators the relationship is not as stark.

The treatment effect results are summarized in Table 8 and Table 9 for contactless-credit and stored-value cards, respectively. The ATE/ATT estimates are computed using both OLS and PSM methods. OLS ATE/ATT is estimated using the cash ratio regression (1) and computing the ATE/ATT parameters. The PSM estimates are computed using kernel matching (KM) method.[8] Angrist and Pischke (2008) suggest that OLS estimates be provided to serve as a baseline comparison to the PSM results. We use the Stata module *-psmatch2-* to implement PSM estimation in *Stata*, see Leuven and Sianesi (2003).[9]

Overall, the results suggest that recent payment innovations is negatively impacting cash usage, in terms of both value and volume. The results are statistically significant and change little across DEMO and FULL specifications. For most of the cases the PSM results are similar to OLS estimates as there confidence intervals intersect so they are almost observationally equivalent. The results are not surprising since both estimators are semiparametric and are robust to some parametric assumptions. We concentrate our discussions to the estimates from the FULL model. The $\widehat{ATE}$ on the cash value share is roughly -14 and -12 percent for contactless-credit and stored-value cards, respectively. The $\widehat{ATE}$ on the cash volume share is roughly -13 and -15 percent, respectively. As a back-of-the-envelope calculation, for an average non-user of contactless who spends 221 dollars in total transactions with a cash ratio of 32 percent, the treatment estimates would imply that cash spending would drop by roughly 32 dollars if they had used contactless-credit card. Similarly, the treatment estimates imply that cash spending for the average non-user of stored-value cards would fall by roughly 24 dollars if they had used a stored-value card. Overall, the number of cash transactions would fall by close to one transaction on average.

4.1 Sensitivity Analysis

The PSM results are quite significant but are smaller than the difference in means obtained from analyzing Table 4. Results from OLS are similar but have large confidence intervals. Controlling for additional observable characteristics in the FULL model seems to reduce potential bias. To understand the potential effect of unobserved heterogeneity on the PSM result we compute the RB using the *rbounds* program, see Gangl (2004). The estimates of the RB range from 1.37 to 2.55 and suggest that our results are quite tolerant to unobserved bias. Only the results for the impact on the cash value share due to stored-value cards are somewhat less

[8] We also use nearest neighbour matching (NM) and found that the results are similar. We calculate standard errors via 1000 bootstrap replications. Abadie and Imbens (2008) show that the bootstrap with NM fails while it is valid for the KM, thus, another reason only to present the KM results.

[9] The probit specification was also implemented for robustness and the results were quite similar. We also use the link test to check if the logit link function is correctly specified.

convincing, which seems to intuitively follow from the fact that stored-value cards are mostly used for small value transactions.

For concreteness, we relate the RB to observable factors. For the case of $\widehat{RB} = 2$, if an unobserved factor caused a payment innovator to be twice as likely to innovate than a non-innovator, our results would lose statistical significance. Following Bharath, Dahiya, Saunders, and Srinivasan (2009), we can solve for the magnitude of a change in an observed covariate necessary to obtain $\widehat{RB} = 2$. Based on the logit model, the ratio of propensities should change by a factor of

$$\widehat{RB} = \exp(\beta_k s_k n), \tag{9}$$

where β_k is the logit coefficient and s_k is the standard deviation of variable k. Setting this quantity equal to $\widehat{RB} = 2$, we can solve for n for each continuous variable in our model. For example, *ceteris paribus*, for an individual from a matched pair the perception on cost would have to change by roughly one standard deviation for the treatment effects for contactless-credit and stored-value cards to become insignificant. These findings suggest our results may remain statistically significant even in the presence of unobserved factors.

4.2 Definition of Treatment Group

Table 11 provides a summary of the robustness for various definitions of treatment and control groups. The analysis undertaken considers Case 1. We find that the results are qualitatively the same when the treatment group is defined as users of payment innovation (N_U) with the control group being either defined as non-users (N_{AN}) or non-adopters (N_N), see Case 2 and 3. The only marginally negative impact occurs when the treatment group is adopters non-users (N_{AN}) and users (N_U) of payment innovation and control group is non-adopters (N_N), see Case 4. However, when we exclude the users of payment innovation (N_U), the impact of payment innovation is zero, see Case 5. Exhausting the possible cases demonstrates that the impact is primarily due to using payment innovation. In the case of contactless-credit, adoption is not necessarily a choice of the individual and those who have this feature may not use them. Adoption of stored-value cards is also not necessarily a permanent feature of one's portfolio and therefore the impact from solely adopting this payment feature may not be evident.[10]

5 Conclusion

We investigate the effects of innovations of retail payment instruments on the use of cash for retail transactions in Canada. We find some evidence that recent innovations in Canada such as contactless-credit cards and stored-value cards have led to a reduction in cash usage. We find that stored-value cards are primarily used for low-value transactions, under 10 dollars, while contactless-credit cards are mostly used for intermediate-value transactions, ranging from 10 to 40 dollars.

These results confirm the hypothesis that payment innovations have led to a decrease in cash usage. The increasing popularity of credit cards and debit cards over the past 20 years have resulted in a shrinking share of bank notes in retail transactions, both in terms of volume and value. However, the advent of contactless-credit cards and stored-value cards, which are designed to be more convenient and less costly, may further reduce cash usage.

