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Consumer Cash Withdrawal Behaviour: Branch Networks and Online Financial Innovation

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Abstract

Constructing a novel micro-geographic individual-level data set, we study the relevance of shoe-leather costs on cash withdrawals. An unexplored issue in the literature is the consistent estimation of the marginal effect of travel distance on withdrawals when a fraction of unobserved withdrawals have free/low shoe-leather cost, i.e., consumers withdraw upon conveniently encountering a free/low cost withdrawal opportunity. To overcome this challenge, we propose a classification technique to identify respondents who have incurred these free/low cost withdrawals, and subsequently account for such endogenous selection from the exclusion restriction of the adoption of recent online financial innovations. We find that there exist significant threshold effects of distance on typical monthly withdrawal frequency. For respondents living within 1.56 kilometers of their affiliated financial institution, a one-kilometer reduction in distance is associated with an average marginal increase of 0.31 withdrawals per month. In terms of heterogeneous effects, distance plays a larger role in higher-income and older-age cohorts. These results are robust to various econometric specifications.

Topics: Bank notes, Digital currency and fintech

JEL codes: G21, R22

1. Introduction

The Canadian bank branch network facilitates access to a variety of banking services for consumers. It is through this physical network that consumers access depository and withdrawal services to help manage their household cash expenditures.[1] In particular, the bank branch network (i.e., the spatial distribution of bank branches) is directly related to consumer cash accessibility and affects the frequency and value of consumer cash withdrawals. Using aggregate data, Kosse et al. (2017) and Fung et al. (2017) find that the shoe-leather cost of withdrawals make up a large part of consumers' cash costs. In this paper, we complement the existing literature by shifting our focus to the individual level. In this study, rather than studying the importance of ABM surcharge fees, we set out to estimate the marginal effect of shoe-leather costs on withdrawal frequency. Our analysis utilizes the 2009, 2013 and 2017 Bank of Canada Method of Payments (MOP) Survey Questionnaire (SQ) with data on respondent monthly withdrawal behavior and demographic characteristics. To proxy shoe-leather costs, we develop a distance-based proxy that measures the average distance between granular consumer residential locations within the Canadian forward sortation areas (FSAs) and exact locations of financial institutions (FIs). The distance-based measure of shoe-leather costs used in this study is most closely related to Ho and Ishii (2011) and Chen and Strathearn (2020). We improve upon these measures by focusing on the nearest consumer affiliated bank branch rather than the nearest bank branch.

One of the empirical issues we face is that only a fraction of consumers are associated with costly withdrawals. These costs are not relevant for all consumers because a certain subset have a tendency to make cash withdrawals upon randomly/conveniently encountering a free/low cost withdrawal opportunity (i.e., on their commute to work). To this end, one of our major contributions is a classification methodology that aims to remove respondents

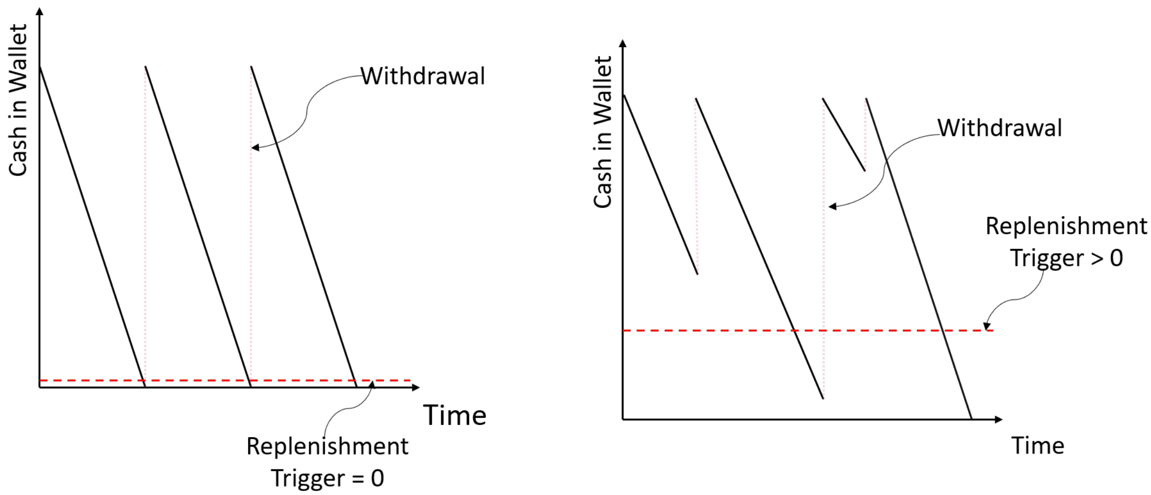
[1] According to Henry et al. (2018), on average, consumers are making more withdrawals at ABMs than at cash-back locations.

whose withdrawals consist of these negligible shoe-leather costs. In the context of Alvarez and Lippi (2009a), this translates to respondents who have a large proportion of free withdrawal opportunities. We start by classifying respondents into two types: the costly type and the free type. The costly type is the subset of respondents that are likely to incur shoe-leather costs, whereas the free type is the subset of respondents where distance is not applicable or is free/low due to randomly/conveniently encountering a free/low cost withdrawal opportunity (based on Alvarez and Lippi (2009a)). As an example, a free withdrawal may occur when a respondent is shopping at a grocery store and withdraws cash at a conveniently co-located bank branch. In other words, there is no/low shoe-leather costs attached to this particular withdrawal.

To classify respondents as either the free or costly withdrawal types, we focus on deviations from Baumol-Tobin behavior (Baumol (1952) and Tobin (1956)). One of the key differences between the Baumol-Tobin and Alvarez-Lippi (Alvarez and Lippi (2009a)) models is that in the latter consumers take advantage of free withdrawal opportunities and, as such, generally have larger average cash replenishment triggers (i.e., they do not wait until cash inventories go to zero). Based on this, the average cash replenishment trigger ($\underline{M}$) is a useful indicator for pinning down the average withdrawal type of a given respondent.[2] In Figure 1, we demonstrate how the underlying replenishment trigger relates to both Baumol-Tobin and Alvarez-Lippi types.

[2]Based on a small sample of transaction level data from the MOP Diary of Survey Instruments (DSI), we observe that in both 2013 and 2017 the average replenishment trigger for respondents that take advantage of convenient withdrawals (i.e., free type) is 2.78 and 1.42 times greater than all other withdrawals. Refer to Appendix G. Our main empirical analysis is based on respondent level MOP SQ data because the MOP DSI only covers a small subset of total MOP respondents. Furthermore, we only have withdrawal transaction classifications for the 2013 and 2017 MOP DSI. These classifications are not observed at the respondent MOP SQ level.

Figure 1: Baumol-Tobin vs. Alvaerz-Lippi Types



(a) Costly (Baumol-Tobin) Type

(b) Free (Alvarez-Lippi) Type

Given that $\underline{M}$ can be used as a tool to classify respondents, we apply the structural model of Alvarez and Lippi (2009a) to empirically identify respondents who have a positive expected number of free withdrawals. As we will discuss in Section 3, $\underline{M}$ can indicate deviations from Baumol-Tobin behavior and is tied into the notion of free withdrawal opportunities (see Alvarez and Lippi (2009a)). Using $\underline{M}$, we calibrate the number of free withdrawal opportunities in a typical month and use this as a method of classifying respondents as the free or costly type. Once we have classified respondents by type, we focus our analysis on the costly type, where distance is a relevant withdrawal cost.[3]

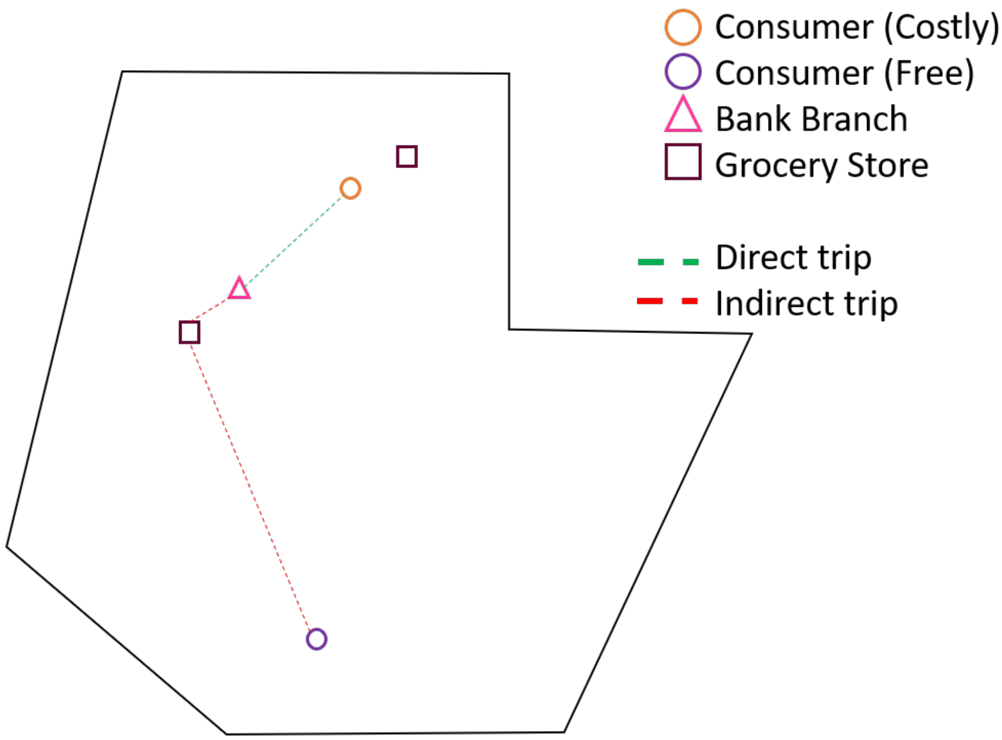
Equipped with our classification method, we set out to estimate the marginal effect of shoe-leather costs on withdrawal frequency for the costly type. Our proxy for shoe-leather costs is the distance between consumers and the nearest affiliated bank branch. Different from Alvarez and Lippi (2009a), our paper draws attention to the withdrawal cost implied from the bank branch network and studies the effect of consumers' travel cost on their cash inventory

[3]As an alternative, we could consider classification as the intensive margin (e.g. the expected number of free withdrawals per month). In Appendix D, we adopt an approximate approach based on Carroll et al. (2006) to assess the degree of the misclassification of free withdrawals into costly ones.

management. To compute shoe-leather cost, our paper directly constructs a distance-based measure and quantifies its effect on withdrawals, while Alvarez and Lippi (2009a) only have a rough measure of the diffusion of cash access sources based on the city-level.

Since our study focuses on the costly type, this naturally introduces the possibility of sample selection bias. We conjecture that this leads to a non-random selection issue whereby selection into the costly type is based on the availability of free withdrawal opportunities, which is in turn linked to a respondent's physical interactions with the branch network. It is expected that reduced interactions with the physical branch networks are correlated with the adoption of online financial innovations and online shopping. To deal with the selection issue, we apply a Heckman correction for Poisson count regression models. We include exclusion restrictions that account for the adoption of online financial innovations (i.e., online banking, online payment accounts, Interac e-transfer, etc.). The relevant channel for the adoption of online financial innovations is a reduction in the demand for cash withdrawals and fewer physical interactions with the bank branch network. This will decrease both the total number of withdrawals and the probability of free withdrawals. Both of these effects will lower the absolute number of free withdrawals and, as such, increase the probability of being selected as the costly type. In addition to this channel, the non-randomness of these adoptions may further contribute to the probability of being a costly type. This differs from Alvarez and Lippi (2009a) who study financial innovations defined as proliferation in the ABM cash access network and adoptions of ABM card technology. The channel between demand side financial innovations and free withdrawal opportunities is characterized by decreased physical interactions with the bank branch network. In Figure 2, we present a situation where two types of consumers withdraw cash from a bank branch. We show that the orange consumer would be classified as the costly type since her cash withdrawals are associated with a direct trip (the nearest branch is in the opposite direction/route to the grocery store). On the other hand, the purple consumer is classified as the free type since his withdrawal is associated with indirect trips (i.e., the shoe-leather cost is distributed across the entire trip).

Figure 2: Direct vs. Indirect Trips



The focus of our research is on the urban sub-sample.[4] By narrowing our focus to urban respondents, we can improve the accuracy of our average distance measure, reduce confounding from white label ABM surcharge fees, and it allows us to ignore withdrawals coming from the white label ABM access network (we do not have data on white label ABMs). First, since our distance measure is based on the assumption that consumers are equally spatially distributed within each spatial unit, its accuracy depends on the true underlying spatial distribution. As such, the closer the underlying consumer spatial distribution is to spatial uniformity, the more accurate our distance measure. Second, in terms of confounding from

[4]We use the Canada Post definition of wide-area rural regions. These rural regions are identified as having a second digit equal to zero. Everything else is classified as urban. Research by Stix et al. (2020) is based on all geographic regions within Austria (a smaller geographic size), while our study is restricted to the urban sub-sample.

