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Dynamic Consumer Cash Inventory Model

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Abstract

We study consumer cash inventory behavior by developing a dynamic model of forward-looking consumers and estimating structural parameters of the model using detailed consumer survey data. Consumers facing holding and withdrawal costs solve a discrete-time continuous-control dynamic programming problem to optimally use cash at the point of sale. Our findings suggest that it is crucial to account for persistent heterogeneity in consumer preferences to accurately measure the demand for cash and consumer welfare. We show that deteriorating access to cash triggers a bi-modal response. Some consumers substantially reduce or even stop the use of cash in favor of digital means of payment, while others exhibit a limited response and instead withdraw and hold larger amounts.

Topics: Bank Notes, Digital currencies and fintech, Econometric and statistical methods, Financial services
JEL codes: E41, E42, D12, D14, G21

Résumé

Nous étudions la façon dont les consommateurs gèrent leur stock d'espèces en élaborant un modèle dynamique dans lequel les consommateurs ont un comportement prospectif et en estimant les paramètres structurels du modèle à l'aide de données d'enquête détaillées menées auprès des consommateurs. Les consommateurs qui doivent assumer des coûts de détention et de retrait des espèces résolvent un problème de programmation dynamique à temps discret et à contrôle continu afin de faire une utilisation optimale de l'argent comptant au point de vente. Nos résultats indiquent qu'il est essentiel de tenir compte de l'hétérogénéité persistante des préférences des consommateurs pour mesurer avec précision la demande d'argent comptant et le bien-être des consommateurs. Nous montrons que la détérioration de l'accès à l'argent comptant déclenche une réponse bimodale. Certains consommateurs réduisent considérablement, voire cessent, leur utilisation de l'argent comptant et se tournent vers des modes de paiement numériques, tandis que d'autres ont une réaction moins vive et choisissent plutôt de retirer et de conserver des sommes plus importantes.

Sujets : Billets de banque ; Monnaies numériques et technologies financières ; Méthodes économétriques et statistiques ; Services financiers
Codes JEL : E41, E42, D12, D14, G21

1 Introduction

Over the past decade, the use of cash for transactions at the point of sale has been declining in most developed economies. Together with a concomitant increase in the use of payment cards and other digital means of payment, this has in fact led to calls to abandon cash (see, most prominently, Rogoff 2017) and potentially replace it with digital alternatives.[1] However, cash remains a source of substantial consumer surplus and social benefits (Alvarez et al. 2022, Alvarez and Argente 2024). In many jurisdictions, including Canada, it remains highly valued by consumers and has even seen a partial resurgence after the Covid-19 pandemic (Henry et al. 2024). In line with this, the demand for bank notes, particularly high-value notes, has been constant or even increasing in most countries over the last 20 years (Engert et al. 2019).

In this paper, we propose and estimate a structural model of dynamic cash inventory management that accounts for payment choice when making transactions at the point of sale. We build a Baumol (1952) and Tobin (1956)–style model of cash inventory management which allows for consumer-specific preferences to make payments using either cash or digital non-cash methods of payment. In doing so, we account for the changing infrastructure enabling consumers' access to cash given the importance of shoe-leather costs for consumers' withdrawal behaviors. We estimate the model using multiple waves of detailed diary and survey data in which Canadian consumers record their expenditures and means of payments in addition to withdrawal behavior. Importantly, our estimation approach allows for consumer-level heterogeneity in preferences.

We show that this heterogeneity is paramount in accurately capturing consumer behavior and responses to changes in the access-to-cash infrastructure. Specifically, we show a bi-modal response by consumers to a worsening infrastructure. One group of consumers only moderately adjusts their cash use and withdraws and holds larger amounts to economize on more costly withdrawals. The second group, in contrast, adjusts their cash use more and may even give up on using cash entirely. We show that the second group is disproportionately composed of younger and less affluent consumers. Their reduction in cash is not necessarily due to a lower intrinsic preference for its use but is instead related to holding and withdrawal cost considerations. Moreover, these consumers bear the brunt of the negative welfare impact of a worsening access to cash infrastructure. Our findings therefore have important policy implications. As the cash system infrastructure evolves, it is the duty of central banks, including the Bank of Canada, to ensure an adequate supply of notes required for circulation (see the *Bank of Canada Act* and Engert and Huynh 2022, for a detailed discussion).

In our model, forward-looking consumers decide in each period which proportion of exogenously evolving expenditures to settle in cash and non-cash. This decision is shaped by their intrinsic and consumer-specific preference for cash, their current cash inventory, and the cost of withdrawing funds. Holding cash inventories is costly due to forgone interest and potential exposure to theft, but increases the flexibility to pay for their transactions using their preferred means of payment. This holding cost may similarly differ across consumers. Finally, withdrawals themselves are costly, with the specific cost reflecting both a consumer-specific cost parameter and the access to cash infrastructure in their geographic area. Overall, there

[1] The emergence of a cashless society has been explicitly stated as a condition that warrants the issuance of a Digital Canadian Dollar (see Lane 2021). In Europe, the ECB released its progress report on the preparation phase for a digital euro in June 2024 (ECB 2024).

are thus three preference parameters which shape consumers' actions: the relative preference for cash, the cost to hold cash inventories, and the consumer-specific withdrawal cost.

A key feature of the model is that the current-period withdrawal and cash usage affects the future only via the amount of cash carried forward to the next period. This allows us to recast the problem with the cash holdings carried forward as the control variable and with the optimal withdrawal-usage pair uniquely determined for any given (target) change in cash inventories. This reduction in dimensionality of the dynamic problem faced by consumers greatly facilitates the empirical implementation.

To estimate the model, we leverage three waves of detailed diary and survey data from the 2009, 2013, and 2017 Methods-of-Payment survey (MOP) in Canada, which allows us to assess the evolution of consumer preferences over time. We observe a rich set of consumer demographics and their geographic location in terms of their forward sortation area (FSA), which we use to construct a consumer-specific measure of cash accessibility based on the number of bank branches in the FSA.[2] We employ and contrast two estimation approaches. Our main *heterogeneous approach* is based on Ackerberg (2009) and matches each consumer to the parameters that best describe her behavior. For comparison purposes, we also estimate a *representative approach* which assumes that consumers in large demographic-specific groups share the same preference parameters, which allows us to estimate parameters using generalized method of moments (GMM). For both approaches, we use a nested fixed-point algorithm in the spirit of Rust (1987), where we solve the consumers' dynamic programming problem for a given parameter vector and use this to simulate the cash management behavior. By comparing the predictions with the data, we obtain four moment conditions based on (1) the average cash withdrawal amount, (2) the average cash use, (3) the withdrawal probability in a given period, and (4) the average cash holding, which are then used for estimation.