One of the limitations of using the 2009 MOP Survey data in this type of study is that it can provide only a snapshot of the impact of innovation on cash usage. In 2009, the contactless-credit card was in nascent stage of deployment and therefore our results may be underestimating the current impact. The Canadian Financial Monitor is a household dataset that is conducted on a biannual basis. To better understand the impact of innovation on cash usage, it would be useful to consider how innovation affects cash usage over time. Also, it would be useful to consider supply-side factors such as merchant acceptance and the inherent two-sided markets issues. We leave these issues for future research.

References

ABADIE, A., AND G. W. IMBENS (2008): "On the Failure of the Bootstrap for Matching Estimators," *Econometrica*, 76(6), 1537–1557.

AMROMIN, G., AND S. CHAKRAVORTI (2009): "Whither Loose Change? The Diminishing

[10]Canadian banks issue new cards with the irregardless whether the consumers ask for it or not. Therefore, in this case adoption of contactless feature is considered passive. Therefore, there maybe a case when consumers have the contactless feature but do not use it.

Demand for Small-Denomination Currency," *Journal of Money, Credit and Banking*, 41(2-3), 315–335.

ANGRIST, J. D., AND J.-S. PISCHKE (2008): *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 1 edn.

ARANGO, C., K. HUYNH, AND L. SABETTI (2011): "How Do You Pay? The Role of Incentives at the Point-of-Sale," Working Paper 11-23, Bank of Canada.

ATTANASIO, O. R., L. GUISO, AND T. JAPPELLI (2002): "The Demand for Money, Financial Innovation, and the Welfare Cost of Inflation: An Analysis with Household Data," *Journal of Political Economy*, 110(2), 317–351.

BHARATH, S. T., S. DAHIYA, A. SAUNDERS, AND A. SRINIVASAN (2009): "Lending Relationships and Loan Contract Terms," *Review of Financial Studies*, 24(4), 1141–1203.

BORZEKOWSKI, R., AND E. K. KISER (2008): "The choice at the checkout: Quantifying demand across payment instruments," *International Journal of Industrial Organization*, 26(4), 889–902.

DUCA, J. V., AND W. C. WHITESELL (1995): "Credit Cards and Money Demand: A Cross-sectional Study," *Journal of Money, Credit and Banking*, 27(2), 604–23.

FUJIKI, H., AND M. TANAKA (2009): "Demand for Currency, New Technology and the Adoption of Electronic Money: Evidence Using Individual Household Data," IMES Discussion Paper Series 09-E-27, Institute for Monetary and Economic Studies, Bank of Japan.

GANGL, M. (2004): "RBOUNDS: Stata module to perform Rosenbaum sensitivity analysis for average treatment effects on the treated," Statistical Software Components, Boston College Department of Economics.

HSIAO, C. (2002): *Analysis of Panel Data.* Cambridge University Press, second edition edn.

JONKER, N., AND A. KOSSE (2009): "The impact of survey design on research outcomes: A case study of seven pilots measuring cash usage in the Netherlands," DNB Working Papers 221, Netherlands Central Bank, Research Department.

LEUVEN, E., AND B. SIANESI (2003): "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing," Statistical Software Components, Boston College Department of Economics.

LIPPI, F., AND A. SECCHI (2009): "Technological change and the households' demand for currency," *Journal of Monetary Economics*, 56(2), 222–230.

MULLIGAN, C. B., AND X. SALA-I-MARTIN (2000): "Extensive Margins and the Demand for Money at Low Interest Rates," *Journal of Political Economy*, 108(5), 961–991.

ROSENBAUM, P. (2002): *Observational Studies*. Springer, New York, NY.

RYSMAN, M. (2007): "An Empirical Analysis of Payment Card Usage," *Journal of Industrial Economics*, 55(1), 1–36.

SCHUH, S., AND J. STAVINS (2010): "Why are (some) consumers (finally) writing fewer checks? The role of payment characteristics," *Journal of Banking & Finance*, 34(8), 1745–1758.

STANGO, V. (2000): "Competition And Pricing In The Credit Card Market," *The Review of Economics and Statistics*, 82(3), 499–508.

STAVINS, J. (2001): "Effect of Consumer Characteristics on the Use of Payment Instruments," *New England Economic Review*, 3, 19–31.

STIX, H. (2004): "How Do Debit Cards Affect Cash Demand? Survey Data Evidence," *Empirica*, 31(2), 93–115.

STUBER, G. (1996): "The Electronic Purse: An Overview of Recent Developments and Policy Issues," Technical reports, Bank of Canada.

A Appendix

A.1 Variable List

Demographics:

- *Income*: The SQ asks, "Which of the following categories best describes your current annual household income?"
- *Education*: The SQ asks, "What is the highest level of education you have completed?"
- *Region*: The SQ asks, "What region of Canada do you reside in?"
- *Age*: The SQ asks, "In what year were you born?"
- *Family size*: The SQ asks, "How many family members, including yourself, live in your household?"
- *Gender*: The SQ asks, "What is your gender?"
- *Homeowner or renter*: The SQ asks "Do you rent or own your home?"
- *Bank account balance*: The SQ asks "What was the lowest balance and the highest balance in your main bank account in the last month?" From these responses we obtain an average bank account balance.
- *Survey access panel*: We control for whether respondents stemmed from the offline panel.