ABM surcharge fees (e.g., withdrawals from non-affifilated FIs or white label ABMs), respondents living in urban areas are generally less affected by ABM withdrawal fees because these regions are well served by the bank branch network. In these regions, foreign ABMs act as complementary cash access points rather than substitutes.[5] This has also been found by Gowrisankaran and Krainer (2011), who demonstrate that consumers are balancing a trade-off between shoe-leather costs and surcharge fees, and in general, the cost from the surcharge fee on withdrawals exceeds the shoe-leather cost (consumers value 1 kilometer of distance between 4 and 13 cents), so that urban respondents might typically travel to their affiliated branch instead of foreign ABMs. Since urban respondents face a lower shoe-leather cost given dense branch networks, there is a greater benefit to seeking out surcharge free withdrawal opportunities. Finally, since urban respondents mostly withdraw from affiliated FI branches (89% incur no surcharge fee based on 2013 and 2017 DSI) and most FI's ABMs are co-located with branches, we study combined withdrawals from both teller and on-site ABMs.

We define p as the number of free withdrawals and δ as the cut-off for classifying the costly/free type. In our analysis of selecting costly respondents whose expected number of free withdrawal opportunities is less than two ($p \leq \delta$, where $\delta = 2$),[6] we find that distance from the branch network is a significant determinant of cash management behavior below a distance threshold of 1.56 kilometers. Furthermore, for respondents located further than the 1.56 kilometers, the marginal effect of distance is negligible. We conjecture that the emergence of threshold effects is a result of differences in modes of transportation; those who live within the threshold of their nearest bank branch may be more inclined to walk and make a withdrawal, and thus might be more adversely affected by changes in distance. These

[5] In the 2013 and 2017 MOP DSI, approximately 13% of rural withdrawals incurred a fee whereas 11% of urban withdrawals incurred a fee.

[6] To pin down a reasonable cut-off for the number of monthly free withdrawal opportunities we use evidence from the MOP DSI. Considering the 2013 and 2017 MOP DSI, for withdrawals with the listed reason "convenience" (this is our survey analogue of free withdrawals), those respondents, on average, had approximately 2 monthly free withdrawal opportunities. As such, for the remainder of our main analysis, we focus on the cut-off where $p \leq 2$. Refer to Section 6 for estimation results across various cut-off points.

results hold true when we consider other cut-offs $\delta \in \{3, 4, 5, 6\}$ as a robustness check. We also find that the effect of distance differs across demographics. As a final contribution, we account for heterogeneity coming from age and income by estimating marginal effects across the high/low[7] income and young/old[8] subsets of the costly type. We find that the high income and older age groups are more responsive to variations in shoe-leather costs.

The remainder of our paper is as follows: in Section 2 we discuss some of the pertinent literature. In Section 3 we discuss the development of our classification method and identify measurement issues. In Section 4, we present our data and summary statistics. In Section 5, we present the results of our analysis. In Section 6, we perform various robustness checks. Finally, Section 7 concludes the paper.

2. Literature Review

This section provides a brief overview of two literatures, financial markets' geography and cash inventory management, that are inherently related, but the interaction of these two strands of literature remain largely under-studied from an empirical perspective. This paper is part of an emerging research program that is attempting to more fully integrate them.

2.1. Cash Inventory Management

Cash withdrawals as the optimal solution of an inventory management problem has been popularized by Baumol (1952) and Tobin (1956). The core objective of this problem is the minimization of cost, that is, the sum of opportunity and withdrawal costs. Opportunity costs arise from interest-differentials between liquid assets that don't bear interest and interest-bearing assets that cannot be used for payment. Withdrawal costs are usually modeled as improvements in withdrawal technologies such as ATMs. Lippi and Secchi

[7]We split the sample by looking at respondents above and below the median income.
[8]We split the sample by looking at respondents above and below the median age.

(2009) and Alvarez and Lippi (2009a) generalize the Baumol-Tobin model by introducing financial innovation to capture free withdrawal opportunities. This modification introduces a precautionary motive for holding cash and naturally captures developments in withdrawal technology, such as the increasing diffusion of bank branches and ATM terminals. Lippi and Secchi (2009) and Alvarez and Lippi (2009a) utilize changes in both opportunity and withdrawal costs to study the interest rate elasticity between ATM and non-ATM users. Bachas et al. (2018) study a natural experiment of the Mexican cash transfer program that reduces the travel distance of beneficiaries and find that beneficiaries facing the largest reduction in road distance increase their number of withdrawals most. Recently, Briglevics and Schuh (2020) and Scherbakov and Xu (2020) introduce the element of dynamic cash inventory into consumer payment choice with transactions level data and find the importance of cash management cost.

2.2. Geography of Financial Markets

Our results highlight the importance of geography in financial markets in the context of consumer banking. This work is not the first to highlight the importance of geography in the area of economics and finance; in fact, geography has been shown in the literature to be an important determinant. For example, research that has studied geography of financial markets: the home or familiarity bias of investment (Grinblatt and Keloharju (2001) and Coval and Moskowitz (1999)), the accuracy of sell-side research (Malloy (2005)), dividend policy (John et al. (2011)), financial health (Brown et al. (2017), Goodstein and Rhine (2017), and Célerier and Matray (2019)), and even financial misconduct (Parsons et al. (2018)). In addition, distance to the bank has been shown to be related to financial products pricing; see Degryse and Ongena (2005), Agarwal and Hauswald (2010), Carbo-Valverde and Perez-Saiz (2018), Herpfer et al. (2019), and Nguyen (2019). In the end, the geography of financial markets is also linked to consumers' banking habits and adoptions of various financial services. Atio et al. (2002) find that branch networking (as measured by the count of ABMs in a given province) is significant and positively correlated with the probability of opening a bank account, and the probability of having an ATM card conditional on the consumer having a bank account. Allen et al. (2009) look at the effect of branch closure/density on the adoption of online banking. Recently, Choi and Loh (2019) study how physical ABM frictions (e.g., shut-downs due to renovations) affect digital banking adoption.

3. Classification and Measurement

In this section, we discuss three important aspects that surround our classification and measurement techniques. In sub-section 3.1, we discuss our application of Alvarez and Lippi (2009a) to identify costly and free respondent types. In sub-section 3.2, we discuss measurement issues related to confounding from unobservable ABM fees. Finally, in sub-section 3.3, we discuss the precise measurement of our distance metric and its statistical features.

3.1. Identification of Free Withdrawals

As we have discussed extensively in previous sections, to address the identification issue, our strategy is based on the structural work of Alvarez and Lippi (2009a). This model recognizes that deviations in Baumol-Tobin behavior are associated with the presence of free withdrawal opportunities. This comes about because consumers have a precautionary motive to replenish cash stores when they pass a withdrawal opportunity during the course of pursuing other business – even when their cash inventories are bountiful. Based on this, we try to identify individuals who are likely to incur a shoe-leather cost when making a withdrawal by selecting those whose withdrawal behavior is most closely representative of Baumol-Tobin behavior. That is, we select respondents who have a tendency to make withdrawals when their cash stores approach zero ($\underline{M} \to 0$ – no precautionary motive – refer to Figure 1).

We want to identify withdrawal trips that are affected by shoe-leather costs in terms of well-defined travel distance. However, some proportion of withdrawal trips are associated with a negligible shoe-leather cost, and as such, it would be difficult to separate out the self-reported typical withdrawals into these types (in the ideal case, we should only run the number of costly withdrawals on shoe-leather cost, but we do not observe the number of costly withdrawals directly from the data). We can think of these free withdrawals as passing by a bank branch with a low opportunity cost at random times. Part of the challenge we face is identifying respondents that have a propensity for costly withdrawals so that we can estimate the shoe-leather cost as in the Baumol-Tobin model. Since we cannot use individual transaction level data to do this, the next best method is to use respondent level data and classify respondents as being either the costly or free type. In order to do this, we rely on the structural model of Alvarez and Lippi (2009a) to identify respondents that have a propensity to make free withdrawals. We outline this method below and define the following variables:

M : Avearge cash holdings

m^* : Optimal cash replenishment level

$\underline{M}$: Withdrawal trigger

W : Avearge withdrawal amount

n : Monthly withdrawal frequency

p : Monthly free withdrawal opportunities

c : Monthly cash purchases (DSI)

π : Monthly rate of inflation

We choose to use the observations on $(n, \underline{M}/M)$ to exactly identify p, where:

$$p = n\frac{\underline{M}}{M} \tag{1}$$

Other data that can be used to compute p when $\underline{M}/M$ is missing include the following:

$$\begin{aligned}
\frac{M}{c}\left(\frac{m^*}{c}, \pi, p\right) &= \frac{\left(1+\pi\frac{m^*}{c}\right)^{\frac{p}{\pi}}\left(\frac{m^*}{c} - \frac{\left(1+\pi\frac{m^*}{c}\right)}{p+\pi}\right) + \frac{1}{p+\pi}}{\left(1+\pi\frac{m^*}{c}\right)^{\frac{p}{\pi}} - 1} \\
\frac{W}{M}(m^*.p, n) &= \frac{m^*}{M} - \frac{p}{n} \\
n\left(\frac{m^*}{c}, \pi, p\right) &= \frac{p}{1-\left(1+\pi\frac{m^*}{c}\right)^{-\frac{p}{\pi}}}
\end{aligned} \tag{2}$$

Using data pair $(n, \frac{M}{c})$ we compute p_i^1 and using $(n, \frac{W}{M})$ we compute p_i^2. If $\underline{M}_i/M$ is missing, then we set $p_i = \max\left\{\frac{p_i^1+p_i^2}{2}, 0\right\}$.[9]

To pin down a reasonable cut-off for the number of monthly free withdrawal opportunities we use evidence from the MOP Diary of Survey Instruments (DSI). Considering 2013 and 2017, for withdrawals with the listed reason "convenience" (this is our survey analogue of free withdrawals), those respondents on average had approximately 2 monthly free withdrawal opportunities. As such, for the remainder of our analysis, we focus on the cut-off where $\delta = 2$ (we consider other cut-offs in Section 6). As argued in Appendix I of Alvarez and Lippi (2009b), there is lack of information on the minimum size of withdrawals in the surveys. Thus, instead of calibrating the more comprehensive model of Alvarez and Lippi (2009b) with extra parameter f (small fixed costs of free withdrawals), we adopt a sensitivity analysis to allow the cut-off δ between free and costly withdrawals to be larger than 0. This positive cut-off point for costly random withdrawals implies that not every random contact with a financial intermediary would lead to a withdrawal due to the cost f. Thus, the calibrated

[9] Our primary classification technique relies on using the identity $p = n\frac{\underline{M}}{M}$. We can use the DSI to complement the SQ data in computing p and also provide information on monthly cash purchases.

p under the model without f will be underestimated, and raising the cut-off above zero to a positive integer will off-set this issue. Another justification for having the cutoff above zero is discussed in Appendix H of Alvarez and Lippi (2009b). The existence of totally free withdrawals may be unrealistic in the sense that it would prompt respondents to make small value withdrawals every time they interacted with a financial institution. Based on this inconvenient property, relaxing the assumption of totally free withdrawals with costly random withdrawals may improve the fitness of the data, and motivates a non-zero cut-off point for differentiating between costly and free types.

To account for selection that results from censoring in the number of costly withdrawal opportunities, we include the adoption of online financial innovations as an exclusion restriction and the independent variables from the count regression model into the selection equation. To understand the impact that each variable will have on selection, in Table 1 we present summary statistics for $\delta = 2$ and report both above and below this cutoff. One of the notable findings is that the average degree of adoption of online financial innovation is larger in the low free withdrawal opportunity group (i.e., $p \leq 2$) by a margin of 8%. A plausible explanation for this finding is that the adoption of online financial innovations leads to a reduction in the demand for cash withdrawals and fewer physical interactions with the bank branch network. This will decrease both the total number of withdrawals and the probability of free withdrawals. This will decrease the absolute number of free withdrawal opportunities.

Table 1: Group Statistics for p Above and Below 2

Variables	$p > 2$ (A)	$p \leq 2$ (B)	$(A/B) - 1$
Age (Years)	46.96	47.34	-1%
Education (Years > Primary)	6.524	6.659	-2%
Income ($)	65,087	66,137	-2%
Family Size	2.283	2.258	1%
Adoption of Financial Innovation	0.596	0.646	-8%
Distance Measure (kilometers)	4.679	4.408	6%
Withdrawal Value (W)	155.1	145.9	6%

One of the key steps is correctly classifying consumer withdrawals into free and costly withdrawals so that we can study the effect of shoe-leather costs for costly withdrawals. Our main method of doing this is by applying Alvarez and Lippi (2009a) to classify respondents into the binary types of costly and free ones. To gain an idea of the necessity of accounting for free withdrawals on the intensive margin (e.g. the expected number of free withdrawals per month), we adopt an approximate approach based on Carroll et al. (2006) to assess the degree of the misclassification of free withdrawals into costly ones.[10] We apply either Negative Binomial (NB), Poisson (PPML) or Gamma PML (GPML) methods to reweight observations at different parts of the overall withdrawal frequency's distribution. Applying PPML or GPML is akin to studying the robustness of the intensive margin (e.g., the number of costly withdrawals as the dependent variable), while filtering out free types based on the Alvarez and Lippi (2009a) classification is similar to the extensive margin (e.g. whether costly or free types). Refer to Appendix D for the results of the PPML and GPML regressions.