Our main findings are as follows. First, we find that consumer preferences indeed evolve over time. Between 2009 and 2017, consumers' preference towards cash as their preferred means of payment declines. On the cost side, we find that so does their holding cost—in line with declining benchmark interest rates—while their individual withdrawal cost increases. In addition, our results show that accounting for individual-level consumer heterogeneity is paramount in accurately capturing consumer behavior: there is substantial within-group heterogeneity which is evident when comparing individual-level estimates with those obtained from the representative approach. Importantly, this relates to the preference for cash as well as the costs associated with withdrawals and cash holdings. We use our estimates to assess the impact of factual infrastructure changes and find a limited average impact on consumer behavior and outcomes. However, consumers that experience a sharper decline in their access-to-cash infrastructure are more severely affected and reduce their average cash use by 11.3%. While this is associated with a reduction in their average cash holdings of 2.2%, the median cash holdings actually increase by 5.4%.

We further investigate the latter finding in our main counterfactual analysis, which considers consumer responses to changes in the access-to-cash infrastructure for all consumers. Holding preferences fixed, we simulate how consumers would adjust their cash inventory and

[2]While cash is most frequently obtained from automated banking machines (ABMs; see Henry et al. 2024), 80% of withdrawals occur at ABMs owned by financial intermediaries which in turn are co-located with bank branches 88% of the time (Chen et al. 2021).

use when cash withdrawals become more costly. While consumers as a whole withdraw cash less frequently and use it less often at the point of sale, the specific response differs and exhibits a clear bi-modality. One group of consumers moderately adjusts their cash use and withdraws and holds larger amounts to economize on costlier withdrawals. A second group, in contrast, adjusts their cash use more harshly and may even give up on using cash entirely.

Specifically, we find that a 25% increase in the withdrawal cost induces almost a quarter of consumers to forgo the use of cash. Importantly, the negative welfare impact of a deteriorating cash infrastructure is concentrated among this *extensive margin* of consumers. While the overall reduction in expected consumer payoff on average is limited to 4.13%, it is 10.93% for consumers who stop using cash as a response to costlier withdrawals. The concentrated impact is also evidenced by the much more muted median reduction in cash use ($\approx 7\%$) and welfare ($\approx 0.25\%$).

Importantly, we show that this is not necessarily due to a lower intrinsic preference for using cash. Instead, it is younger and less affluent consumers—who are also more likely to keep revolving credit card balances—who are more likely to substitute away from cash despite a comparable preference for its use. This is due to higher opportunity costs of holding cash, as well as higher individual costs of withdrawals which imply a larger impact of the changing infrastructure. On the flip side of this, the increased cash holdings by affluent consumers due to a worsening access-to-cash infrastructure may play a role in explaining the "cash puzzle" of increased notes in circulation despite decreasing use for transactions at the point of sale.

Overall, our results complement and connect recent contributions on the costs and benefits of phasing out cash. As in Alvarez and Lippi (2017), representative models work well in rationalizing country-specific average behavior and predict a limited impact of reduced accessibility of cash. However, a subset of consumers—and, in particular, less affluent ones whose intrinsic preference for the use of cash is larger—is much more heavily affected and disproportionately bears the losses, corroborating the findings in Alvarez et al. (2022). More generally, our results complement the analysis in Engert et al. (2025) which shows that Canada is unlikely to become cashless in the foreseeable future.

We conclude by showing robustness of our analysis to a variety of extensions. Most importantly, because our model is heavily overidentified, we are able to treat the level of consumer discounting not as an exogenous input to the model but as a parameter to be estimated. In line with Fulford and Schuh (2017), we find heterogeneity in the degree of consumers' forward-lookingness. However, this heterogeneity is limited, and the vast majority of consumers exhibits an estimated discounted factor close to the exogenously assumed one in the baseline model. Moreover, the key factual and counterfactual insights are unchanged when allowing for this type of consumer heterogeneity.

Related Literature We contribute to the literature focusing on (cash) inventory management problems dating back to Baumol (1952) and Tobin (1956) which trade off the opportunity costs of holding cash with the transaction cost of withdrawal. More recently, Alvarez and Lippi (2017) build on prior work (Alvarez and Lippi 2009) and provide a model of dynamic cash management combined with a cash-or-credit choice. While the model inherently features cash being used first (i.e., credit only being used when cash is unavailable), it allows to rationalize cross-country variation in cash inventory and withdrawal behavior via differences in cash withdrawal technology. Our model differs by having consumers use non-cash means of payment even when cash is available, depending on their preferences.

Our work is thus more closely related to concurrent work by Moracci (2022) and Briglevics and Schuh (2020). Moracci (2022) proposes a framework building on Whitesell (1989) that relates the payment choice to the size of transactions and allows for the use of credit or debit even when cash is available. He matches the model to the observed cross-country heterogeneity in the Euro Area and shows that differences in payment and cash management behavior are not driven exclusively by different levels of merchant acceptance. The main contrast of our approach is that we focus on within-country consumer heterogeneity and its importance for accurately matching individual-level data and assessing (counterfactual) responses to a changing access-to-cash infrastructure.

Like us, Briglevics and Schuh (2020) structurally estimate a model which blends cash inventory management and payment instrument choice at the point of sale. However, there are important differences. Briglevics and Schuh (2020) estimate the payment choice for each individual transaction among cash, debit, and credit via separate utility functions for each payment instrument, while we aggregate transactions on a daily basis and estimate a fundamental parameter governing the preference for cash relative to non-cash. Briglevics and Schuh (2020) use 2012 consumer diary data as the basis for their analysis, while we exploit multiple waves (2009, 2013, 2017) to document the changing preference for cash across heterogeneous consumers.

In terms of estimation, Briglevics and Schuh (2020) employ a two-step simulation technique similar to the one originally developed by Hotz and Miller (1993) and Hotz et al. (1994) and extended by Bajari et al. (2007) and Pakes et al. (2007). These techniques avoid solving the dynamic cash management problem by estimating policy functions directly from the data and recovering continuation values either by forward simulation or by inverting transition probability matrices. Different from these studies, we use a nested fixed-point algorithm where we solve the consumer dynamic programming problem for a large set of candidate parameter vectors. Another key difference is that we overcome the difficulty of having two continuous control variables (cash use and cash withdrawal) by recasting the model in terms of a single dynamic control—the adjustment to the cash inventory—which renders the full solution approach feasible. In the empirical application, we assume a finite cash management planning horizon of 183 days (6 months) and estimate consumers' discount factor in an extension.

To assess the importance of individual consumer heterogeneity, we adapt the methodology originally proposed by Ackerberg (2009)—more recently used by Malone et al. (2021), which is closest to our implementation, and McManus et al. (2022)—to our setting. Alternative approaches using semi-parametric mixtures estimators are discussed in Fox et al. (2011; 2016), Nevo et al. (2016). A notable difference is that instead of assigning a probability distribution over all consumer types, we use a nearest-neighbour type matching procedure that finds a unique consumer type that best matches the average observed behavior at a point in our data. That is, instead of constructing a likelihood of observing a particular realization of a sequence of choices, we match four moments reported by consumers, each interacted with three instrumental variables. We minimize the differences between model predictions and each consumer's average behavior by using an optimal weighting matrix from a representative consumer version of the model. As a result, every observation in our data is associated with a consumer type that is likely to exhibit similar behavior on average.