- *Credit card revolvers*: We include a dummy variable indicating whether respondents are revolving on their credit card balance.

DSI: We define strata according to age and income groups, and then construct relative measures (RDSI) for each respondent in terms of a ratio to the average within their respective stratum. For each participant i, we calculate:

$$RDSI_i = \frac{DSI_i}{\overline{DSI}_{ym}}, \tag{10}$$

where $\overline{DSI}_{ym}$ denotes the average of the DSI variable for the particular stratum, where y and m index over the age and income strata, respectively.

- *Initial cash holdings:* The DSI asks the respondent to report the amount of cash, both bills and coins, in their wallet prior to starting the diary.
- *Credit/Debit card accepted:* The DSI asks the respondent for each method of payment respectively, "Which method of payment would NOT have been accepted?" For each individual, we calculate the share of transactions for which both credit and debit were accepted.
- *Type of Transaction*: For every transaction, the DSI asks the respondent, "What was the main type of goods or service purchased during this transaction?" The following categories: gasoline, goods/retail, services, hobby/sports, entertainment, other. For each individual, we calculate the share of purchases made of each type relative to the total number of purchases.
- *Weekend*: The DSI asks the respondent for each transaction to report the day of the week on which it was made. Based on this, we calculate the share of weekend purchases for each individual.
- *Time of day*: The DSI asks the respondent for each transaction to report the time of day on which it was made. Based on this, we calculate the share of PM purchases for each individual.

Perceptions:

- *Ease of Use:* The SQ asks the respondent "When making a payment, in your opinion how easy is it for you to use each of the following methods of payment? Please use a scale from '1' to '5', where '1' means it is "not at all easy to use" and '5' means it is 'very easy to use.' We calculate the perception for cash relative to credit and debit.
- *Record Keeping:* The SQ asks the respondent "In your opinion how useful are (or would be) the following methods of payment in terms of helping you to keep a record of your spending. Please use a scale from '1' to '5', where '1' means it is "not at all useful" and '5' means it is 'very useful.' We calculate the perception for cash relative to credit and debit.

- *Cost:* The SQ asks the respondent "Taking into consideration costs such as withdrawal fees, account fees, and interest paid, in your opinion how costly is it (or would it be) to make a payment using the following methods of payment. Please use a scale from '1' to '5', where '1' means it is "not at all costly" and '5' means it is 'very costly.' We calculate the perception for cash relative to credit and debit.

- *Risk/Fraud:* The SQ asks the respondent "In your opinion, how likely is it (or would it be) that you will experience fraud in the next year when using the following methods of payment? Please use a scale from '1' to '5', where '1' means it is "not at all likely" and '5' means it is 'very likely.' We calculate the perception for cash relative to credit and debit.

We construct relative measures of perceived attributes (RCHAR) for cash in terms of payment cards, debit and credit, for each participant i in the following way:

$$RCHAR_{ki(cash)} = \frac{CHAR_{ki(cash)}}{CHAR_{ki(credit)} + CHAR_{ki(debit)}}, \tag{11}$$

where k indexes the payment characteristics.

B Tables and Figures

Table 1: Volume and Value Shares for Cash, Credit Cards and Debit Cards

	Value			**Volume**		
	Cash	Debit Card	Credit Card	Cash	Debit Card	Credit Card
1989	0.375	0.001	0.623	0.743	0.001	0.256
1999	0.332	0.269	0.399	0.679	0.190	0.131
2009	0.194	0.300	0.506	0.498	0.297	0.205

Note: Numbers displayed are in proportions. Cash proportions are based on projections using ATM withdrawals. The source of the data is derived from the Bank for International Settlements.

Table 2: 2009 Means of Payment Survey

	Value				**Volume**			
TV	Overall	< 10	10-40	40 +	Overall	< 10	10-40	40 +
Cash	0.211	0.744	0.397	0.109	0.513	0.797	0.429	0.168
Debit	0.437	0.168	0.359	0.330	0.271	0.125	0.351	0.382
Credit	0.328	0.065	0.225	0.537	0.191	0.047	0.204	0.417
Contactless-Credit	0.012	0.003	0.011	0.013	0.009	0.003	0.009	0.022
Stored-Value	0.011	0.019	0.009	0.011	0.016	0.028	0.008	0.012

Note: TV denotes transaction value. Numbers displayed in proportions, based on 12,271 transactions conducted by 2,185 respondents in DSI. Survey weights used.

Table 3: Who is Using New Payment Instruments?

	Contactless-Credit		**Stored-Value**	
	Non-Users	Users	Non-Users	Users
Under 30K	0.104	0.041	0.159	0.041
30K-80K	0.433	0.369	0.450	0.378
Over 80K	0.462	0.590	0.391	0.581
High School	0.209	0.119	0.251	0.203
College	0.791	0.881	0.749	0.797
Credit Card Revolvers	0.367	0.147	0.477	0.368
Beginning cash (in \$)	79.32	76.68	77.10	64.30
Total spending (in \$)	221.18	260.92	205.43	247.11
Bank balance (in \$)	3328.79	3881.58	2975.84	3027.05
Respondents	1779	126	2051	134

Note: Statistics are computed for respondents with three or more retail purchases in DSI. Income, education statistics are in proportions. Bank Balance and Total Spending DSI are in dollars. Non-users of contactless-credit exclude respondents without access to a credit card.