3.2. Measurement Issues

The primary measurement challenge we face is that the decision to withdraw, in some cases, is confounded by ABM withdrawal fees. To deal with the contamination from ABM withdrawal fees we focus on the urban subset of respondents. Cash access networks are structurally different in rural and urban regions. On the one hand, urban regions are generally well served by bank branches and off-site FI ABMs. White label ABMs exist to meet demand associated with emergency cash withdrawals. On the other hand, in rural regions, we find that white label ABMs are used to expand cash access networks and cash accessibility that is not met by the large financial institutions. Ultimately, white label ABMs complement the bank branch network in urban regions whereas they are substitutes in rural regions. Focusing our analysis on urban regions allows us to further eliminate confounding from ABM withdrawal fees. Given that we focus on the urban area where the distance is usually

[10] Although approximate methods yield inconsistent parameter estimates, they are expected to diagnosis the sensitivity of costly withdrawals when estimating the effect of shoe-leather costs.

short and the ATM fee is comparatively expensive, people might prefer to avoid the ATM fee by seeking out an ATM with no surcharge fee (Gowrisankaran and Krainer (2011)).

Generally speaking we can classify withdrawals into the following sources:

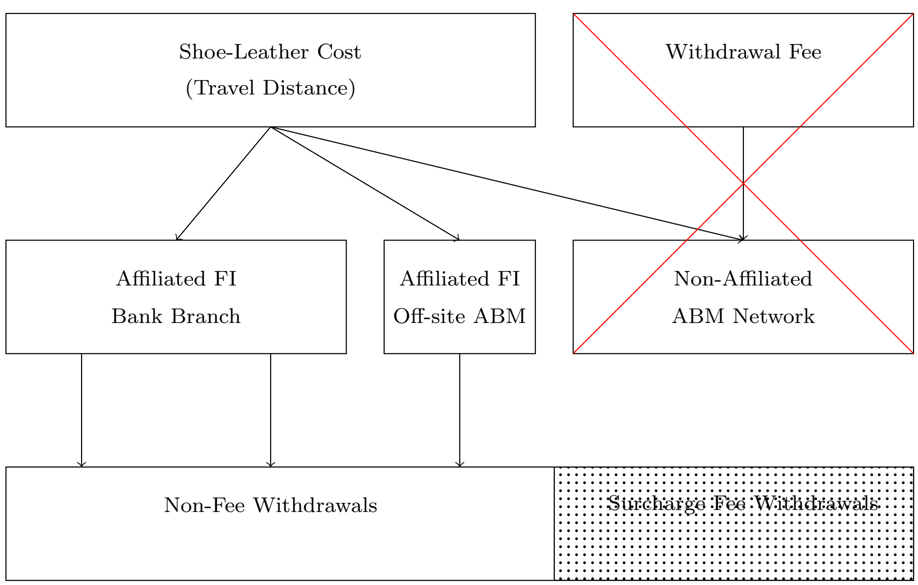
1. Affiliated FI branch network

2. Affiliated FI off-site ABM (a small percentage of the network)

3. Non-affiliated or white label ABM network

Given that we are isolating respondents that are likely to incur shoe-leather costs but that also do not incur ABM fees, the first class of withdrawals apply (refer to Figure 3). We note that there may be some misclassification bias stemming from the second class of withdrawals, however, this makes up only a small portion of the network.

Figure 3: Consumer Withdrawal Choice – Travel Distance and Withdrawal Fee



3.3. A Distance Measure

Since respondents are likely to withdraw from their affiliated financial institution, our average distance measure is computed as follows: first, we overlay each spatial unit (the FSA) with a uniform grid of pixel points (128×128);[11] second, we compute the distance from the centroid of each pixel point to the nearest respondent affiliated bank branch; finally, we take the average of these distances. Next, we assign to each respondent the average distance measure that corresponds to their residence FSA and affiliated financial institution.[12] This measure is similar to Ho and Ishii (2011) and Chen and Strathearn (2020) with one major improvement being the use of respondents' nearest affiliated bank branch. In addition, the focus on residence FSAs (rather than employment FSAs) is empirically relevant because we observe that in the 2017 MOP DSI approximately 72% of withdrawals are made near home.

The distance $d_{i,t}$ is directly related to the Berkson measurement error (Berkson (1950)), whose distance is an optimal predictor (group average) for people living in that particular FSA. When regressing on the Berkson-contaminated independent variable in (non-) linear models, we still have consistent estimates up to the constant term without extra information or assumptions as in Hyslop and Imbens (2001) and Wang et al. (2004).[13] To see this, for individual i, let $d^*_{i,t}$ be the unobserved true distance and $d_{i,t}$ be the average distance, so by construction we have

$$d^*_{i,t} = d_{i,t} + u_{i,t}, \text{ with } E\left(n_{i,t} | d^*_{i,t}, \boldsymbol{x}'_{i,t}\right) = \exp\left[k\left(d^*_{i,t}\right) + \boldsymbol{x}'_{i,t}\boldsymbol{\beta}\right] \tag{3}$$

Note that the empirical conditional mean function can be expressed as $E\left(n_{i,t} | d_{i,t}, \boldsymbol{x}'_{i,t}\right) = \psi \exp\left[k\left(d_{i,t}\right) + \boldsymbol{x}'_{i,t}\boldsymbol{\beta}\right]$, where ψ is a constant. In our case, Berkson error in the generalized

[11]This is a reasonable assumption since we base our analysis on respondents who reside in urban FSAs.
[12]Refer to Appendix A for a detailed discussion of the affiliated branch distance measure.
[13]For the case of classical measurement error, the unbiased estimates can only be achieved if sufficient instrumental variables (IV) are available. Recently, the IV is extended to deal with the classical measurement error problems in generalized linear models by Abarin and Wang (2012) and Li and Wang (2012).

linear model will not bias the estimates up to the constant term compared to Mulligan and Sala-i Martin (1996), who use the self-reported distance between the individual (home or workplace) and a financial institution. This self-reported distance suffers from the classical measurement error issue and leads to attenuation bias in both estimates and t-statistics. Thus, Mulligan and Sala-i Martin (1996) fail to find a significant effect of distance in their study.

At the same time, from Equation (6) of Wang et al. (2004), when the second moment of withdrawal frequency is

$$E\left(n_{i,t}^2 | d_{i,t}^*, x_{i,t}\right) = E\left(n_{i,t}^2\right), \tag{4}$$

then we have

$$\begin{aligned} E\left(n_{i,t}^2 | d_{i,t}, x_{i,t}\right) &= \exp\left[\varphi_2 \cdot Var\left(u_{i,t}\right)\right] \cdot \exp\left\{2\left[\alpha d_{i,t} + x_{i,t}\beta\right]\right\} + E\left(n_{i,t}^2\right) \\ &\geq E\left(n_{i,t}^2\right), \end{aligned} \tag{5}$$

where $\varphi_2 > 0$. Hence, when the regressor is contaminated by the Berkson measurement error, the variance would be inflated so that it results in less precise estimates. Moreover, the larger the $Var\left(u_{i,t}\right)$, the larger the $E\left(n_{i,t}^2 | d_{i,t}, x_{i,t}\right)$. Alvarez and Lippi (2009a) report the weak (close to zero) correlation between the city-level density of financial intermediaries and the expected number of free withdrawal opportunities, which can be explained by the large $Var\left(u_{i,t}\right)$ using the city-level measurement. It is because of this variance consideration that we choose to measure distance at the FSA level rather than the city-level in order to increase the estimation precision.

4. Data and Summary Statistics

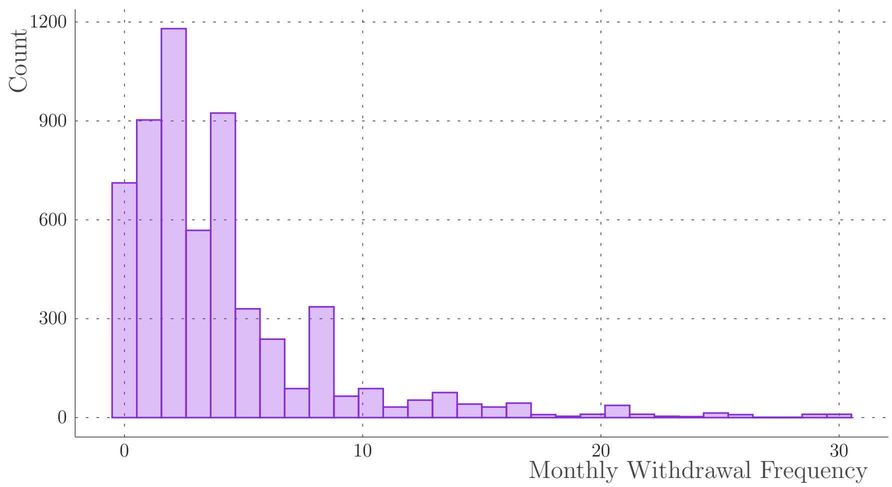
We set out to study the effect of shoe-leather costs (distance) on respondent withdrawal frequency while accounting for sample selection bias associated with contamination from free withdrawal opportunities. To account for other factors that influence withdrawal behavior, we also control for observable demographic characteristics that include income, employment status, family size, age, education, sex, time and province fixed-effects, and the adoption of online financial innovations. We use a rich micro-geographic data set at the respondent level, which relies on linkages between the Payments Canada Financial Institutions File (FIF), the Bank of Canada quadrennial Method of Payments (MOP) surveys (2009, 2013 and 2017), and the Statistics Canada FSA boundary files for 2011. The variables used in our analysis are presented in Appendix E, Table 10, with corresponding summary statistics in Table 2.

Table 2: Summary Statistics – Main Variables (Urban Sub-sample)

	2009			2013			2017		
	N	Mean	Median	N	Mean	Median	N	Mean	Median
Withdrawal Value - ATM (W_{ATM})	2,039	109.3	80	841	129.2	100	960	159.0	100
Withdrawal Value - Branch (W_{Branch})	754	193.0	100	297	257.8	100	253	307.5	200
Withdrawal Value - All (W)	2,177	126.5	100	907	157.5	100	1,056	182.4	100
Withdrawal Frequency (n)	3,010	4.897	4	1,174	3.415	2	1,593	2.593	2
Cash Holdings (M)	3,010	139.1	40	1,174	89.76	50	1,593	114.0	58
Replenishment Trigger ($\underline{M}$)	2,394	26.36	10	888	30.56	15	1,041	42.15	20
Age (Years)	3,010	46.67	48	1,174	48.15	49	1,593	47.77	49
Education (Years > Primary)	3,007	6.581	6	1,168	6.610	6	1,588	6.759	7
Income ($)	3,010	65,219	55,000	1,173	62,835	55,000	1,592	69,642	55,000
Family Size	3,010	2.388	2	1,173	1.969	2	1,593	2.239	2
Distance Measure (kilometers)	3,010	5.150	2.600	1,174	3.830	1.981	1,593	3.603	1.938

To account for additional econometric issues, in Figure 4 typical withdrawal frequency may exhibit excessive zeros. To deal with this, we model the likelihood of withdrawal frequency using the NB distribution whose variance function is a specific quadratic function of the mean. Not only does it allow for over-dispersion, but it also can be understood as incorporating an additive Berkson measurement error from our constructed distance measure as the unobserved heterogeneity with random effects (Section 13.3.5 in Cameron and Trivedi (2013)).

Figure 4: Withdrawal Frequency Histogram – Sample (Urban Sub-sample)



5. Empirical Model and Estimation

As we have discussed, isolating a sub-sample of respondents with a high probability of making costly withdrawals allows us to accurately measure the marginal effect of distance on withdrawal behavior. In the context of Alvarez and Lippi (2009a), when p is small, the resulting model will converge to the Baumol-Tobin model (Baumol (1952) and Tobin (1956)). Our cross-sectional dimension, i, is a respondent where the temporal dimension, t, is the year.[14][15] We define $n_{i,t}$ as monthly withdrawal frequency, $p_{i,t}$ as the monthly free withdrawal opportunities, $d_{i,t}$ as the distance measure (in km), $\boldsymbol{x}'_{i,t}$ is a $1 \times k$ vector of observable demographic characteristics (refer to Appendix E for a list), and $\boldsymbol{\beta}$ is a $k \times 1$

[14] The Bank of Canada Methods of Payment Survey is a cross-sectional survey administered to a new set of respondents every four years rather than a longitudinal survey.

[15] Most of the variation in the distance measure is between cross-sections. Refer to Appendix B for a discussion on the persistence in the distance measure.

vector of parameters. The conditional mean function is modeled below:

$$E\left(n_{i,t}|d_{i,t},\boldsymbol{x}'_{i,t}\right)=\exp\left[k\left(d_{i,t}\right)+\boldsymbol{x}'_{i,t}\boldsymbol{\beta}\right]. \tag{6}$$

Notice that Equation (6) is the empirical analog of (3) where we replace $d^*_{i,t}$ with the observed distance metric $d_{i,t}$. We define $k'\left(d_{i,t}\right)\leq 0$ and δ as the cut-off point to differentiate respondents based on their type. In other words, those respondents that fall below the cut-off are likely to make costly withdrawals, and thus their withdrawal behavior is affected by distance.