Accounting for this heterogeneity allows us to bridge findings in the literature. While the cost of phasing out cash is found to be small when quantified using country-level data on the size of cash withdrawals and average cash holdings (see Alvarez and Lippi 2017), recent contributions found that cash has sizable benefits in terms of consumer surplus and social welfare. A positive impact of cash on consumer surplus has been documented in the context of its use as a payment method for Uber rides (Alvarez and Argente 2024). As in our work, this impact is concentrated on least-advantaged, i.e., less affluent, households. From a social perspective, Alvarez et al. (2022) find that private costs of taxing the use of cash in Mexico outweigh social benefits which arise, e.g., via its impact on criminal activities and informality.

More broadly, we relate to the literature on the demand for payment instruments. Koulayev et al. (2016) differentiate between the adoption and use of payment instruments and show that low-income consumers disproportionally rely on debit instead of credit—and correspondingly suffer more when debit cards become more expensive—while the reverse is true for high-income consumers. Wakamori and Welte (2017) show that cash usage by consumers for small-value transactions is driven mainly by consumer preferences. Huynh et al. (2022) construct and estimate a structural two-stage model of equilibrium in a market for payments in order to quantify the network externalities and identify the main determinants of consumer and merchant decisions. Their results suggest significant heterogeneity in consumer adoption costs and benefits. This model has been extended by Engert et al. (2024a) to estimate the impact of a potential CBDC in the market for payments at the point of sale in Canada.

Data Overview Before we proceed to set up the model, we briefly outline the data sources available for estimation. We revisit and describe the data in more detail when taking the model to the data in Section 2.1.

The consumer behavior data is extracted from the Method-of-Payment surveys conducted by the Bank of Canada in 2009, 2013, and 2017. Each MOP survey consists of a survey questionnaire (SQ) and a three-day diary survey instrument (DSI). The SQ component includes consumer characteristics such as location, age, income, and education. Moreover, it asks cash-management-related questions such as the threshold which triggers cash withdrawals and how often they withdraw cash. The DSI component records detailed transaction-level information over a period of three days. Each respondent reports the cash at hand at the beginning of at the day and then records each transaction, including cash withdrawal activities.

An important ingredient of our analysis is that we account for the fact that withdrawing cash is costly and that this cost varies across individuals. Towards this, we use bank branch data collated by Chen and Strathearn (2020). By relating this information to the location information contained in the SQ, we obtain consumer-specific measures of the local access-to-cash infrastructure.

Specifically, we use a distance measure reflecting the number of bank branches in a forward sortation area (FSA), which accounts for the size of the FSA.[3] Formally, our distance

[3] A forward sortation area is a geographical region in which all postal codes start with the same three characters. There are 1643 such areas in Canada; see `https://www150.statcan.gc.ca/n1/pub/92-179-g/`

measure is given by $d = \frac{\text{area of FSA in sqkm}}{1+\#\text{of branches}}$: it is the ratio between the geographic area of the FSA that a given consumer is located in in square kilometers and the number of available bank branches (increased by 1). A larger distance measure thus reflects a lower density of branches and thus cash access points for consumers in the FSA.

The accessibility of bank branches serves as a good proxy for the distance to the access-to-cash infrastructure for a variety of reasons. First, we have reliable data on the number and location of bank branches in Canada. Second, while consumers do withdraw cash at ABMs, only 20% of these withdrawals occur at white-label ABMs instead of ABMs by major financial intermediaries (FIs; see Chen et al. 2021). ABMs by FIs, however, are co-located with branches 88% of the time (Chen et al. 2021). Third, other methods of withdrawal, such as cash-back when paying with a debit card in supermarkets, see limited use in Canada (see, e.g., Henry et al. 2018).

2 Model

We proceed by setting up a formal model of consumer cash inventory management in the spirit of Baumol (1952) and Tobin (1956). The key ingredients are (i) that consumers use both cash and non-cash means of payment for their per-period (daily) expenditures, (ii) that the use of cash is constrained by the cash inventory, which can be replenished with costly withdrawals, (iii) that the cost of these withdrawals depends on the distance to the bank network, and (iv) that holding cash is costly.

In every period, a consumer $i \in \{1, \ldots, N\}$ allocates her expenditure between cash and non-cash purchases. Let $s_{it} \geq 0$ denote the aggregate level of expenditure in dollars in period t, and let $c_{it} \geq 0$ and $s_{it} - c_{it} \geq 0$ denote current period cash and non-cash consumer expenditures, respectively. We assume s_{it} is exogenous and evolves stochastically over time. To make cash purchases, a consumer has to have enough cash on hand. Cash on hand in turn is defined as the sum of cash inventories from the previous period, $h_{it-1} \geq 0$, and the current period withdrawal amount, $w_{it} \geq 0$.The cost of withdrawal does not depend on the withdrawal amount and is a function of the distance to the nearest ATM or bank branch. Holding cash inventories is costly due to the forgone interest and potential exposure to theft.

We assume that the per-period consumer reward function takes the form of a log-linearized Cobb-Douglas utility, specifically

$$\begin{aligned} u\left(h_{it-1}, s_{it}, d_{it}, w_{it}, c_{it}\right) =& \alpha \ln\left(1 + c_{it}\right) + (1-\alpha)\ln\left(1 + s_{it} - c_{it}\right) \\ & - F \times \mathbb{1}_{w_{it}>0} \ln(1 + d_{it}) - \gamma\left(h_{it-1} + w_{it} - c_{it}\right) \\ & s.t. \quad 0 \leq c_{it} \leq h_{it-1} + w_{it}\,,\ c_{it} \leq s_{it}. \end{aligned} \tag{1}$$

In (1), $\alpha \in (0,1)$ is the preference parameter governing the consumer's preference for cash, d_{it} is the distance to the nearest ATM or bank branch, $F \geq 0$ is a parameter governing the withdrawal cost, $\mathbb{1}_{w_{it}>0}$ is an indicator function with value 1 if the withdrawal amount is positive, and γ parameterizes the cost of holding cash inventories until the next time period. The constraints reflect that the cash expenditure is bounded by the cash available $(h_{it-1} + w_{it})$ as well as the overall expenditure (s_{it}) from above, and by zero from below. These bounds

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also ensure that the non-cash expenditure $s_{it} - c_{it}$ is well-behaved in that it is non-negative and does not exceed the overall expenditure.

We assume that consumers are forward-looking, discount the future at a common rate $\beta \in [0, 1)$, and maximize the present discounted value of future utility flows over the (common) time horizon $T \leq \infty$ by choosing a combination of cash use and cash withdrawal (c_{it}, w_{it}) in every period, i.e.,

$$\max_{(c_{i0}, w_{i0}, \ldots, c_{iT}, w_{iT})} \sum_{t=0}^{T} \beta^t u\left(h_{it-1}, s_{it}, d_i, w_{it}, c_{it}\right) \text{ s.t. } w_{it} \geq 0, 0 \leq c_{it} \leq \min\{h_{i,t-1} + w_{it}, s_{it}\}, \tag{2}$$

where, in every period, a consumer observes the realization of the aggregate expenditure level s_{it} and chooses a pair of controls (c_{it}, w_{it}) representing current period cash use and cash withdrawal levels. In addition, we fix initial cash inventories at zero, $h_{i0} = 0$.