Table 4: Cash Ratios in Value and Volume

	Value				**Volume**			
	NI	CTC	NI	SVC	NI	CTC	NI	SVC
Overall	0.317	0.127	0.368	0.173	0.484	0.337	0.521	0.293
Under 30K	0.466	0.178	0.498	0.296	0.597	0.239	0.613	0.363
30-80K	0.323	0.124	0.390	0.131	0.488	0.345	0.537	0.268
Over 80K	0.279	0.126	0.290	0.191	0.456	0.339	0.466	0.303
Bank balance $<$ 1000	0.355	0.090	0.409	0.162	0.500	0.288	0.536	0.258
Bank balance 1000 to 2000	0.288	0.227	0.346	0.170	0.450	0.416	0.496	0.305
Bank balance 2000 to 4500	0.345	0.134	0.367	0.168	0.504	0.381	0.527	0.247
Bank balance $>$ 4500	0.279	0.086	0.329	0.194	0.480	0.288	0.517	0.373
Age $<$25 years	0.372	0.084	0.411	0.288	0.501	0.141	0.535	0.337
Age 25 to 45 years	0.281	0.119	0.317	0.122	0.446	0.337	0.468	0.249
Age over 45 years	0.336	0.144	0.399	0.185	0.510	0.365	0.559	0.315
Cards accepted (-)	0.434	0.177	0.485	0.233	0.641	0.491	0.665	0.403
Cards accepted (+)	0.219	0.098	0.260	0.143	0.353	0.246	0.388	0.239
Recordkeeping (-)	0.262	0.117	0.295	0.156	0.440	0.289	0.463	0.296
Recordkeeping (+)	0.395	0.146	0.451	0.203	0.546	0.422	0.587	0.287
Credit Card Revolvers	0.335	0.125	0.429	0.166	0.489	0.301	0.554	0.275
Non-Revolvers	0.307	0.128	0.313	0.177	0.482	0.343	0.492	0.303

Note: Statistics are computed for respondents with three or more retail purchases in DSI. The numbers displayed in percent. CTC: contactless-credit users, SVC: stored-value users and NI:non-innovators. Bank balance reports the respondent's average bank account balance over the previous month's period. Record keeping (+) indicates whether the respondent held a perception on cash for record keeping purposes that was above average. Cards accepted (+) denotes whether the respondent's reported shopping experience was characterized by an above average share of retail locations for which both debit and credit cards were accepted. Credit card revolvers characterizes respondents who report not paying their previous month's credit card bill in full. Survey weights used.

Table 5: Transaction Type Across Payment Methods

	Cash	SVC	Debit	Credit	CTC
Groceries	0.327	0.243	0.426	0.327	0.562
Gasoline	0.043	0.067	0.088	0.124	0.235
Retail Goods	0.066	0.090	0.134	0.218	0.031
Services	0.028	0.010	0.031	0.049	0.019
Hobby/Sports	0.036	0.014	0.045	0.056	0.012
Entertainment/Meals	0.338	0.429	0.176	0.133	0.086
Other	0.162	0.148	0.100	0.093	0.056
Number of Transactions	5676	210	3391	2832	162

Note: Numbers are in proportions. Based on 12,271 transactions in DSI. CTC: contactless-credit, SVC: stored-value card.

Table 6: Payment Shares at Various Time Intervals

		Value				
		Cash	SVC	Debit	Credit	CTC
Weekday	AM	0.174	0.048	0.159	0.123	0.078
	PM	0.418	0.494	0.390	0.436	0.537
Weekend	AM	0.121	0.069	0.138	0.094	0.121
	PM	0.287	0.389	0.314	0.346	0.265

		Volume				
		Cash	SVC	Debit	Credit	CTC
Weekday	AM	0.221	0.221	0.153	0.149	0.196
	PM	0.407	0.394	0.434	0.450	0.438
Weekend	AM	0.123	0.130	0.107	0.098	0.098
	PM	0.249	0.255	0.306	0.302	0.268

Note: Numbers are in proportions for each payment method. Based on 12,271 transactions in DSI. CTC: contactless-credit, SVC: stored-value card.

Table 7: Logit Propensity Score Marginal Effects

	Contactless-credit		**Stored-value card**	
	Demo	Full	Demo	Full
30k-50k	0.038	0.035	0.052**	0.054**
	0.03	0.03	0.03	0.03
More than 80k	0.044	0.040	0.073**	0.081***
	0.03	0.03	0.03	0.03
Some college	0.013	0.010	0.001	0.002
	0.03	0.03	0.02	0.02
Western Canada	-0.044**	-0.047**	0.017	0.015
	0.02	0.02	0.02	0.02
Family size over 3	0.045***	0.046***	0.019	0.021
	0.02	0.02	0.02	0.02
Credit card revolver	-0.072***	-0.063***	-0.015	-0.022
	0.02	0.02	0.02	0.02
Ease of use		-0.034		-0.025
		0.11		0.06
Fear of fraud		-0.060**		0.038*
		0.02		0.02
Cost		0.070**		-0.070**
		0.03		0.03
Recordkeeping		-0.009		-0.004
		0.03		0.03
Relative initial cash holdings		0.025		-0.015
		0.02		0.01
Relative share of weekend shopping		0.008		0.006
		0.01		0.01
Relative share of entertainment expenditures		-0.008*		0.005
		0.00		0.00
Relative share of retail goods expenditures		-0.008**		0.004
		0.00		0.00
Relative share of merchant acceptance of cards		0.027		0.018
		0.02		0.02
Observations	1905	1905	2185	2185