There are three aspects that we consider for the empirical specification of Equation (6). First, we need to account for the multiplicative form of withdrawal frequency by applying a pseudo-maximum-likelihood (PML) estimation technique.[16] Using the PML only requires that the conditional mean function be correctly specified in order to obtain consistent estimates. Although incorrectly specifying the variance function leads to efficiency losses, the inference can be corrected using robust (sandwich) estimators for the variance–covariance matrix. Thus, the PML estimator protects against the problems from a misspecified distribution function.[17]

Second, we should allow for potential threshold or localized effects of distance on withdrawal frequency. Regarding the functional form of $k\left(d_{i,t}\right)$, we employ a piecewise linear specification to flexibly accommodate for potential threshold effects of distance. Such threshold effects have been well documented in the literature. For example, Goodwin and Piggott (2001) document spatial market integration in the presence of threshold effects; Gallego and Llano (2014) use the segmented distance approach to study the border effect between trade and

[16]To draw a parallel, Silva and Tenreyro (2006) argue that estimating gravity equations in their log-linearization additive form by OLS leads to inconsistency in the presence of heteroskedasticity and suggest estimating gravity models in their multiplicative form.

[17]This is related to an estimator proposed by Papke and Wooldridge (1996) for the estimation of models of fractional data.

distance; Cheema et al. (2019) document a stark boundary effect, whereby training take-up for women falls substantially as they cross a (virtual) village boundary (this dates back to Schelling (1971), who studied racial residential segregation). Recently, Baum-Snow et al. (2020) find that very local productivity spillovers occur at within 75 meters radius area and fully decay within 250 meters. Similar to the notion of threshold effects, Ho and Ishii (2011) find that there are significant differences in cross price elasticity between financial institutions located within one mile of their customers, "close" and "far" banks. Our method to study the threshold between withdrawal frequency and distance is to allow for change in slopes for different segments, where these segments correspond to different distances traveled by consumers. In our paper, we estimate linear segments jointly with a number of knots using structural change analysis for a nonlinear model (Andrews and Fair (1988)).

Third, it is crucial to correct for the non-random selection conditioning on people with $p \leq \delta$.[18] We begin by assessing whether the estimated coefficients were affected by the choice of the Heckman estimation method.[19] The identification of the distance coefficients in the presence of sample endogeneity hinges on the specification of the probit selection equation of people with $p \leq \delta$.

Based on these three aspects, we present the first order Taylor series approximation of the Terza (1998) conditional mean function with a Heckman correction term (Greene (1995)). Our focus on the Greene (1995) model is for exposition, whereas our model estimates are based on the Terza (1998) version of the model.

$$\ln E\left[n_{i,t}|d_{i,t}, \boldsymbol{x}'_{i,t}, p_{i,t} \leq \delta\right] = \theta_0 d_{it} + \sum_{j=1}^{l} \theta_j \mathbb{1}(d_{it} > h_j)(d_{it} - h_j) + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \rho\sigma \frac{\phi(\boldsymbol{z}'_{i,t}\boldsymbol{\alpha})}{\Phi(\boldsymbol{z}'_{i,t}\boldsymbol{\alpha})} \quad (7)$$

[18]Both Lippi and Secchi (2009) and Atio et al. (2002) use the Mills ratio to control for non-random selection of ATM card users.

[19]Alternatively, it is possible to use Lewbel (2007) to correct for such selection of using support and an independence assumption, rather than strong assumptions of joint distribution of unobservables affecting selection and outcome.

where

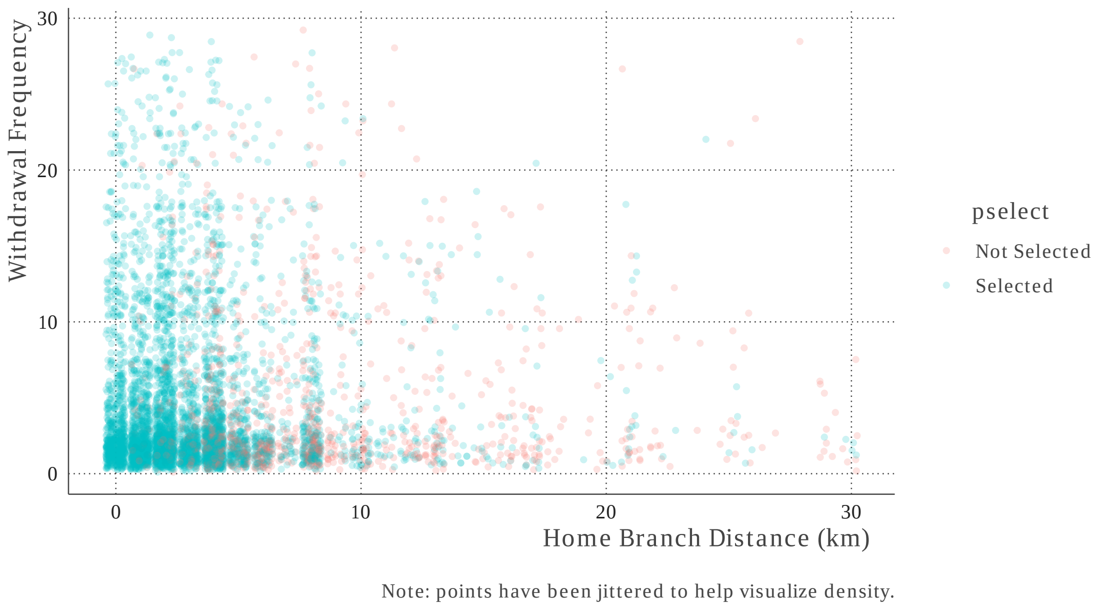
$$\text{Prob}(\text{Costly}_{i,t} = 1|\boldsymbol{z}) = \Phi(\boldsymbol{z}'_{i,t}\boldsymbol{\alpha}) \tag{8}$$

where the selection equation includes a set of observable characteristics $\boldsymbol{z}'_{i,t}$. In our application, this includes $k\,(d_{i,t})$, income, education, employment status, family size, age, sex, and adoption of online financial innovations. ρ is the correlation between unobserved heterogeneity in the main model and the selection equation. In terms of the threshold effects, h_j is the estimated kink points coming from a segmented negative binomial regression model without selection where l is determined by the model. Finally, θ_j is net marginal effect of distance moving from the region h_{j-1} to h_j. We assume that $h_1 < h_2 < \cdots < h_l$.

5.1. Estimation Results

Since we are correcting for sample selection, if the first and the second stage estimates have a large set of variables in common, a collinearity problem may occur as the Mills ratio is approximately a linear function of these variables over a wide range of values. This problem might be particularly relevant in our case due to a limited availability of appropriate instruments. However, our identification is helped by the inclusion of a binary dummy variable for the adoption of recent online financial innovations for checking balances and making financial transactions. The validity of using the adoption of online financial innovations as exclusion restrictions is because the financially innovative respondents might not need to visit the branch, so that their expected number of free withdrawals is small. As we discussed earlier, the group with fewer free withdrawal opportunities had a greater degree of financial innovation adoption. An alternative "sanity check" is to plot withdrawal frequency against the distance to the nearest affiliated branch and check whether there is clustering among the selection and non-selection groups. Referring to Figure 5 we observe that the selection group ($p \leq 2$) appears to cluster at distances below 5 kilometers.

Figure 5: Withdrawal Frequency vs. Afiliated Branch Distance by $p > 2$ (Not Selected) and $p \leq 2$ (Selected)



Our main estimation results can be found in Table 3. The sample used in all regression models is urban respondents that withdraw less than 30 times per month and live within 30 kilometers of their affiliated financial institution. Model (1) is a negative binomial count regression (with both costly and free types). We find that distance is an important explanatory factor of withdrawal frequency. Furthermore, we find that there are strong threshold effects within 0.91 kilometers. In particular, we find that for consumers living within 0.91 kilometers of their affiliated financial institution, all else being equal, the average marginal effect on the count outcome given a 1 kilometer increase in distance is a decrease in monthly withdrawals by 1.66. As we have discussed, the distance coefficient in Model (1) suffers from bias due to the inclusion of the free withdrawal types. In Model (2), we select on respondents who make fewer or equal to two free withdrawal opportunities. Once accounting for selection is done, we find that the magnitude of the distance coefficient decreases. In fact, for those respondents living within 1.56 kilometers of their affiliated financial institution, a 1 kilometer increase is associated with an average marginal effect on the count outcome of a decrease in monthly withdrawals by 0.31. The associated selection equation is presented in Model (3), where we see that the probability of selection is positively correlated with the indicator for online financial innovations. This suggests that those respondents who have adopted recent online financial innovations are more likely to be selected into the costly type. The reason is that reduced interactions with the physical branch network lead to fewer free withdrawal opportunities. As a robustness check, we include cash expenditures in Model (4) to account for the fact that cash management behavior is directly linked to individual cash expenditures (Baumol (1952) and Alvarez and Lippi (2009a)). We find that the results in Model (2) hold with the inclusion of cash expenditures.

Given that we find strong threshold effects that occur between 1 kilometer and 2 kilometers, we conjecture that these effects result from differences in travel methods. In other words, those that live outside 1.56 kilometers of their affiliated financial institution (Figure 6) may be more likely to drive to the nearest branch, and thus marginal changes to distances are unlikely to impact the demand for withdrawals. However, for consumers living within 1.56 kilometers (Figure 7), there may be a preference for walking or using public transportation. In this case, even a small change in distance can be followed by a large change in withdrawal behavior due to the higher relative cost of walking/public transit.

Table 3: Main Estimation Results ($p = 2$)

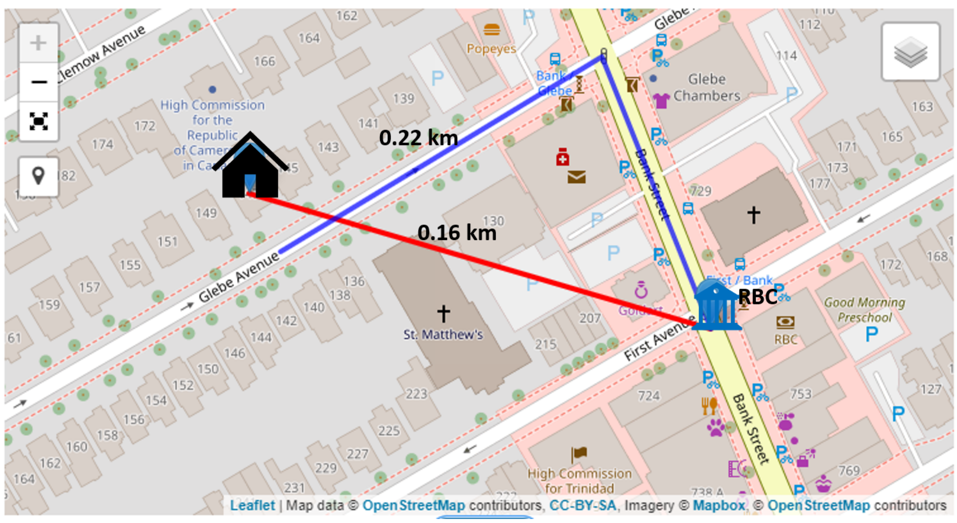
	Negative Binomial	Poisson ($< p$)	Poisson ($< p$) Selection	Poisson ($< p$) Cash Expenditure	Poisson ($< p$) Cash Expenditure Selection
	(1)	(2)	(3)	(4)	(5)
Distance (< kink)	-0.466^{***}	-0.118^{**}	0.009	-0.134^{**}	-0.004
	(0.102)	(0.047)	(0.064)	(0.054)	(0.082)
Distance	0.464^{***}	0.115^{**}	-0.015	0.130^{**}	0.002
	(0.103)	(0.048)	(0.066)	(0.055)	(0.084)
Log Cash Exp.				0.093^{***}	
				(0.007)	
Log Total Exp.					-0.037^{**}
					(0.019)
Log Income	0.025	0.040^{*}	0.046	0.053^{**}	0.033
	(0.016)	(0.021)	(0.030)	(0.025)	(0.038)
Education (Years)	-0.042^{***}	-0.031^{***}	0.016	-0.027^{***}	0.005
	(0.006)	(0.008)	(0.011)	(0.009)	(0.014)
Not in LF	-0.162^{***}	-0.082^{**}	0.208^{***}	-0.070	0.204^{***}
	(0.029)	(0.037)	(0.053)	(0.043)	(0.067)
Unemployed	-0.050	-0.072	-0.021	-0.026	-0.021
	(0.051)	(0.083)	(0.099)	(0.090)	(0.129)
Financial Innovation			0.107^{***}		0.106^{**}
			(0.040)		(0.050)
Family Size	0.019^{**}	0.00005	-0.014	0.018	-0.028
	(0.009)	(0.012)	(0.016)	(0.016)	(0.022)
Age	0.012^{***}	0.004	-0.007	0.001	-0.022^{**}
	(0.004)	(0.005)	(0.007)	(0.006)	(0.011)
Age^2	-0.0001^{***}	-0.00005	0.0001	-0.00002	0.0002^{*}
	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Male	0.141^{***}	0.025	-0.171^{***}	0.041	-0.183^{***}
	(0.022)	(0.028)	(0.039)	(0.033)	(0.051)
Constant	1.462^{***}	0.682^{***}	0.450	0.080	1.398^{***}
	(0.207)	(0.257)	(0.350)	(0.300)	(0.459)
Observations	9300	4737	4737	3145	3145
Log Likelihood	-21914.19	-12975.57		-8226.26	
ρ		0.73		0.97	
Wald (indep. eqn.)		13.88		110.03	
Wald (p-value)		0		0	
σ		0.73		0.67	
Kink (KM)	0.91	1.56	1.56	1.56	1.56

Note: *p<0.1; **p<0.05; ***p<0.01

Model coefficients are reported here. Robust standard errors are estimated.