Evolution of payoff-relevant variables Cash holdings evolve deterministically over time and only depend on the withdrawal and cash expenditure,

$$h_{it} = h_{it-1} - c_{it} + w_{it}. \tag{3}$$

The total level of expenditure s_{it} evolves according to the following stochastic process,

$$s_{it} = \max\{s_i + \epsilon_{it}, 0\} \; \epsilon_{it} \overset{iid}{\sim} N\left(0, \sigma^2_{s_i}\right), \tag{4}$$

that is, each period a consumer receives a random innovation ϵ_{it} to the average expenditure level s_i, with the restriction that the overall expenditure remains non-negative. Effectively, this implies that ϵ_{it} is drawn from a truncated normal distribution F_{ϵ_i} with a variance parameter that varies by the level of average expenditure. We fix the distance to the nearest ATM or bank branch to be constant but allow it to vary by consumer, $d_{it} = d_i$.

Representation We can rewrite the maximization problem (2) recursively as follows.

$$\begin{aligned} V\left(h_{it-1}, s_i, d_{it}, \varepsilon_{it}\right) = \max_{c_{it} \geq 0, w_{it} \geq 0} \Big\{ & u(h_{it-1}, s_i + \varepsilon_{it}, d_i, w_{it}, c_{it}) \\ & + \beta \int V(h_{it}, s_i, d_i, \varepsilon_{it+1}) dF_{\varepsilon_i} \Big\} \end{aligned} \tag{5}$$

$$s.t.$$

$$c_{it} \leq \min\{h_{it-1} + w_{it}, s_{it}\} \tag{6}$$

$$h_{it} = h_{it-1} + w_{it} - c_{it} \tag{7}$$

Note that consumers observe realizations of the current period total expenditure prior to making the withdrawal and cash usage decisions. Another important observation is that the dynamic effect of the choice pair (c_{it}, w_{it}) on the continuation value occurs only via the evolution of the state variable h_{it}, i.e., via the cash inventory carried forward into the next period. In other words, all pairs of withdrawal and cash usage (c_{it}, w_{it}) that result in the same cash inventory h_{it} yield the same inventory cost $\gamma \cdot h_{it}$ and the same continuation value. We use this to recast the problem with the cash holdings h_{it} as the control variable, which facilitates the numerical solution of the dynamic programming problem as the optimal cash-withdrawal pair (c_{it}, w_{it}) conditional on target cash-holdings h_{it} is uniquely determined.

Recasting the Problem The key observation is that we can analytically solve for the optimal (c_{it}, w_{it}) given h_{it} (conditional on h_{it-1}, ϵ_{it}). Specifically, we can decompose (5) into

$$\begin{aligned} & u\left(h_{it-1}, s_{it}, d_i, w_{it}, c_{it}\right) + \beta \int V\left(h_{it}, s_i, d_i, \epsilon_{it+1}\right) dF_{\epsilon_i} && (8) \\ = \; & \alpha \ln\left(1 + c_{it}\right) + (1-\alpha) \ln\left(1 + s_{it} - c_{it}\right) && (9) \\ & -F \times \mathbb{1}_{w_{it}>0} \ln(1 + d_{it}) && (10) \\ & -\gamma\left(h_{it-1} + w_{it} - c_{it}\right) && (11) \\ & +\beta \int V\left(h_{it}, s_i, d_i, \epsilon_{it+1}\right) dF_{\epsilon_i}. && (12) \end{aligned}$$

We can see that only (9) and (10) depend on the choice of c_{it} and w_{it}, while (11) and (12) depend only on h_{it}. Lemma 1 establishes that, given any h_{it}, the optimal c_{it}, w_{it}, which maximizes the sum of (9) and (10), is uniquely determined.

Lemma 1 *For a given $(h_{it-1}, \epsilon_{it})$ and a target h_{it} which translates into $\Delta h = h_{it} - h_{it-1}$, and which satisfies*

$$h_{it} \geq \max\{0, h_{it-1} - s_{it}\} \iff \Delta h \geq \max\{-s_{it}, -h_{it-1}\}$$

there is a unique (c^*, w^*) which solves

$$\max_{(c,w)} \{\hat{u}(c, w) = \alpha \ln\left(1 + c\right) + (1-\alpha) \ln\left(1 + s_i + \epsilon_{it} - c\right) - F \times \mathbb{1}_{w>0} \ln(1 + d_{it})\} \quad (13)$$

$$\begin{aligned} s.t. \; & w \geq 0 \\ & s_{it} \geq c \geq 0 \\ & w - c = \Delta h. \end{aligned}$$

Denoting $\tilde{c} = \min\left\{\max\{(2 + s_{it})\alpha - 1, 0\}, s_{it}\right\}$ the desired level of cash usage absent inventory constraints and $\bar{d}$ the solution to

$$F \ln\left[1 + \bar{d}\right] = \alpha \ln\left[1 + \tilde{c}\right] + (1-\alpha) \ln\left[1 + s_{it} - \tilde{c}\right] - \alpha \ln\left[1 - \Delta h\right] - (1-\alpha) \ln\left[1 + s_{it} + \Delta h\right], \quad (14)$$

$$(c^*, w^*) = \begin{cases} (-\Delta h, 0) & \text{if} \quad \max\{-h_{i,t-1}, -s_{it}\} \leq \Delta h \leq -\tilde{c} \\ (-\Delta h, 0) & \text{if} \quad \Delta h \in (-\tilde{c}, 0] \wedge d_{it} \geq \bar{d} \\ (\tilde{c}, \Delta h + \tilde{c}) & \text{if} \quad \Delta h \in (-\tilde{c}, 0] \wedge d_{it} < \bar{d} \\ (\tilde{c}, \Delta h + \tilde{c}) & \text{if} \quad \Delta h > 0 \end{cases}. \quad (15)$$

Proof. See Appendix A.2 ■

The intuition behind Lemma 1 is as follows. Depending on the target change in cash inventory Δh, there are three regions. If Δh is positive, this can only be achieved by costly withdrawal, i.e., $w^* > 0$. As the withdrawal fee is independent of the amount of cash withdrawn, it follows that the consumer will always implement her desired (unconstrained) level of cash usage $c^* = \tilde{c}$ implying a withdrawal of $w^* = \Delta h + \tilde{c}$. Second, absent the option of depositing cash—see Appendix A.3 for an extension allowing for deposits—any reduction in cash inventory exceeding the desired level of cash usage will always be implemented by using exactly the amount of cash necessary, $c^* = -\Delta h$, as this avoids the withdrawal cost by inducing $w^* = 0$. This is because any withdrawal would necessitate an even more distorted excessive cash usage. Third, an intermediate reduction in cash holdings yields two choices for the consumer. She could either implement her desired level of cash usage which necessitates a costly withdrawal or alternatively distort her cash usage by using inefficiently little cash to avoid incurring the withdrawal cost. The specific resolution of this trade-off depends on the withdrawal fee F as well as the distance parameter d_{it}.