Note: We report average marginal or partial effects. Standard errors in parentheses while one, five, and ten percent level of significance are denoted via ***, **, *, respectively. Estimates are computed with survey weights. The base category for income is Less than 30K, for education is High School, and for region is Ontario. The estimation sample for contactless-credit excludes respondents without access to credit cards.

Table 8: Contactless-Credit Impact on Cash

	Value		**Volume**	
	Demo	Full	Demo	Full
ATE_{OLS}	-0.156	-0.155	-0.166	-0.138
	(-0.199 -0.112)	(-0.203 -0.108)	(-0.225 -0.107)	(-0.203 -0.074)
ATT_{OLS}	-0.132	-0.115	-0.123	-0.100
	(-0.170 -0.094)	(-0.154 -0.076)	(-0.173 -0.073)	(-0.146 -0.053)
ATE_{PSM}	-0.145	-0.144	-0.142	-0.134
	(-0.188 -0.102)	(-0.186 -0.101)	(-0.198 -0.085)	(-0.194 -0.075)
ATT_{PSM}	-0.138	-0.125	-0.124	-0.109
	(-0.175 -0.100)	(-0.163 -0.087)	(-0.175 -0.074)	(-0.161 -0.058)
$\widehat{RB}$	1.69	1.67	2.29	2.19

Note: We provide estimates for both OLS and PSM-kernel matching. 95 percent confidence intervals displayed in parentheses and are constructed with 1000 bootstrap replications. Demo denotes Demographics while Full is Demographics + DSI + Perceptions. Please refer to appendix for complete list of variables.

Table 9: Stored-Value Card Impact on Cash

	Value		**Volume**	
	Demo	Full	Demo	Full
ATE_{OLS}	-0.115	-0.115	-0.148	-0.153
	(-0.168 -0.061)	(-0.164 -0.066)	(-0.194 -0.102)	(-0.196 -0.110)
ATT_{OLS}	-0.097	-0.102	-0.136	-0.137
	(-0.140 -0.055)	(-0.143 -0.061)	(-0.176 -0.096)	(-0.176 -0.099)
ATE_{PSM}	-0.128	-0.119	-0.157	-0.145
	(-0.174 -0.082)	(-0.165 -0.072)	(-0.199 -0.114)	(-0.187 -0.102)
ATT_{PSM}	-0.115	-0.099	-0.153	-0.131
	(-0.158 -0.072)	(-0.142 -0.056)	(-0.194 -0.112)	(-0.174 -0.089)
$\widehat{RB}$	1.47	1.37	2.55	2.31

Note: We provide estimates for both OLS and PSM-kernel matching. 95 percent confidence intervals displayed in parentheses and are constructed with 1000 bootstrap replications. Demo denotes Demographics while Full is Demographics + DSI + Perceptions. Please refer to appendix for complete list of variables.

Table 10: Rosenbaum bounds sensitivity analysis

CTC	1.50	1.75	2.00	2.25	$\hat{\beta}$	s_k	mean
Acceptance	0.81	1.12	1.39	1.62	0.53	0.41	1.08
Cost	0.57	0.79	0.98	1.15	1.39	0.22	0.34
Fraud	0.50	0.69	0.86	1.00	1.19	0.30	0.45
SVC							
Acceptance	1.14	1.58	1.95	2.28	0.35	0.44	1.10
Cost	0.61	0.85	1.05	1.23	1.33	0.22	0.33
Fraud	0.81	1.12	1.39	1.62	0.72	0.30	0.46

Note: For each level of $RB = 1.5, 1.75, 2.0$ and 2.25, we calculate the number of standard deviations, n, such that $\widehat{RB} = \exp(\beta_k s_k n)$.

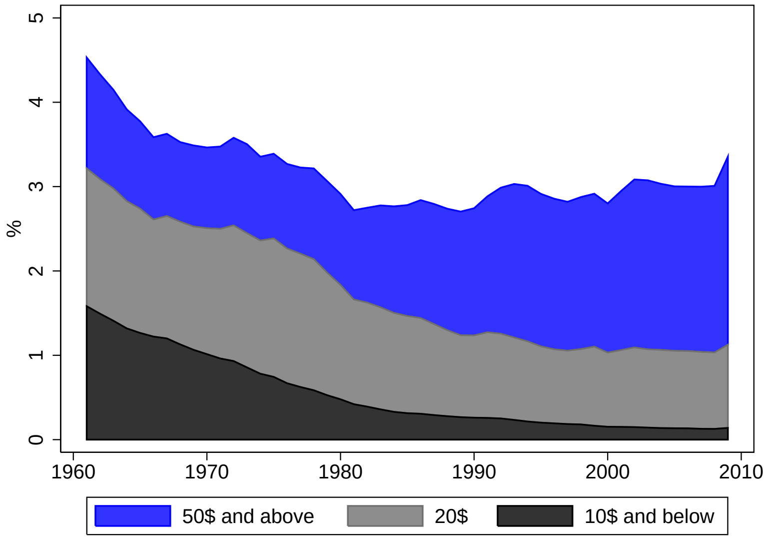
Table 11: Treatment and Control Groups

	Non-adopters	Adopters non-users	Users
	N_N	N_{AN}	N_U
Contactless Credit Card	1487	292	126
Stored-Value Cards	1590	461	134