Figure 6: Example – Outside Kink (Withdraw When Going to Town)

Figure 7: Example – Inside Kink (Planned Withdrawals)



Finally, we account for heterogeneous effects of distance across high/low income and age cohorts (based on the median). In terms of income, we conjecture that higher income groups are more sensitive to changes in distance because they exhibit a higher opportunity cost of time. As such, we would expect that the marginal effect of distance is larger for those in higher income groups. In terms of age, we believe that withdrawing cash for younger individuals is relatively less expensive in terms of effort and opportunity cost and, thus, we should expect that younger individuals are less responsive to changes in distance. In these models we run a Poisson count regression model with a Heckman correction on each subsample. The results are based on $\delta = 2$ and can be found in Table 4. We report the average marginal effects on the count outcome.

Table 4: Heterogeneous Effects for $p \leq 2$ (Average Marginal Effect on Count Outcome)

	Income		Age	
$p \leq 2$	Low	High	Low	High
Before Kink	-0.325*	-0.341*	-0.289	-0.531***
	(0.187)	(0.190)	(0.191)	(0.204)
After Kink	0.331*	0.324*	0.278	0.529
	(0.191)	(0.194)	(0.195)	(0.207)

We observe very modest differences in the coefficient of distance before the kink in the low/high income groups. Considering cut-off values greater than 2, this difference becomes more pronounced (refer to Sections 6.3 and 6.4). This result suggest that higher income groups are more sensitive to distance. This may result because they have an easier time substituting across payment methods and face a higher opportunity cost of withdrawing cash. In terms of age, as expected, we find that older segments of the population are more sensitive to distance. As an alternative estimation method, we calibrate withdrawal cost and regress this cost against our distance measure (refer to Appendix F). Finally, as an alternative way to study the effect of distance on cash management behaviors, we estimate the effect of distance on withdrawal value (refer to Appendix C).

6. Robustness Check and Heterogeneous Effects

6.1. Frequency Regression – Various Cut-offs

As a robustness check, we verify our main results by changing the cut-off value for free withdrawals. The distribution of free withdrawals is presented in Table 5.

Table 5: Average Replenishment and Free Withdrawal Opportunities (2009, 2013 and 2017)

p^a	$\underline{M}^b$	Proportion^c (%)
0	12.30	38.79
1	22.48	32.00
2	34.14	10.61
3	38.01	5.01
4	36.85	3.32
5	44.42	1.49
≥ 6	76.23	8.78

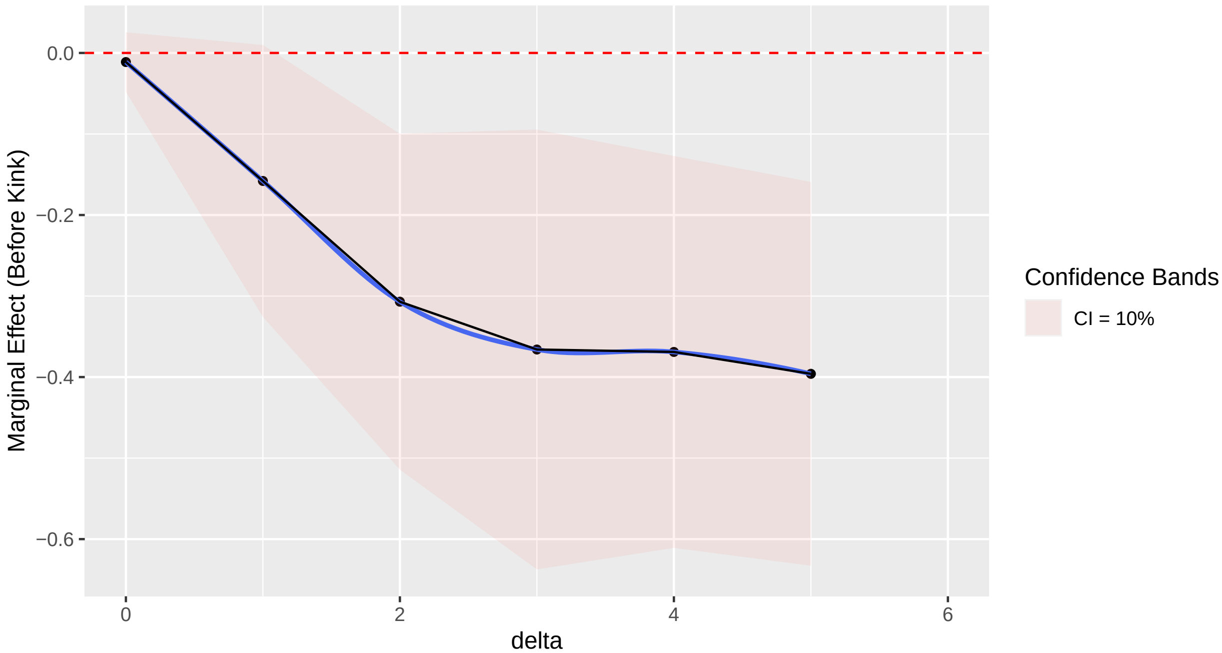
[a] Calibrated based on Alvarez and Lippi (2009a) $p = n\frac{\underline{M}}{M}$

[b] Values are Winsorized at the 99^{th} percentile.

[c] Represents the proportion of withdrawals with given p across all withdrawals. Results are pooled.

Figure 8 presents the average marginal effects on the count outcome for the Poisson regression with Heckman selection. We find that, consistent across values of $\delta \in \{2, 3, 4, 5\}$, when we account for selection, the marginal effect of distance below the kink point is negative. In other words, for individuals residing close to their affiliated financial institution, an increase in distance is associated with a reduction in monthly withdrawals. However, once we look outside the kink distance, we find that the net marginal effect of distance is approximately zero (sum before and after kink). This suggests that those respondents living close to their affiliated financial institution are more sensitive to distance, which may be associated with their preferred method of travel — walking or public transportation. Even a small increase in distance could be prohibitively expensive for respondents choosing to walk or use public transit.

Figure 8: Average Marginal Effect $p \leq \delta$ (Before Kink)

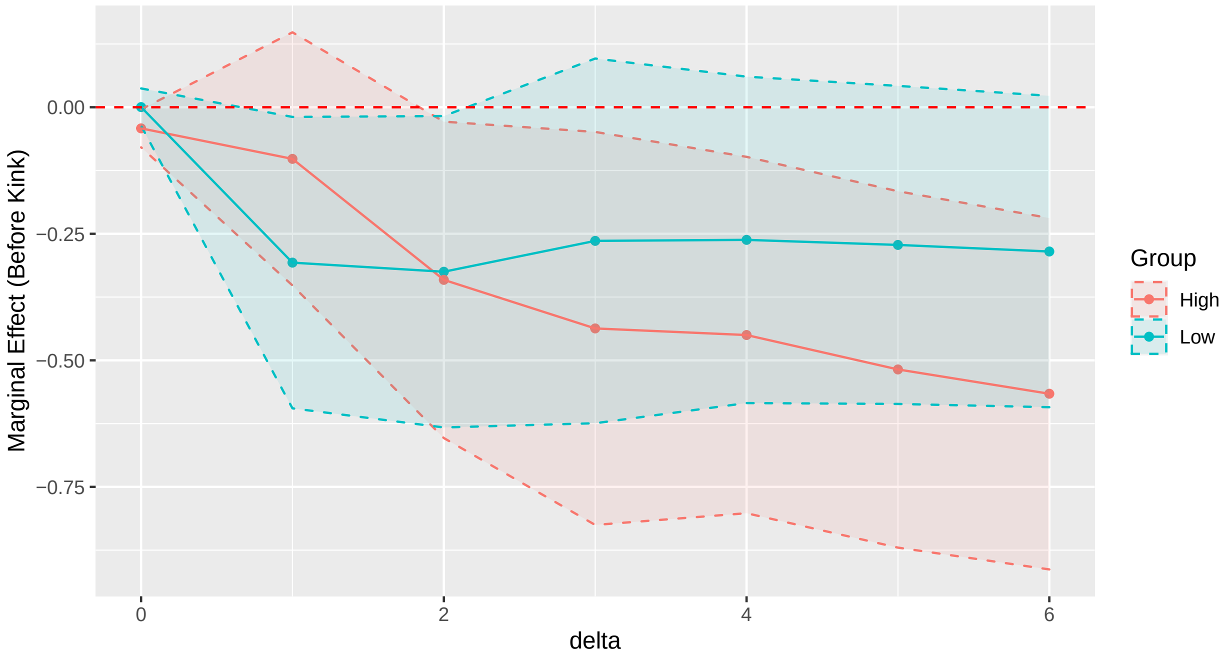


Sub−sample: distance measure less than 30 km, withdraw less than 30 times per month, and live in urban regions.

6.2. Frequency Regression – Income Effects (Below Cut-off)

In Figure 9 we present the average marginal effect on the count outcome when we split the sample at the median income of \$55,000. We run separate regressions for the low/high income groups. We find that for $p \in \{2, 3, 4, 5, 6\}$, the marginal effect of distance below the kink among the high income group is negative and significant, whereas in the low income group it is not significant. In both groups, the net effect of distance above the kink is zero. Our interpretation of these heterogeneous effects is that wealthier individuals are able to freely adjust their withdrawal behavior in response to changes in distance. For example, if distance increases they may substitute cash usage for credit/debit card usage and face a higher opportunity cost of time. However, the low income group does not respond to changes in distance, which may suggest that they absorb the full cost of an increase in distance.

Figure 9: Average Marginal Effect by Income Group and $p \leq \delta$ (Before Kink)

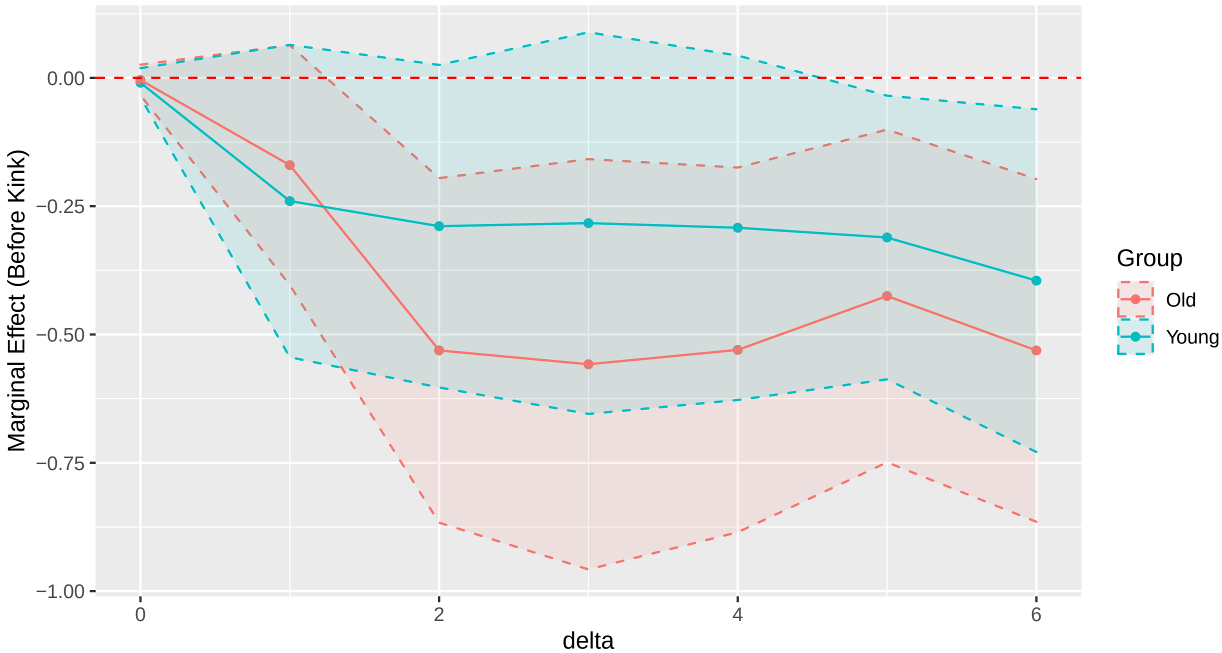


Sub−sample: distance measure less than 30 km, withdraw less than 30 times per month, and live in urban regions.

6.3. Frequency Regression – Age Effects (Below Cut-off)

In Figure 10 we present the average marginal effect on the count outcome regression results when we split the sample at the median age of 47. We run separate regressions for the young/old age groups. We find that for $p \in \{2, 3, 4, 5, 6\}$, the marginal effect of distance below the kink among the older age group is negative and significant, whereas in the younger age group it is not significant. In both groups, the net effect of distance above the kink is zero. Our interpretation of these heterogeneous effects is that older individuals adjust their withdrawal behavior out of necessity because traversing the additional distance becomes more expensive with age.