Lemma 1 is useful because it allows us to define

$$\tilde{u}(h_{it}; h_{it-1}, s_{it}, d_{it}) \equiv u(h_{it-1}, s_{it}, d_{it}, w^*(h_{it}), c^*(h_{it})), \tag{16}$$

where (c^*, w^*) are functions of h_{it} as characterized by (15). Note that $\tilde{u}$ is weakly concave in h_{it}.[4] The above allows us to recast the dynamic programming problem as

$$V(h_{it-1}, s_i, d_i, \epsilon_{it}) = \max_{h_{it} \geq \max\{0, h_{i,t-1} - s_{it}\}} \left\{ \tilde{u}\left(h_{it}; h_{it-1}, s_{it}, d_{it}\right) + \beta \int V\left(h_{it}, s_i, d_i, \epsilon_{it+1}\right) dF_{\epsilon_i} \right\} \tag{17}$$

We numerically approximate the value function in (17) by considering a six-month (183 days) planning horizon and a constant common-to-all discount factor of $\beta \approx 0.95$, which allows us to solve the consumer's problem by backward induction.[5] The resulting value functions, which imply the policy functions forming the basis for our empirical estimation, are robust to perturbations in the planning horizon.

2.1 Matching the model to the data

In the diary data, we observe consumer purchase behavior at the point-of-sale (POS) over three days. We use this information to classify consumers into 30 *expenditure types* based on their level of aggregate daily expenditures, $s_i \equiv \mathbb{E}_t[s_{it}]$. We use variation both across consumers within a given expenditure type, as well as within-consumer variation across the three days to calculate type-specific variance of innovations, $\sigma^2_{s_i}$. This corresponds to the evolution of total expenditures for each consumer type as per equation (4) of the formal model.

In addition to the total daily expenditures extracted from the diary data, we observe consumers' reported daily cash expenditures, expected withdrawal amounts, withdrawal frequency, cash holdings, and cash holdings at withdrawal from the survey questionnaire. Using consumer locations, we also obtain the distance measure. Table 1 provides summary statistics by consumer expenditure type. Columns (1) and (2) characterize the evolution of total expenditures. Column (3) reports expected cash expenditures calculated as the product of the expected withdrawal amount, $\mathbb{E}[w_{it}]$, reported in column (5), and the withdrawal frequency reported in column (6), i.e.,

$$\mathbb{E}[c_{it}] = \mathbb{E}[w_{it}] \times \mathbb{E}[\mathbb{1}_{w_{it}>0}],$$

[4] It is strictly concave when no withdrawal takes place and linear in h_{it} when withdrawal takes place.

[5] Specifically, we choose $\beta = 0.950652901$, which ensures that $\beta^{182} < 0.0001$, i.e., that the final period has a weight of less than $\frac{1}{10000}$ of that of the first period.

Table 1: Summary statistics by consumer total expenditure type (full sample)

(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
type	s_i	$\sigma^2_{s_i}$	$\mathbb{E}[c_{it}]$	c_{it}	$\mathbb{E}[w_{it}]$	withdr. freq.	$\mathbb{E}[h_{it}]$	Dist.	$\max\{h_{it}\}$	Age	Income
0	5.09	3.26	2.45	2.38	50.68	0.06	35.06	222.95	160.00	38.35	40454.55
1	10.27	7.21	4.15	4.54	66.23	0.07	35.25	97.29	223.00	40.57	44539.47
2	14.62	8.78	5.49	5.79	79.54	0.08	44.62	152.08	276.09	43.68	38131.87
3	18.76	13.19	6.55	7.65	108.58	0.07	48.85	229.64	371.66	45.42	38250.00
4	22.45	14.56	6.89	6.76	91.96	0.08	53.34	169.11	262.17	45.69	44009.90
5	26.05	15.52	8.21	10.69	104.14	0.10	54.00	327.91	323.88	47.68	42196.26
6	29.93	20.97	8.89	8.73	109.95	0.09	57.14	428.10	478.74	44.37	40700.00
7	33.84	22.64	9.97	9.53	118.74	0.10	53.16	127.67	530.00	46.31	44322.03
8	37.72	26.55	10.82	9.94	118.78	0.10	61.48	249.09	435.37	46.15	39957.63
9	41.49	28.84	14.17	11.50	153.83	0.10	62.08	276.96	796.42	49.08	46741.07
10	45.16	28.73	14.66	12.21	147.80	0.11	67.48	271.24	1020.00	48.23	45526.32
11	48.76	32.56	13.19	13.87	138.94	0.10	63.93	172.77	610.00	47.28	43839.29
12	52.67	36.42	13.27	13.74	141.94	0.11	70.59	313.66	743.32	45.68	46271.93
13	56.85	41.27	13.98	12.29	149.11	0.10	79.88	130.81	725.00	50.91	45818.97
14	61.14	43.29	16.34	13.38	177.77	0.10	74.00	207.36	658.37	50.03	47563.03
15	65.58	42.84	16.14	13.93	163.60	0.11	69.69	83.38	701.01	49.41	38793.10
16	70.57	47.03	14.19	13.61	142.72	0.11	71.37	156.05	658.37	49.48	49262.30
17	76.11	47.85	14.53	15.44	151.11	0.12	75.56	265.60	700.00	49.18	49618.64
18	82.07	53.24	15.55	16.91	143.83	0.11	63.66	154.23	638.32	47.04	47000.00
19	88.28	64.82	15.38	16.66	146.47	0.11	73.67	286.72	1050.00	48.11	48975.41
20	96.41	64.14	18.18	21.15	165.27	0.12	82.95	181.29	826.40	49.60	50079.37
21	106.11	74.45	18.47	20.83	192.17	0.10	84.76	246.67	1100.00	53.44	39570.31
22	115.87	77.04	17.18	18.80	162.86	0.11	79.99	196.02	1185.45	48.24	62521.01
23	127.85	90.20	20.44	23.71	168.37	0.12	86.76	191.34	797.90	50.14	46968.50
24	141.56	105.31	18.66	18.51	155.49	0.11	73.63	135.50	820.70	49.35	51360.00
25	160.05	119.04	15.69	25.76	161.81	0.09	64.64	120.84	530.94	48.22	54960.00
26	185.47	131.29	20.31	28.07	169.32	0.12	72.70	158.48	650.00	52.23	53389.83
27	218.28	168.17	21.35	27.53	211.64	0.11	89.76	292.40	1500.00	49.24	59000.00
28	289.71	247.54	19.81	33.20	184.29	0.10	83.68	262.98	957.48	49.79	55610.69
29	512.10	558.13	25.98	47.80	208.99	0.11	101.53	201.97	1200.00	53.11	58473.28
Avg	102.91	81.58	14.72	17.13	147.80	0.10	69.75	210.50	731.24	48.27	47635.19

Notes: all values are computed per one day; column (0) indicates the expenditure type; columns (1) and (2) depict the mean and variance of consumers' total expenditure; column (3) reports expected cash expenditures computed from averaging over the long-run steady-state expected cash usage of consumers that belong to the same type, while column (4) reports average daily realizations of consumer cash expenditures; column (5) reports average withdrawal amount conditional on withdrawing cash; column (6) reports the proportion of days on which consumers withdraw cash; column (7) shows the average cash holdings; column (8) reports the average distance measured as the ratio between the geographic area of the forward sortation area (FSA) in square kilometers and one plus the number of available bank branches; column (9) reports the maximal cash holding; column (10) reports the average age per spending type; column (11) reports the average income.

such that in a steady state there is no accumulation of cash holdings; put differently, we assume that on average, consumers' expected cash withdrawals match the expected cash usage.[6] Column (4) reports the average realized daily cash purchases reported by consumers in the DSI. Consistency requires long-run consumer expected daily cash expenditures and the realized daily cash purchases to not be too different. We find that numbers in columns (3) and (4) appear to be reasonably close to each other.