Case	1	2	3	4	5
Treatment Group	N_U	N_U	N_U	$N_U + N_{AN}$	N_{AN}
Control Group	$N_{AN} + N_N$	N_N	N_{AN}	N_N	N_N
ATE$_{PSM}$: CTC	(-)***	(-)***	(-)***	(-)*	0
ATE$_{PSM}$: SVC	(-)***	(-)***	(-)***	(-)*	0

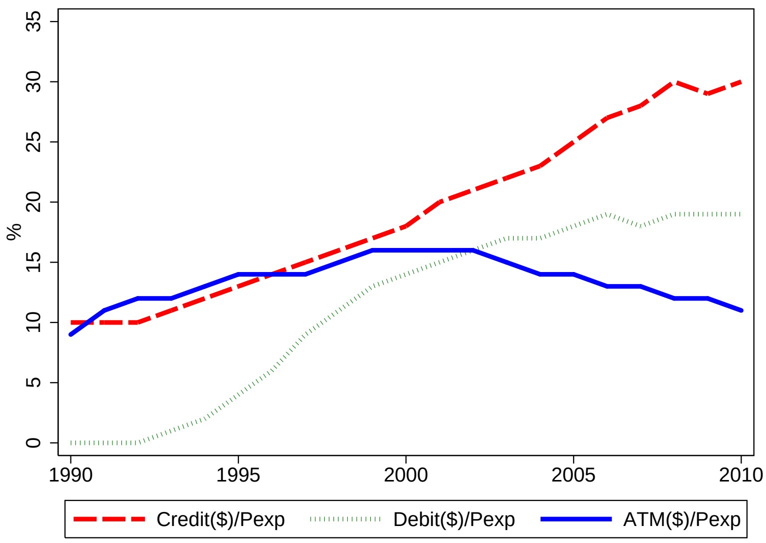
Note: We define non-adopters (N_N) as respondents who do not have access to the technology during the diary. Adopters non-users (N_{AN}) defines respondents who have access but do not report using the technology. Users (N_U) are respondents who report using the technology at least once during the diary. ATE are the average treatment effects and one, five, and ten percent level of significance are denoted via ***, **, *, respectively. Results displayed for PSM-kernel method with the Full model.

Figure 1: Notes in Circulation as a Ratio to GDP



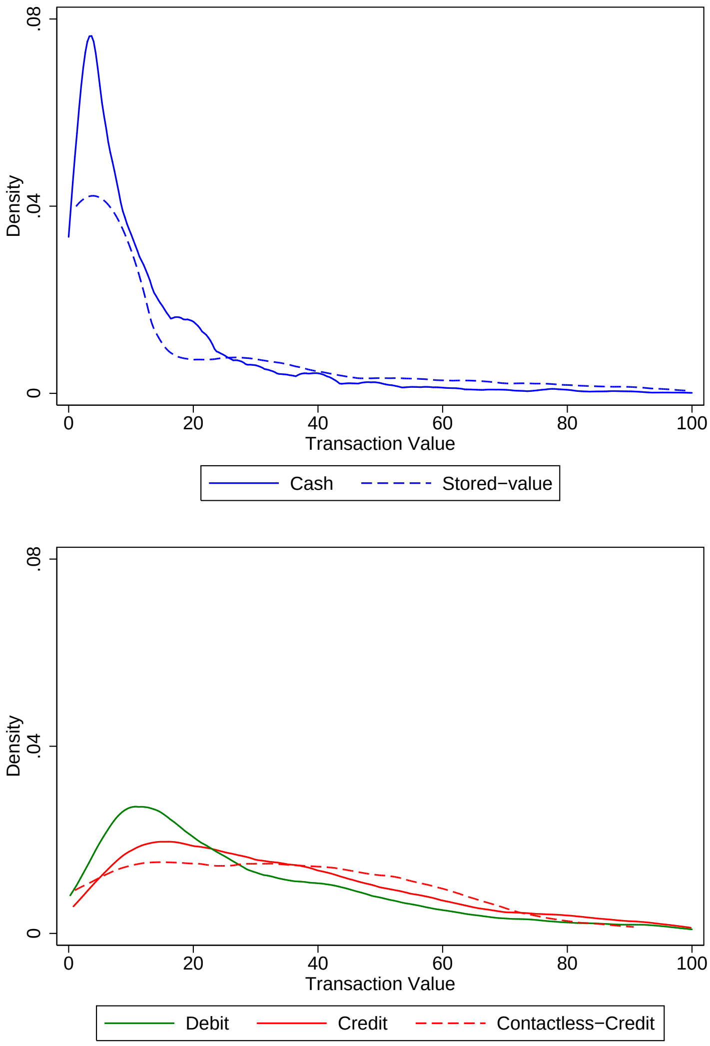
Source: Bank of Canada. This figure illustrates the value of bank note as a ratio to GDP in terms of three denominations: small (10 dollars and below), medium (20 dollars) and large (50 dollars and above).