Figure 10: Average Marginal Effect by Age Group and $p \leq \delta$ (Before Kink)



Sub−sample: distance measure less than 30 km, withdraw less than 30 times per month, and live in urban regions.

7. Conclusion

We study the effect of the shoe-leather cost on consumers' cash withdrawal frequency. One of our major contributions to the literature is a classification methodology to help eliminate confounding bias resulting from withdrawal transactions with a negligible shoe-leather cost. To identify the free withdrawal type and filter out respondents likely incurring negligible shoe-leather costs, we calibrate the average withdrawal behaviors following Alvarez and Lippi (2009a), and then we estimate the effect of our distance measure on costly withdrawals. We find that, consistent with the Baumol-Tobin model, consumers who face smaller travel distance tend to withdraw more frequently. Interestingly, this effect is most pronounced for consumers that live within 1.56 kilometers of their nearest affiliated bank branch. We also find strong evidence that consumers who adopt online financial innovations, like online payment accounts, mobile payment applications, and Interac e-transfer, have fewer free withdrawal opportunities, which result from fewer physical interactions with the physical bank branch network. An important finding is that the marginal effects of shoe-leather costs do not apply uniformly across the entire population. In fact, we observe two important heterogeneous effects. First, we observe that wealthy segments of the population are more responsive to changes in distance. This suggests that wealthier individuals have a higher opportunity cost of time or are substituting cash purchases for card purchases when withdrawals become more expensive. Second, we find that younger individuals are less responsive to changes in distance likely because they have a lower opportunity cost.

In future work, we would like to extend the current approach to study effects of retailer locations on consumers' cash-back transactions. Based on the 2017 MOP, respondents tend to withdraw 0.9 times per month from cash-back, compared to 2.3 times from ATMs and 0.6 times from tellers. In terms of the mean withdrawal size, the typical cash-back amount is \$56, compared to \$140 from the ABM and \$289 from the bank teller. Therefore, obtaining cash from cash-back is an important channel and source of cash withdrawals for consumers that warrant additional research. Other directions for future research include the collection of longitudinal data and ABM surcharge fees so that we can allow for more flexible unobserved heterogeneity and study the intertemporal withdrawal choice.

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Appendix A: Affiliated Branch Distance Measure

To compute this measure, we couple the exact location (geo-coordinates) of the branch with the postal code of the consumer's residence. The reason that we assign the origin of the withdrawal distance to be the residential FSA is because 72% of withdrawals were made near home (based on the 2017 MOP three-day DSI). Since our data do not have the exact location of each customer, we proxy the consumer's location by overlaying a uniform grid of points over each FSA. Then, for each respondent, we compute the FSA average Haversine distance between the uniform grid and the respondent's nearest affiliated bank branch (the branch could be outside the studied FSA to allow for spillovers).[20]

Let I_j be the set of grid points in FSA j, where $x \in I_j$ is a set of latitude and longitude points. The grid points are generated by constructing the smallest rectangular window around a given FSA and overlaying a uniformly distributed 128×128 point grid[21], where the grid points represent mass points of consumers. Next, we subset the grid of estimated consumer locations and consider only those locations that are bounded within the given FSA j. We define $B_{k,t}$ as the set of bank branch locations associated with the financial institution k at time t, and $k \in K = \{\text{RBC, Scotia, TD, BMO, CIBC, Other}\}$ where "Other" captures all other banks and credit unions. We compute this distance measure over the period 2008–2018 and for all Canadian urban FSAs as defined by the Canada Post delivery classifications (e.g, second digit of FSA is $\neq 0$). Given that the uniformity of the pixel grid ignores consumers clustering within the FSA, our study instead focuses exclusively on urban FSAs, which tend to be small geographic units with evenly-distributed residents.

Let the function $d(x, y)$ be the Haversine distance (in kilometers) between two latitude/longitude

[20] This measure comes from Chen and Strathearn (2020) and is similar to Fogel (1963) and Donaldson and Hornbeck (2016) where they approximate the distance to the U.S. railroad network.

[21] The 128x128 pixel grid is the default value from the *spatstat* package (Baddeley et al. (2004)). We found the default to be a good choice in balancing computational intensity and precision.

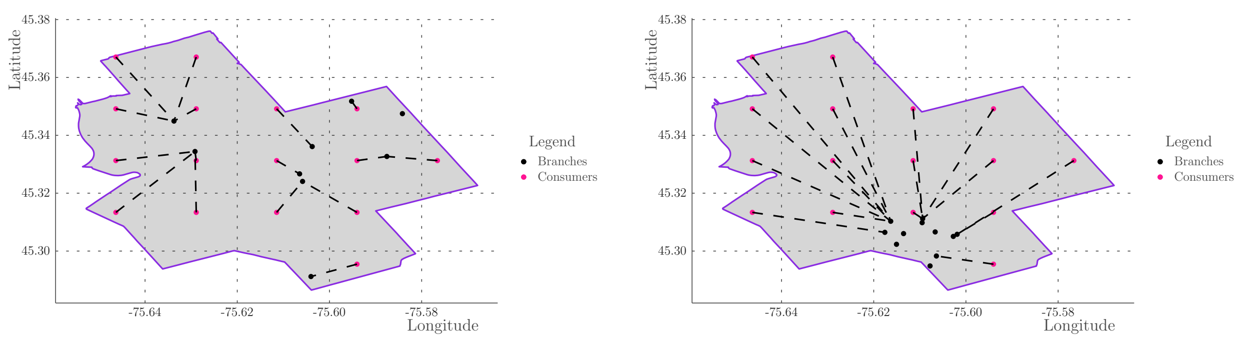
coordinates x and y. Based on our definitions, respondent affiliated branch distance is computed as:

$$d_{k,j,t} := \frac{1}{|I_j|} \sum_{i \in I_j} \min_{b \in B_{k,t}} d(i,b), \tag{9}$$

where $|\cdot|$ denotes cardinality.

One advantage of our distance measure is that it allows us to capture clustering among bank branches. Since the measure uses the exact location of branches we can better estimate distance in areas where branches are clustered. We demonstrate how our distance measure is computed in Figure 11. Based on the illustration, as the degree of clustering intensifies, the grid points on the peripheries have a further distance between themselves and the cluster of bank branches; as such, the distance measure increases.

Figure 11: Geographic Concentration (GC): Random vs. Clustered

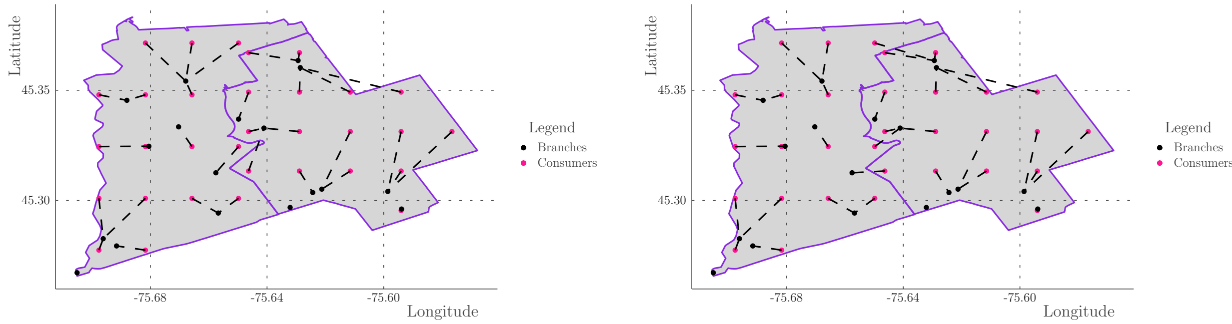


Distance = 1.3 km

Distance = 3.2 km

The other feature of our measure is that we can control for spillover across FSAs – the consumer in FSA j might travel to nearby FSA j' to withdraw cash if her nearest affiliated branch is located in FSA j'. Accounting for spillovers across FSAs is important because we are dealing with relatively small spatial units. To see how we account for spillovers, referring to equation (9), the element $B_{k,t}$ is the complete set of affiliated branch locations and is not indexed on the FSA j. Such construction is equivalent to an edge correction in statistics,

Figure 12: Geographic Concentration – Spillovers



where this edge correction allows the nearest bank branch to a given grid point to lie in an adjacent FSA. This is demonstrated in Figure 12. Without capturing spillovers, the spatial distance measure in the left spatial unit (FSA - K1V) is 4.81 kilometers and the spatial unit on the right (FSA - K1T) is 1.29 kilometers. Once we account for spillovers, the distance measure lowers to 3.45 kilometers in K1V and 1.23 kilometers in K1T.

Appendix B: Temporal vs. Cross-Sectional Variation

The main identification power stems from the cross-sectional variation, rather than the temporal dimension. Referring to Figure 13, a box plot analysis suggests that the distribution of distance at the FSA level largely remains the same across time with small variations in the median. Exploring this a little further, we compute the variation in distance across time for each FSA. We present a histogram of the results in Figure 14. We observe that almost all FSAs are clustered around zero in terms of their temporal variations. Plotting the persistence in distance in Figure 15, we observe that in many cases the distance measure is equal across time periods.

Figure 13: Cross-sectional Distance Distribution (2008–2018)