Column (7) reports average cash holdings. Column (8) reports the average distance to bank branches. As stated, we measure this as the ratio between the geographic area of the forward sortation area (FSA) in square kilometers and one plus the number of available bank branches. Column (9) summarizes the maximum cash holding observed for each consumer type. Columns (10) and (11) summarize the average age and income per spending type, respectively.[7]

To estimate preference parameters, we operationalize model predictions and data in the following manner. For a given vector of parameter values, we numerically solve the consumer dynamic programming problem assuming a discrete time period of one day, a six-month (183-day) planning horizon, and a daily common discount factor of $\beta = 0.950652901$. The solution is then used to simulate forward 20 sequences of 183 periods (days) for each observation in the data and use the daily average across the 3660-day period to calculate model predictions.

Our model predicts four specific outcome variables, where we denote model predictions with hats: (i) the expected withdrawal amount conditional on withdrawing, $\mathbb{E}\,[\widehat{w_{it}|w_{it}} > 0]$, (ii) the expected withdrawal frequency, $\Pr\,(\widehat{w_{it} >} 0)$, (iii) the expected level of cash holdings, $\widehat{\mathbb{E}\,[h_{it}]}$, (iv) the expected level of cash use, $\widehat{\mathbb{E}\,[c_{it}]}$.

By comparing these model predictions with the data, this yields consumer-specific error terms

$$\varepsilon_{1,it} = \mathbb{E}\,[w_{it}|w_{it} > 0] - \mathbb{E}\,[\widehat{w_{it}|w_{it}} > 0], \tag{18}$$

$$\varepsilon_{2,it} = \Pr\,(w_{it} > 0) - \Pr\,(\widehat{w_{it} >} 0), \tag{19}$$

$$\varepsilon_{3,it} = \mathbb{E}\,[h_{it}] - \widehat{\mathbb{E}\,[h_{it}]}, \tag{20}$$

$$\varepsilon_{4,it} = \mathbb{E}\,[c_{it}] - \widehat{\mathbb{E}\,[c_{it}]}, \tag{21}$$

which we interact with a vector of three instrumental variables, z_i, including a constant term, total daily expenditures, and the distance measure, to obtain the individual moment

[6] While the diary data contains an explicit measure of withdrawals, the three-day nature of the diary implies that many consumers do not withdraw cash in the observation period.

[7] We also have data on the average cash holding at withdrawal per consumer, $E[h_{it}|w_{it} > 0]$, which is omitted from the table. For each consumer type, we observe strictly positive cash holdings at withdrawal and availability of cash despite the use of non-cash means of payment for transactions. The level of cash holdings at withdrawal constitute an important variable that can be used to identify parameters of the consumers' dynamic programming problem. In principle, it therefore seems prudent to include this variable in our empirical analysis. At the same time, this variable has the largest proportion of missing values that can constitute anywhere between 40 and 60 percent of the data sample, even when the remaining variables do not have missing values. In the main part of our estimation, we therefore omit this moment. All results are robust to its inclusion, which is facilitated by setting individual moment conditions for missing data to zero and averaging only over the observed set of values. This way we combine moment conditions based on samples of different size, which is a typical exercise in the industrial organization literature utilizing micro-moments (e.g., see Petrin 2002, Berry et al. 2004).

conditions $g_i(\theta)$. We assume that these variables are exogenous to the error terms in equations (18) through (21). Thus, we obtain 12 overall moments which we use to estimate the three parameters of interest.

For estimation, we employ two approaches which allow for different levels of consumer heterogeneity and which we contrast throughout our analysis. Our main *heterogeneous approach* allows for flexible consumer heterogeneity along all three parameters. It matches each individual consumer to the parameters that best describe her behavior. Specifically, we look for the parameter values such that the weighted square distance of the moments is closest to zero. Towards this, we use Halton Draws to obtain a grid containing 100,000 combinations of parameter tuples (α, F, γ). Our approach mirrors the one employed in finite mixture models with all but one of the weights equal to zero, that is, we employ the K-nearest-neighbor matching approach with $K = 1$.

The weights for the different moments in turn are obtained from the second approach and are used to account for scale differences in the moments. Specifically, the second *representative consumer approach* assumes that all consumers—or large demographic-specific consumer groups—share the same preference parameter and estimates the underlying parameter from the stacked moment conditions using generalized method of moments (GMM). The moments are weighted using a two-stage optimal block-diagonal weighting matrix, where $(Z'Z)^{-1}$ represents a single block in the first stage and $(g_i(\theta)'g_i(\theta))^{-1}$ represents a single block in the second stage and where $g_i(\hat{\theta})$ is a vector of individual moment conditions at the optimal first-stage parameter values. The resulting weighting matrix is used for the main approach of matching individual consumer preferences.[8]

Irrespective of the estimation approach, identification derives from how the different parameters impact the different moments. Overall, the level of cash use relative to overall expenditure is the primary source of identification of the cash elasticity α, with the combination of the remaining moments identifying the withdrawal cost parameter F and the holding cost γ. Specifically, frequent but small withdrawals and low cash holdings point—all else equal—towards a low idiosyncratic withdrawal cost but high holding cost, whereas the reverse is true when withdrawals are large and infrequent, with correspondingly larger holdings. The resolution of this trade-off is naturally affected by the different bank branch density as captured by our distance parameter d, which we take from the data.

3 Estimation results

We first report the baseline estimation results, where we contrast results from the representative consumer approach—stipulating that all consumers, or all consumers from a given observation wave (2009, 2013, 2017), respectively, share the same preferences—with that from the fully heterogeneous one. In doing so, the individual-level matching uses the same set of moments and weighting matrix as in the representative consumer approach, which makes the values of the criterion functions comparable.

Towards this, Table 2 summarizes the average moments in the data which the two

[8]Qualitative results are robust to employing different weighting matrices for the main approach such as equally weighted moments or demographic-group-specific weighting matrices obtained as in the second approach but with consumers grouped according to age and income, and wave in which they appear.

estimation approaches target. It is key to note the simultaneous decline in average daily cash use coupled with an increase in the average cash holdings, which are facilitated by less frequent but larger withdrawals.