Figure 2: Payment Shares



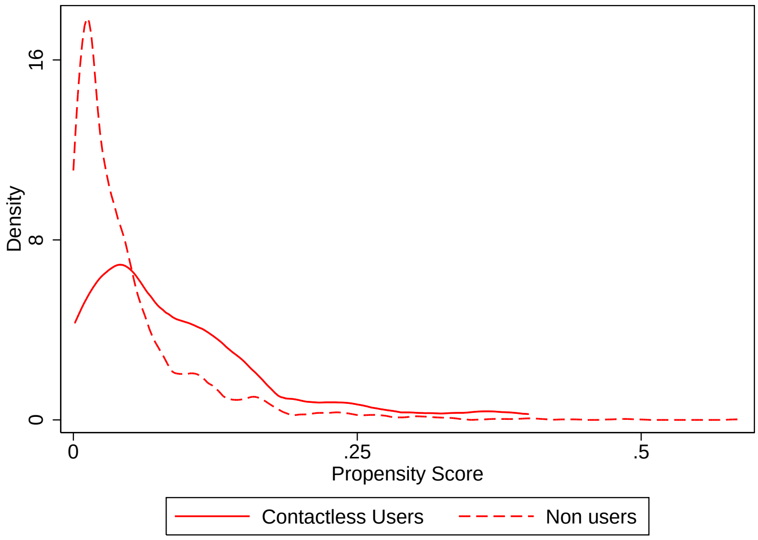
Source: Bank of Canada. Value of debit, credit card and ATM cash withdrawals relative to personal expenditures.

Figure 3: Payment Choice Densities



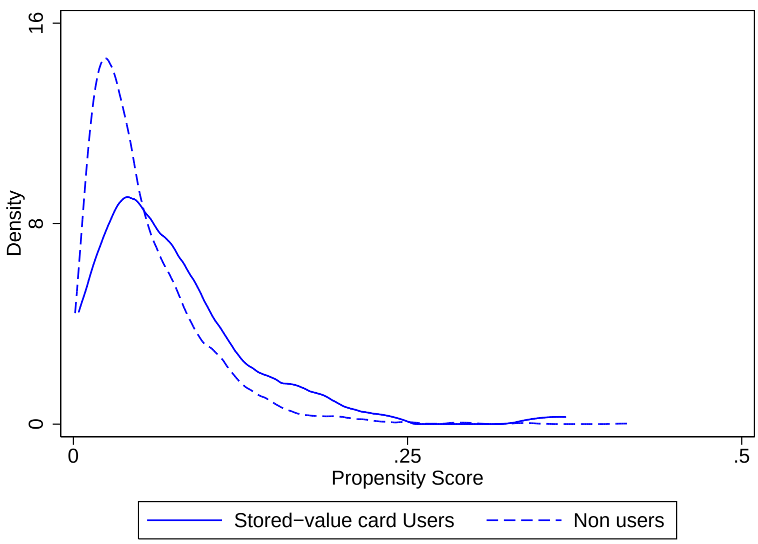
Note: These densities illustrate the probability of using a payment choice at certain transaction value. For example, the probability of using cash is highest for transaction values less than 20 dollars. The transaction value is truncated at 100 dollars and the number of DSI transactions is 11,471.