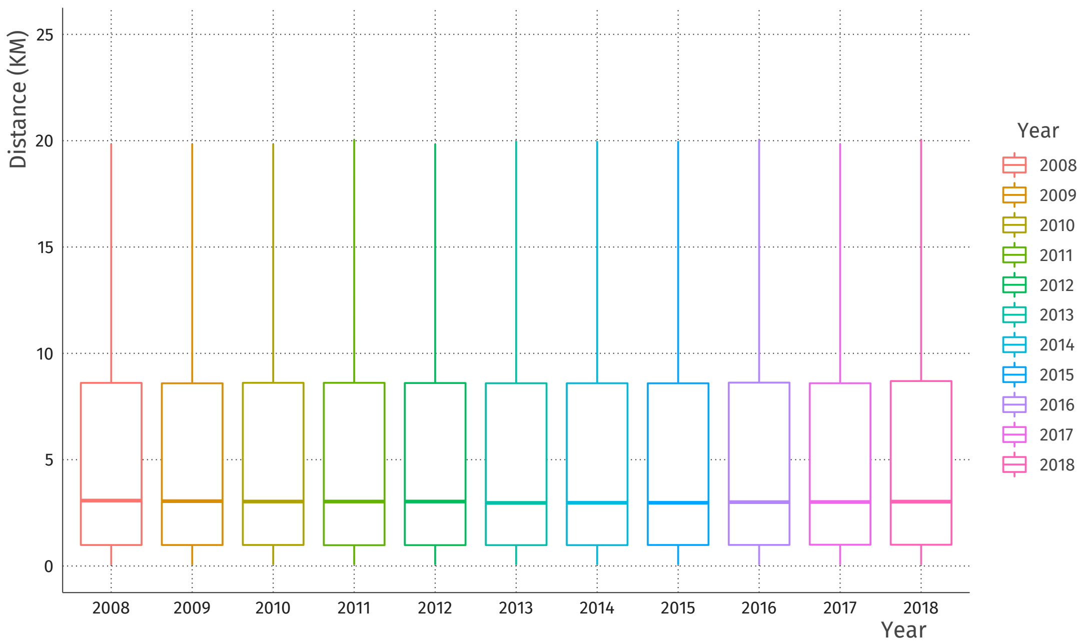


Figure 14: Histogram of Temporal Variation of each FSA

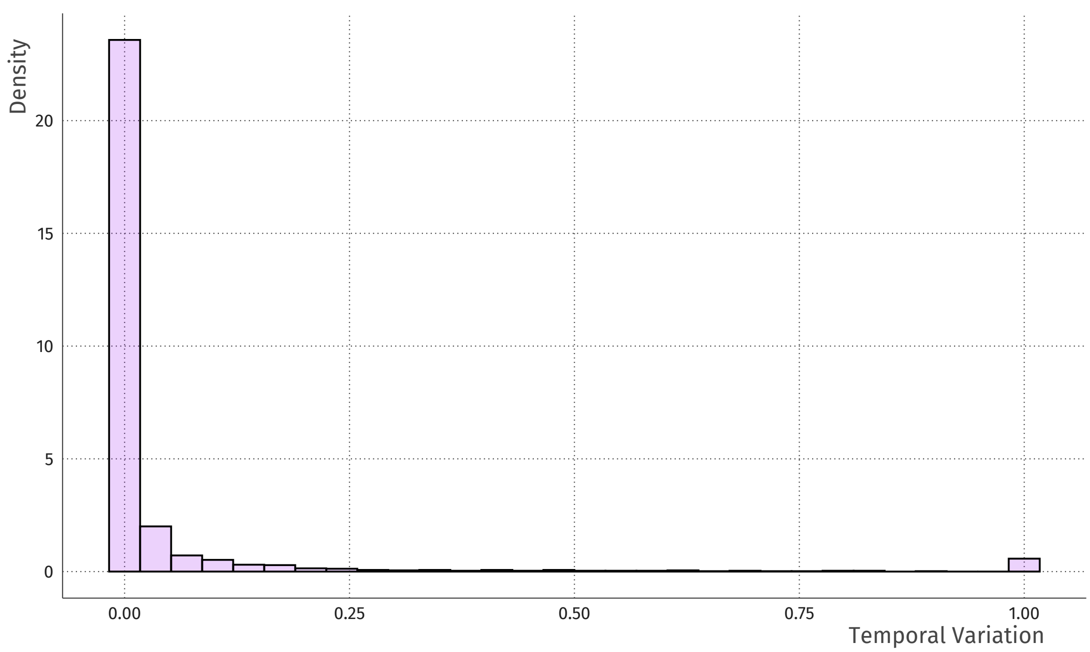
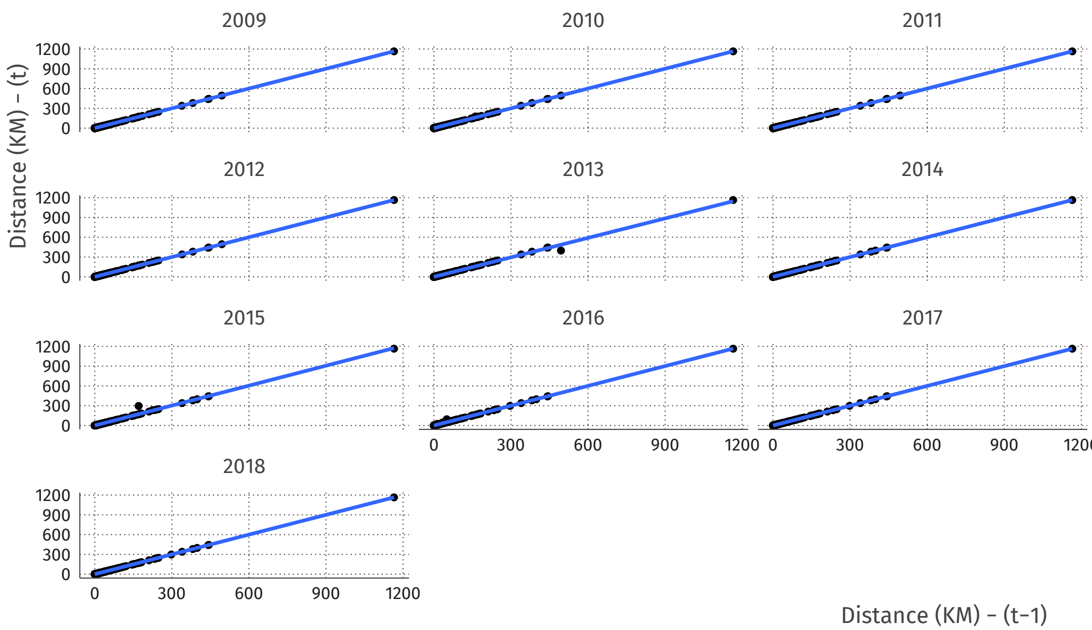


Figure 15: Persistence in Distance (t vs. $t-1$)



Appendix C: Withdrawal Value Analysis

Withdrawal Value – Heterogeneous Effects of Income (Below Cut-off)

For the withdrawal value regression model we run a log-log model while accounting for selection using a linear Heckman correction (with the same exclusion restrictions). Furthermore, to account for income heterogeneity we allow for interaction effects between log distance and log income. To estimate the effect of distance before and after the kink, we split the sample into two sub-samples and re-estimate the model before the kink and after. The results are presented in Table 6. We find that, after the kink, the effect of log distance on log withdrawal is not significant. However, before the kink, we find that distance is positive and significant. In fact, we find that depending on the value of δ, a 1% increase in distance is associated with a 1%–2% increase in withdrawal value. Furthermore, we find that a 1% increase in income is associated with a 0.1–0.2% increase in withdrawal value. Finally, in terms of the interaction effect, we find that interacting log distance and log income produces a negative and significant relationship. In other words, holding all else constant, as income increases, the elasticity of distance decreases. This suggests that respondents coming from high income groups tend to have a weak response to withdrawal value given changes in distance. This is contrary to what we found in the withdrawal frequency case. Looking at both of these results independently, we find that when distance increases, respondents from higher income groups tend to withdraw less frequently, but they also tend to adjust their withdrawal value less than those from low income groups. We conjecture that changes in payment composition is driving this disparity between low and high income groups. In other words, wealthier individuals are likely substituting purchases from cash to card. Looking at distance after the kink, we find that there are no significant effects associated with distance or the interaction between distance and income.

Table 6: Regression Results – Withdrawal Value (Income)

Variables	heckit	linear	heckit	linear	heckit	linear	heckit	linear	heckit	linear	heckit	linear
	$p \leq 1$	$p \leq 1$	$p \leq 2$	$p \leq 2$	$p \leq 3$	$p \leq 3$	$p \leq 4$	$p \leq 4$	$p \leq 5$	$p \leq 5$	$p \leq 6$	$p \leq 6$
	Regression Below The Kink Point											
lnDistance (km)	1.520*	1.513*	1.913**	1.893**	1.941**	1.936**	2.197***	2.194***	1.754**	1.748**	1.551*	1.485*
	(0.892)	(0.898)	(0.844)	(0.854)	(0.884)	(0.894)	(0.826)	(0.833)	(0.830)	(0.838)	(0.814)	(0.831)
lnIncome	0.204***	0.189***	0.195***	0.188***	0.187***	0.183***	0.142***	0.141***	0.142***	0.138***	0.150***	0.141***
	(0.0496)	(0.0465)	(0.0460)	(0.0447)	(0.0481)	(0.0479)	(0.0434)	(0.0435)	(0.0430)	(0.0422)	(0.0430)	(0.0417)
lnDistance × lnIncome	-0.133	-0.137*	-0.165**	-0.166**	-0.168**	-0.168**	-0.198***	-0.198**	-0.157**	-0.157**	-0.141*	-0.136*
	(0.0820)	(0.0826)	(0.0782)	(0.0789)	(0.0817)	(0.0825)	(0.0765)	(0.0771)	(0.0761)	(0.0768)	(0.0744)	(0.0760)
ρ	0.71588		0.575776		0.108064		0.050149		0.162868		0.53016	
	(0.1370122)		(0.2895895)		(0.1842805)		(0.1616366)		(0.294502)		(0.4035857)	
σ	1.027916		0.934149		0.861238		0.859091		0.861419		0.902104	
	(0.0744576)		(0.0755234)		(0.0233204)		(0.0211335)		(0.0227889)		(0.0543789)	
λ	0.735865		0.537861		0.093069		0.043083		0.140297		0.478259	
	(0.1918737)		(0.312331)		(0.1592966)		(0.1390196)		(0.255377)		(0.3910619)	
	exclusion restriction/selection											
Financial Innovation	0.216***		0.139*		0.147		0.117		0.159		0.179*	
	(0.0623)		(0.0740)		(0.0959)		(0.102)		(0.106)		(0.0975)	
lnDistance (km)	0.111		0.125		0.141		0.179*		0.106		0.144	
	(0.0724)		(0.0869)		(0.105)		(0.104)		(0.107)		(0.104)	
wald test ($\rho = 0$)	10.24		2.29		0.34		0.1		0.3		1.11	
wald-p	p=0.0014		p=0.1299		p=0.5607		p=0.7568		p=0.587		p=0.293	
Observations	1,628	1,025	1,467	1,129	1,274	1,047	1,404	1,216	1,427	1,266	1,468	1,328
kink	1.659	1.659	1.559	1.559	1.419	1.419	1.533	1.533	1.559	1.559	1.609	1.609
	Regression Above The Kink Point											
lnDistance (km)	0.128	0.163	0.139	0.150	0.0516	0.0716	0.0337	0.0255	-0.0569	-0.0662	-0.162	-0.186
	(0.419)	(0.425)	(0.383)	(0.386)	(0.348)	(0.348)	(0.354)	(0.357)	(0.352)	(0.354)	(0.354)	(0.354)
lnIncome	0.130**	0.0957	0.145**	0.103*	0.134**	0.104*	0.128**	0.0957*	0.105	0.0811	0.0905	0.0629
	(0.0664)	(0.0656)	(0.0635)	(0.0601)	(0.0565)	(0.0532)	(0.0615)	(0.0563)	(0.0804)	(0.0565)	(0.0690)	(0.0569)
lnDistance × lnIncome	-0.00702	-0.00988	-0.00933	-0.00998	-0.00186	-0.00307	0.00109	0.00155	0.00936	0.00998	0.0178	0.0195
	(0.0380)	(0.0385)	(0.0347)	(0.0350)	(0.0315)	(0.0316)	(0.0321)	(0.0324)	(0.0319)	(0.0321)	(0.0320)	(0.0321)
ρ	0.719717		0.602079		0.551013		0.544587		0.456288		0.485491	
	(0.0942313)		(0.1884882)		(0.2519813)		(0.3112762)		(0.8790997)		(0.5181725)	
σ	1.04937		0.963085		0.931507		0.923288		0.906438		0.907669	
	(0.054825)		(0.0565566)		(0.0536017)		(0.0541836)		(0.1119129)		(0.0641571)	
λ	0.75525		0.579853		0.513272		0.502811		0.413596		0.440665	
	(0.1365011)		(0.2143734)		(0.2632613)		(0.3159262)		(0.8475285)		(0.5007561)	
	exclusion restriction/selection											
Financial Innovation	0.134***		0.161***		0.166***		0.118*		0.147**		0.138**	
	(0.0478)		(0.0524)		(0.0542)		(0.0607)		(0.0659)		(0.0698)	
lnDistance (km)	-0.00590		-0.00859		-0.0232		0.0305		0.0299		0.0534	
	(0.0307)		(0.0326)		(0.0345)		(0.0398)		(0.0448)		(0.0468)	
wald test ($\rho = 0$)	21.53		5.55		2.93		1.9		0.2		0.61	
wald-p	p=0		p=0.0185		p=0.0867		p=0.1676		p=0.6573		p=0.4342	
Observations	2,899	1,808	2,931	2,218	3,058	2,523	2,875	2,492	2,834	2,510	2,771	2,494

Withdrawal Value – Heterogeneous Effects of Age (Below Cut-off)

To account for heterogeneity across age groups we allow for interaction effects between log distance and age. To estimate the effect of distance before and after the kink, we split the sample into two sub-samples and re-estimate the model before the kink and after. The results are found in Table 7. In this model, we find that there are no heterogeneous effects stemming from age. In fact, in this particular setup we find that neither distance nor the interaction between distance and age is a significant predictor of withdrawal value.

Table 7: Regression Results – Withdrawal Value (Age)