Table 2: Factual data by year (average)

Parameter	Overall	2009	2013	2017
Average daily cash use	14.72	15.88	15.56	12.49
Average cash withdrawal	147.80	146.25	143.54	154.99
Probability of withdrawal	0.10	0.11	0.11	0.08
Average cash holding	69.75	66.45	70.24	72.17

Representative Approach Column (1) in Table 3 summarizes the estimation results assuming that parameters are constant over time, while columns (2) through (4) allow the parameters to vary over time and report results for the respective wave.

Table 3: Representative consumer: estimation results by year

Parameter	All Years	2009	2013	2017
Preference for cash, α	0.189	0.194	0.201	0.166
(s.e.)	(0.002)	(0.001)	(0.007)	(0.005)
Holding cost, γ	0.0004	0.0004	0.0004	0.0003
(s.e.)	(0.00002)	(0.00000)	(0.00004)	(0.00001)
Withdrawal cost, F	0.204	0.191	0.204	0.143
(s.e.)	(0.007)	(0.009)	(0.017)	(0.021)
Average daily cash use	14.15	14.88	16.01	12.08
Average cash withdrawal	147.04	158.15	153.66	128.88
Probability of withdrawal	0.11	0.10	0.12	0.11
Average cash holding	56.26	60.39	58.86	52.02
N-obs.	3424	973	1,408	1,043

Notes: Starting values for individual years are taken from the representative consumer model; see Appendix B.1 for details. Moments for estimation are obtained by interacting 4 errors with 3 instrumental variables.

All parameter estimates are statistically significant and have expected signs. We also report the estimation-implied moments of relevance, i.e., the implied average cash usage, the average cash withdrawal, the probability of withdrawing on a given day, and the average cash holdings. Inspecting these moments reveals that the representative approach matches the declining cash use but is not able to capture the larger but less frequent withdrawals leading to larger cash holdings.

The findings of a comparatively constant cash preference between 2009 and 2013 which drops thereafter is intuitive for various reasons. In the period between 2009 and 2013, the uptake of the tap-and-go feature for cards was slow in Canada (largely because merchants' adoption of terminals with this feature was lacking; see Felt 2020), while the Bank of Canada introduced a new series of polymer banknotes starting in 2011, which improved the use of cash (see Rojas et al. 2020, for the importance of bank note durability for distribution patterns). After 2013, the positive impact on the cash preference of more durable notes slowly dissipates, while the tap-and-go feature increasingly penetrated the market, rendering electronic payments more attractive and lowering consumers' preference for using cash.

Heterogeneous approach We next report results from using the flexible heterogeneous matching procedure, which yields individual parameter estimates for each consumer in the sample. Table 4 reports the mean, median, and standard deviation for each of the three parameters, along with the estimation-implied moments of relevance.

Table 4: Heterogeneous consumers: estimation results by year

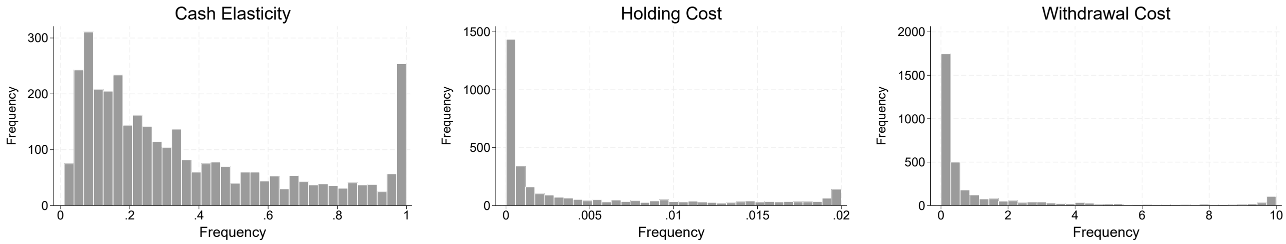
Parameter	(1) Overall	(2) 2009	(3) 2013	(4) 2017
Preference for cash, α				
Mean	0.370	0.379	0.365	0.368
Median	0.259	0.269	0.264	0.245
S.d.	0.299	0.304	0.294	0.301
Holding cost, γ				
Mean	0.0047	0.0048	0.0046	0.0047
Median	0.0010	0.0012	0.0009	0.0009
S.d.	0.0063	0.0064	0.0063	0.0064
Withdrawal cost, F				
Mean	1.398	1.229	1.355	1.613
Median	0.273	0.215	0.273	0.308
S.d.	2.506	2.336	2.471	2.687
Average daily cash use	15.51	16.42	16.49	13.35
Average cash withdrawal	162.12	158.87	159.19	169.10
Probability of withdrawal	0.10	0.11	0.11	0.08
Average cash holding	53.66	51.86	53.48	55.57
N-obs.	3424	973	1,408	1,043

Notes: Results are obtained from matching each consumer to the parameter value, which minimizes the weighted squared distance between the predicted individual moments and those observed in the data. Specification (1) reports averages, median, and standard deviation for each parameter across all years. Specifications (2), (3), and (4) report the same for individual waves. Moments for matching are obtained by interacting 4 errors with 3 instrumental variables. The weighting matrix is the optimal 2-step weighting matrix from the representative approach.

Several observations stand out. First, and most importantly, there is substantial heterogeneity for each of the three parameters, as further evidenced by the distributions depicted in Figure 1.[9]

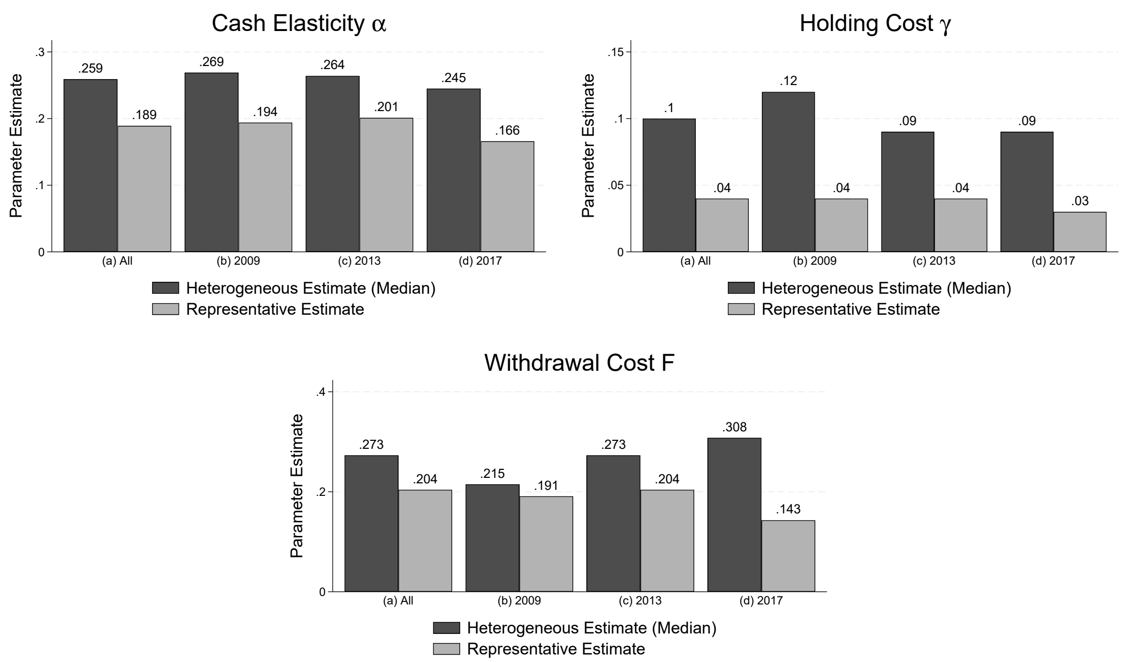
[9]The heterogeneity persists when assessing it on a per-wave basis; see Appendix B.2.