Figure 4: Overlap for Contactless Credit Card



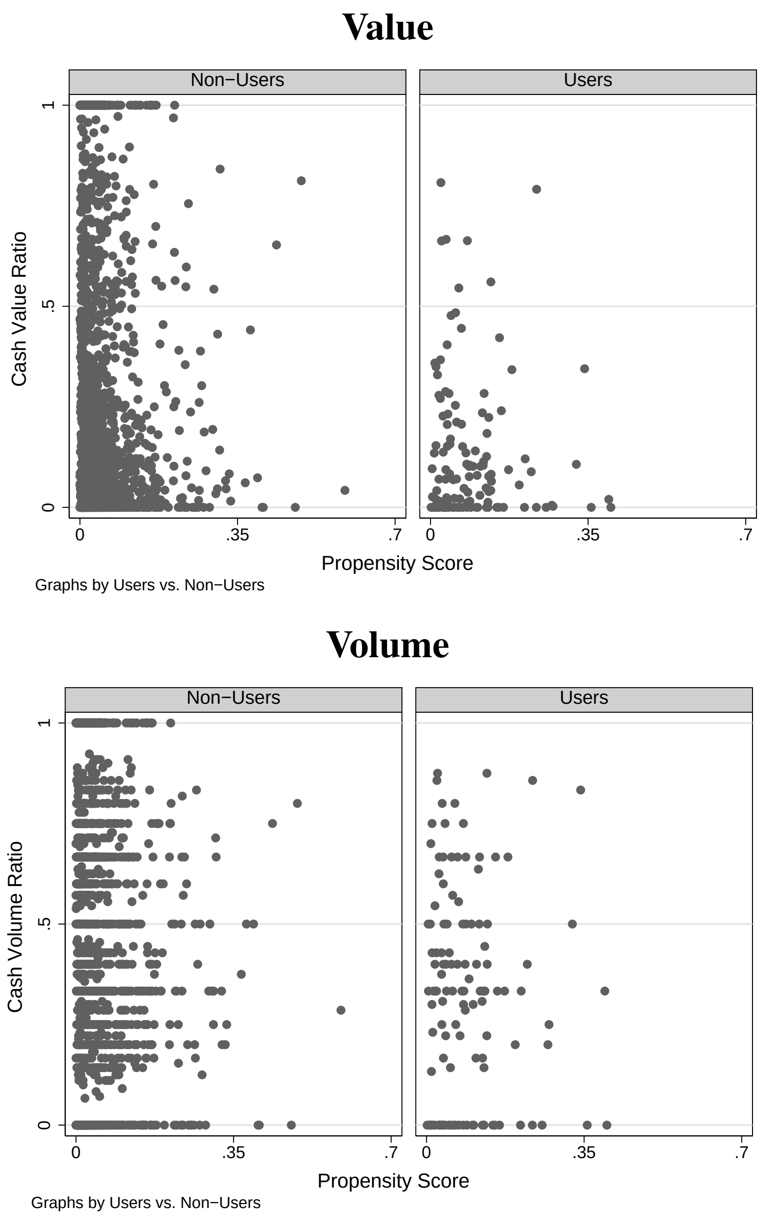
Note: Logit propensity scores displayed for the FULL model.

Figure 5: Overlap for Stored-Value Card



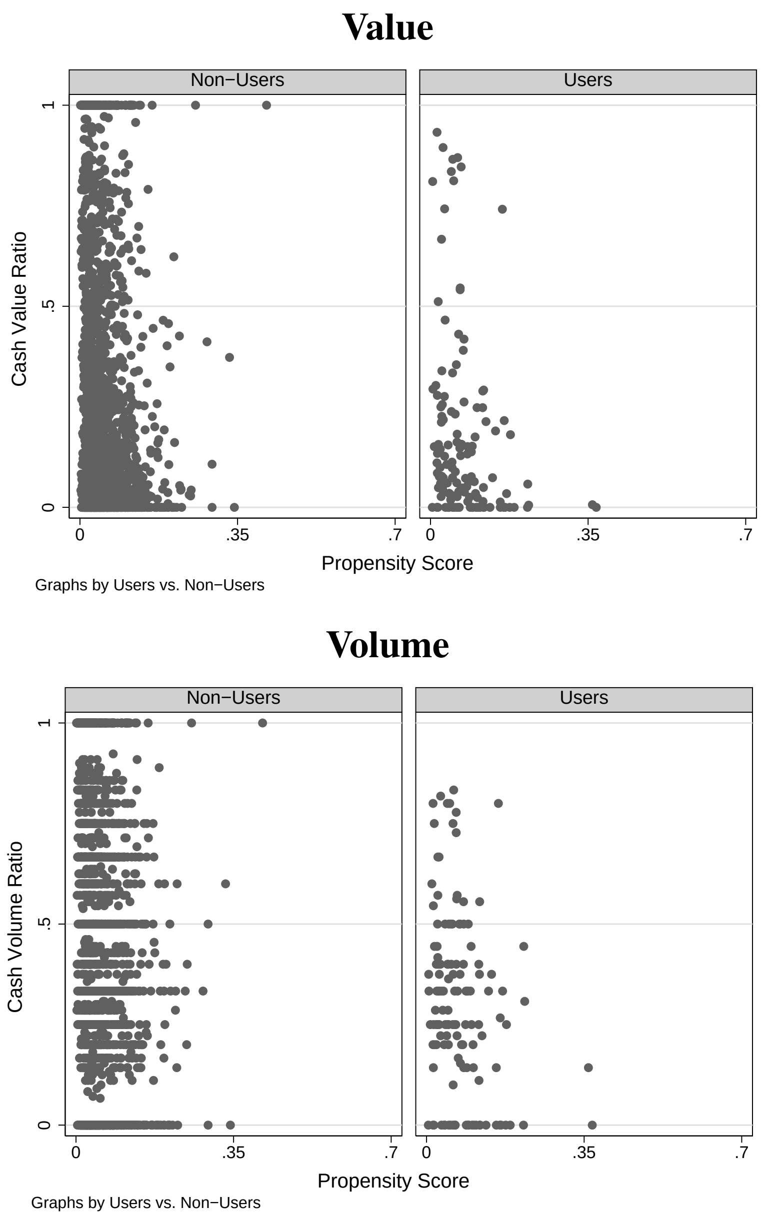
Note: Logit propensity scores displayed for the FULL model.

Figure 6: Cash Ratio versus Propensity Score of Contactless Credit Card



Note: These figures illustrate the cash ratio (in terms of value and volume) versus the propensity scores. Logit propensity scores displayed for the FULL model.

Figure 7: Cash Ratio versus Propensity Score of Stored-value Card



Note: These figures illustrate the cash ratio (in terms of value and volume) versus the propensity scores. Logit propensity scores displayed for the FULL model.