Variables	heckit	linear	heckit	linear	heckit	linear	heckit	linear	heckit	linear	heckit	linear
	$p \leq 1$	$p \leq 1$	$p \leq 2$	$p \leq 2$	$p \leq 3$	$p \leq 3$	$p \leq 4$	$p \leq 4$	$p \leq 5$	$p \leq 5$	$p \leq 6$	$p \leq 6$
	Regression Below The Kink Point											
lnDistance (km)	0.254	0.248	0.308	0.289	0.214	0.209	0.199	0.196	0.133	0.128	0.0858	0.0750
	(0.190)	(0.195)	(0.188)	(0.191)	(0.205)	(0.206)	(0.189)	(0.190)	(0.185)	(0.186)	(0.176)	(0.179)
Age	0.0137	0.0166	0.0148	0.0162	0.0191*	0.0191*	0.0202**	0.0204**	0.0205**	0.0209**	0.0219**	0.0217**
	(0.0129)	(0.0114)	(0.0111)	(0.0105)	(0.0111)	(0.0111)	(0.0101)	(0.0101)	(0.00997)	(0.00999)	(0.0100)	(0.00981)
lnDistance × Age	-0.00404	-0.00504	-0.00407	-0.00440	-0.00219	-0.00220	-0.00328	-0.00327	-0.00196	-0.00198	-0.00151	-0.00169
	(0.00427)	(0.00434)	(0.00409)	(0.00417)	(0.00450)	(0.00454)	(0.00409)	(0.00412)	(0.00403)	(0.00406)	(0.00386)	(0.00391)
ρ	0.71013		0.563507		0.105095		0.051785		0.154157		0.48544	
	(0.1428375)		(0.3168912)		(0.1788033)		(0.1620991)		(0.2598712)		(0.6055233)	
σ	1.025528		0.932313		0.862885		0.861455		0.862654		0.897381	
	(0.0759443)		(0.0798003)		(0.0233197)		(0.021247)		(0.0219934)		(0.0731078)	
λ	0.728258		0.525365		0.090685		0.04461		0.132984		0.435625	
	(0.1981939)		(0.3388588)		(0.1548075)		(0.1397971)		(0.225467)		(0.5776454)	
	exclusion restriction/selection											
Financial Innovation	0.216***		0.139*		0.147		0.117		0.159		0.176*	
	(0.0624)		(0.0743)		(0.0959)		(0.103)		(0.105)		(0.104)	
lnDistance (km)	0.110		0.126		0.141		0.179*		0.106		0.142	
	(0.0725)		(0.0870)		(0.105)		(0.104)		(0.107)		(0.105)	
wald test ($\rho = 0$)	9.49		1.89		0.34		0.1		0.34		0.45	
wald-p	p=0.0021		p=0.1695		p=0.5596		p=0.7498		p=0.5594		p=0.5034	
Observations	1,628	1,025	1,467	1,129	1,274	1,047	1,404	1,216	1,427	1,266	1,468	1,328
kink	1.659	1.659	1.559	1.559	1.419	1.419	1.533	1.533	1.559	1.559	1.609	1.609
	Regression Above The Kink Point											
lnDistance (km)	0.139	0.158*	0.126	0.135	0.0922	0.104	0.147*	0.146*	0.136*	0.135*	0.0978	0.0934
	(0.0947)	(0.0959)	(0.0854)	(0.0859)	(0.0788)	(0.0787)	(0.0811)	(0.0815)	(0.0812)	(0.0815)	(0.0815)	(0.0817)
Age	0.0180*	0.0194**	0.0158*	0.0188**	0.0166**	0.0172**	0.0184**	0.0187**	0.0178**	0.0173**	0.0175**	0.0168**
	(0.00933)	(0.00862)	(0.00825)	(0.00777)	(0.00740)	(0.00717)	(0.00755)	(0.00736)	(0.00756)	(0.00734)	(0.00755)	(0.00739)
lnDistance × Age	-0.00178	-0.00209	-0.00179	-0.00191	-0.00123	-0.00134	-0.00206	-0.00210	-0.00184	-0.00186	-0.00133	-0.00134
	(0.00183)	(0.00185)	(0.00161)	(0.00163)	(0.00148)	(0.00148)	(0.00153)	(0.00154)	(0.00153)	(0.00154)	(0.00153)	(0.00154)
ρ	0.716981		0.597566		0.545405		0.538529		0.443838		0.487686	
	(0.0966093)		(0.1971667)		(0.2656105)		(0.3338406)		(1.090259)		(0.5031776)	
σ	1.047402		0.961393		0.930129		0.921822		0.904565		0.907871	
	(0.0556574)		(0.0583779)		(0.0556651)		(0.0572052)		(0.134664)		(0.0626099)	
λ	0.750967		0.574496		0.507298		0.496428		0.40148		0.442756	
	(0.1393001)		(0.223284)		(0.2764667)		(0.3376384)		(1.045669)		(0.4866149)	
	exclusion restriction/selection											
Financial Innovation	0.134***		0.161***		0.166***		0.118*		0.146**		0.137**	
	(0.0480)		(0.0526)		(0.0543)		(0.0608)		(0.0664)		(0.0698)	
lnDistance (km)	-0.00599		-0.00845		-0.0229		0.0319		0.0314		0.0556	
	(0.0307)		(0.0326)		(0.0346)		(0.0402)		(0.0487)		(0.0477)	
wald test ($\rho = 0$)	20.56		5.05		2.62		1.64		0.12		0.65	
wald-p	p=0		p=0.0246		p=0.1056		p=0.2004		p=0.7253		p=0.4195	
Observations	2,899	1,808	2,931	2,218	3,058	2,523	2,875	2,492	2,834	2,510	2,771	2,494

Appendix D: Apply PPML and GPML to Approximately Adjust for the Number of Costly Withdrawals

Taking NB PML as a benchmark, Poisson (Gamma) PML method down-weights observations in the left (right) tail of overall withdrawal frequency, where the probability of costly withdrawals are more likely to happen (earlier we classified costly withdrawals as binary types, while here we study the degree of the costly withdrawal frequency as the non-negative integer). A relatively large difference of distance estimates from different models (e.g., Poisson, NB or Gamma) would indicate evidence about how non-applicable or negligible distances of free withdrawals would confound the results.

We find that when we consider the full sample (Table 8), correcting for misclassification with either the PPML or GPML methodology reduces the magnitude of the coefficient by approximately 10% when moving from the negative binomial model to the PPML model and 14% when moving to the GPML model. Furthermore, after filtering out free-type respondents (Table 9), we find further evidence of misclassification, which is corrected by either the GPML or the PPML. These coefficients are similar to what we found in Section 5.

Table 8: PPML and GPML with Province and Time Fixed Effects (Costly and Free Type)

	Withdrawal Frequency ($p \leq 2$)		
	Neg. Bin.	PPML	GPML
	(1)	(2)	(3)
Distance (km)	-0.449^{***}	-0.404^{***}	-0.387^{***}
	(0.113)	(0.114)	(0.109)
Distance (kink)	0.447^{***}	0.401^{***}	0.383^{***}
	(0.114)	(0.114)	(0.110)
log(Income)	0.025	0.028	-0.019
	(0.018)	(0.018)	(0.016)
Education (years)	-0.042^{***}	-0.041^{***}	-0.050^{***}
	(0.006)	(0.006)	(0.006)
Not in Labour Force	-0.162^{***}	-0.169^{***}	-0.126^{***}
	(0.031)	(0.033)	(0.028)
Unemployed	-0.050	-0.059	0.004
	(0.060)	(0.061)	(0.052)
Family Size	0.019^{*}	0.021^{**}	0.021^{**}
	(0.010)	(0.010)	(0.009)
Age	0.012^{***}	0.014^{***}	0.007^{*}
	(0.005)	(0.005)	(0.004)
Age^2	-0.0001^{**}	-0.0001^{***}	-0.0001^{**}
	(0.00005)	(0.0001)	(0.00004)
Male	0.141^{***}	0.132^{***}	0.144^{***}
	(0.024)	(0.024)	(0.021)
Constant	1.453^{***}	1.354^{***}	2.322^{***}
	(0.226)	(0.232)	(0.202)
Observations	9,300	9,300	7521
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: PPML and GPML with Province and Time Fixed Effects ($p \leq 2$)

	Withdrawal Frequency ($p \leq 2$)		
	Neg. Bin.	PPML	GPML
	(1)	(2)	(3)
Distance (km)	-0.130^{***}	-0.123^{**}	-0.111^{**}
	(0.050)	(0.051)	(0.046)
Distance (kink)	0.127^{**}	0.121^{**}	0.108^{**}
	(0.051)	(0.052)	(0.046)
log(Income)	0.025	0.024	0.002
	(0.021)	(0.022)	(0.019)
Education (years)	-0.043^{***}	-0.043^{***}	-0.050^{***}
	(0.008)	(0.008)	(0.007)
Not in Labour Force	-0.131^{***}	-0.135^{***}	-0.126^{***}
	(0.037)	(0.039)	(0.033)
Unemployed	-0.055	-0.050	-0.032
	(0.081)	(0.084)	(0.070)
Family Size	0.006	0.008	0.012
	(0.013)	(0.013)	(0.012)
Age	0.004	0.005	0.002
	(0.006)	(0.006)	(0.005)
Age^2	-0.0001	-0.0001	-0.00003
	(0.0001)	(0.0001)	(0.0001)
Male	0.071^{**}	0.061^{**}	0.083^{***}
	(0.029)	(0.030)	(0.026)
Constant	1.359^{***}	1.361^{***}	1.858^{***}
	(0.260)	(0.266)	(0.233)
Observations	4,737	4,737	4033
Note:			*p<0.1; **p<0.05; ***p<0.01

Appendix E: List of Variables

Table 10: List of Key Variables

Variable	Description	Source
Withdrawal Frequency	Number of withdrawals within a monthly period. Composed of both teller and ABM withdrawals.	2009, 2013 and 2017 MOP SQ
Free Withdrawals (p)	Number of free withdrawal opportunities within a monthly period.	Calibrated using Alvarez and Lippi (2009a) (see Section 5.1).
Distance (km)	Average distance measure computed at the FSA level. Based on a 128 x 128 uniform grid of consumers. The distance is computed for Scotibank, RBC, BMO, TD, and CIBC. All other banks are classified as Other. Interpreted as the average distance between a consumer and the nearest bank branch (of a given FI).	2008 to 2018 Financial Institutions File (FIF) and the Statistics Canada 2011 FSA Boundary File. See Appendix A.
Income ($)	Continuous gross household income based on a midpoint mapping from discrete income categories.	2009, 2013 and 2017 MOP SQ
Employment Status (Categorical)	Three employment status categories. Employed, Self-employed, or Not in Labor Force	2009, 2013 and 2017 MOP SQ
Family Size (Count)	Number of members living within the respondent's household. Note: the question changes from family size to household size post-2009.	2009, 2013 and 2017 MOP SQ
Age (Integer)	Age of the respondent.	2009, 2013 and 2017 MOP SQ
Education (Years Past Primary)	The number of years of schooling net a primary education. Integer values based on a mapping from discrete categories. Based on the following: some high school = 2 years, completed high school = 4 years, some/completed technical school = 4 + 2 years, some university = 4 + 3 years, university degree = 4 + 4 years, and some/completed graduate school = 4 + 4 + 2 years.	2009, 2013 and 2017 MOP SQ
Sex (Binary)	Sex based on a male/female classification.	2009, 2013 and 2017 MOP SQ
Cash Purchases ($)	Based on the 3-day diary. We consider those transactions that are not NA and were not made online. 3-day totals are converted into monthly totals using a factor of 10.	2009, 2013 and 2017 MOP DSI
Total Purchases ($)	Based on the 3-day diary. We consider those transactions that are not NA and were not made online. 3-day totals are converted into monthly totals using a factor of 10.	2009, 2013 and 2017 MOP DSI
Average Cash Holdings ($)	Based on asking the respondents how much cash they have in their wallet at this present time.	2009, 2013 and 2017 MOP SQ
Average Replenishment Trigger ($)	How low do you typically let your cash supply get before you go to the bank, an ATM or elsewhere to get more?	2009, 2013 and 2017 MOP SQ
Adoption of Online Financial Innovation (Dummy)	In 2009 this is measured as being very knowledgeable about internet banking, telephone banking, or online payment accounts. In 2013 and 2017 it is based on the adoption of mobile payment apps, online payment accounts, Interac online/e-transfer, or online payments from credit cards.	2009, 2013 and 2017 MOP SQ

Appendix F: Estimated Withdrawal Cost on Frequency

As an alternative exercise, based on Alvarez and Lippi (2009a), we can use the estimate of the effect of distance withdrawal cost b and the relative cost $\beta = b/cR$ where the β measures the cost of withdrawing cash relative to the forgone interest on cash purchases. It is possible that we can evaluate the shoe-leather cost on the withdrawals by regressing b and β on distance d. Although this alternative method does not need to discard the free-type respondents, the estimated/calibrated b would exhibit a large dispersion due to a particular nonlinearity of the model (Alvarez and Lippi, 2009b). We report results based on regressing b and β on d in Table 11. We do not find statistically significant effects of log-distance on log-withdrawal cost. Notice that one reason for not using this regression as the main context is because Section G.1 in Alvarez and Lippi (2009b) points out a particular nonlinearity of the model in (p, b) would create a large right tail in the distribution of the estimated b. Given that estimating withdrawal cost requires information on cash expenditure c from the MOP DSI, the individual-level c would be noisy given that the duration of our DSI is covering three days.[22] We can calibrate b and β as follows:

$$\frac{b}{cR} = \frac{\exp\left[(r+p)\, m^*/c\right] - \left[1 + (r+p)\,(m^*/c)\right]}{(r+p)^2}, \tag{10}$$

where m^* is solved from

$$\frac{M}{c} = \frac{1}{p}\left[n\frac{m^*}{c} - 1\right]$$

[22]Recall that when estimating p using the data $(n, \underline{M}/M)$, all the information comes from the survey questionnaire (SQ) rather than the three-day diary survey instrument (DSI). In general, responses from the SQ are about typical behaviors, compared to the transaction-level behaviors in the DSI. Given our DSI only lasts for three days, it is difficult to precisely measure the individual-level typical/average cash expenditure.

Table 11: Withdrawal Cost (b, β) Against Distance

	log-log	log-log
	β	b
log(Distance)	-0.133	-0.142
	(0.959)	(0.953)
log(Income)	-1.173	-1.228
	(1.173)	(1.164)
log(Education)	5.934***	5.572***
	(1.860)	(1.840)
Not in Labor Force	-2.254	-2.223
	(2.133)	(2.116)
Unemployed	-2.684	-2.583
	(4.114)	(4.089)
log(Family Size)	2.096	2.166
	(1.739)	(1.727)
Age	0.266	0.291
	(0.226)	(0.224)
Age^2	-0.002	-0.002
	(0.002)	(0.002)
Male	1.056	1.184
	(1.481)	(1.469)
Constant	5.218	1.403
	(13.710)	(13.600)
Observations	3,119	3,119
R^2	0.014	0.013
R^2 Adjusted	0.008	0.007
Residual Std. Error	41.625	41.301
F Statistic	2.238***	2.057***

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Appendix G: DSI Withdrawal Classification

Table 12: Average Replenishment Trigger – 2013 and 2017

Year	Reason[a]	$\underline{M}^{b,c,d}$
2013	Other[e]	24.22
2013	Convenience	67.26
2017	Other[e]	31.66
2017	Convenience	45.09

[a] Withdrawal reasons coming from three-day diary transaction level data (DSI).

[b] $\underline{M}$ is coming from respondent level survey data (SQ).

[c] We map $\underline{M}$ to each transaction and take an average across all transactions.

[d] Values are Winsorized at the 99^{th} percentile.

[e] The other category includes low cash stores and planning a cash purchase.

Note: 2009 MOP DSI does not have data on withdrawal reason.