Figure 1: Cash elasticity (left), holding (middle) and withdrawal (right) costs, full sample



Second, accounting for this heterogeneity yields important insights as it also translates into different average model-implied moments. Specifically, the heterogeneous approach is able to match the increased cash holdings facilitated by less frequent but larger withdrawals. Consumer heterogeneity is thus paramount for accurately capturing consumer behavior.

Figure 2: Comparison between representative and heterogeneous approaches



Notes: Results for the holding cost parameter γ are scaled by factor 100 for easier visualization.

Third, there are substantial differences between the mean and median parameter estimates compared to those of the representative approach in terms of their magnitude and pattern. This is particularly apparent when comparing the results graphically in Figure 2. While the qualitative trend across years is comparable for the cash elasticity α and the holding cost γ—both decline over time—the pattern for the individual withdrawal cost parameter F differs starkly. While the representative approach indicates that it declines between 2013 and 2017, the heterogeneous approach reveals that it actually increases (the same holds true for the mean estimates; see Table 4). It is this difference that explains the better ability to match the increase in cash holdings and concomitant drop in withdrawals between 2013 and 2017.

Model Fit More generally, and unsurprisingly, the substantial heterogeneity revealed by the heterogeneous approach translates into a much better model fit. Table 5 summarizes the empirical distributions of the 4 main moments along with the distributions implied from the estimates from the representative and heterogeneous approach, respectively. We can see that the magnitude of the prediction errors across the various moments is consistently lower in absolute terms and particularly so for the size of withdrawals and average cash holdings.

Table 5: Model fit (data vs prediction) full sample, 3424 obs.

	p10	p25	p50	p75	p90
			Data		
Cash Use	1.52	3.54	8.00	18.24	34.20
Withdrawal Level	30.00	50.00	106.19	212.38	318.57
Withdrawal Frequency	0.03	0.07	0.07	0.13	0.20
Average Holding	5.00	19.38	45.59	91.32	170.98
			Representative prediction		
Cash Use	2.87	5.62	10.15	17.54	28.72
Withdrawal Level	44.00	76.94	125.34	190.73	277.87
Withdrawal Frequency	0.03	0.05	0.08	0.13	0.20
Average Holding	17.57	31.97	52.26	73.68	104.11
			Heterogeneous prediction		
Cash Use	2.36	4.78	9.72	20.53	35.34
Withdrawal Level	38.69	64.51	114.31	215.53	352.85
Withdrawal Frequency	0.03	0.06	0.07	0.13	0.19
Average Holding	3.64	16.99	36.83	71.74	129.89
			Differences Data-Representative prediction		
Cash Use	-1.35	-2.08	-2.15	0.70	5.48
Withdrawal Level	-14.00	-26.94	-19.15	21.65	40.70
Withdrawal Frequency	0.00	0.02	-0.01	0.00	0.00
Average Holding	-12.57	-12.59	-6.67	17.64	66.87
			Differences Data-Heterogeneous prediction		
Cash Use	-0.84	-1.24	-1.72	-2.29	-1.14
Withdrawal Level	-8.69	-14.51	-8.12	-3.15	-34.28
Withdrawal Frequency	0.00	0.01	0.00	0.00	0.01
Average Holding	1.36	2.39	8.76	19.58	41.09
	p10	p25	p50	p75	p90

3.1 Consumer heterogeneity and relation to demographics

The comparison between the representative consumer approach and the fully flexible matching revealed the importance of accounting for consumer heterogeneity. To further explore how consumer heterogeneity is related to individual consumer characteristics, we assess how estimated parameter differences are related to observable demographic characteristics such as age and income.

Relation to Demographics We begin our investigation by relating the consumer-specific estimates to two important observable demographics: age and income. Specifically, we classify consumers into *young* and *old* based on the sample average age and into three income brackets corresponding to the ones used by Statistics Canada. "Low Income (LI)" consumers are those earning weakly less than CAD 45,000 per year, "Medium Income (MI)" consumers those earning between CAD 45,000 and 85,000, and "High Income (HI)" consumers those earning more than CAD 85,000. We show the average and median parameter estimates for each demographic group in Table 6 along with the model-implied average moments.[10] Inspecting Table 6 reveals several insights. First, older people tend to exhibit a higher

Table 6: Estimates by demographic type

Parameter	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI
Preference for cash, α						
Mean	0.371	0.351	0.334	0.387	0.357	0.384
Median	0.267	0.236	0.193	0.291	0.245	0.286
S.d.	0.298	0.297	0.302	0.301	0.293	0.302
Holding cost, γ						
Mean	0.0057	0.0055	0.0052	0.0039	0.0039	0.0039
Median	0.0018	0.0016	0.0009	0.0007	0.0006	0.0007
S.d.	0.0068	0.0067	0.0067	0.0058	0.0058	0.0059
Withdrawal cost, F						
Mean	1.617	1.564	1.222	1.257	1.215	1.275
Median	0.337	0.305	0.253	0.235	0.269	0.210
S.d.	2.673	2.623	2.397	2.394	2.308	2.438
Average daily cash use	12.48	12.88	14.10	17.29	18.90	23.08
Average cash withdrawal	133.10	143.73	134.98	179.53	194.34	221.02
Probability of withdrawal	0.10	0.09	0.10	0.10	0.10	0.11
Average cash holding	40.10	43.88	43.26	62.60	68.31	76.89
N-Obs.	924	564	185	1189	435	127

Notes: Results are obtained from matching each consumer to the parameter value which minimizes the weighted squared distance between the predicted moments and those observed in the data. Weights are obtained from the representative consumer approach and averages are reported by demographic types. The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

preference for using cash along with lower costs to both hold and withdraw it. This translates into substantially higher cash use across income brackets. Second, the increasing cash use among income brackets is not driven by preference but simply by higher overall expenditures, which are positively correlated with income.

It is important to once more stress the necessity of allowing for flexible and individual-level consumer heterogeneity. While the above findings bear out qualitatively when estimating consumer preferences by demographic group, the flexible estimation approach continues to provide a much better model fit (see Appendix B.3). This is because of the substantial

[10]For reference, we show the results from estimating the model using the representative consumer approach by imposing that parameters are identical at the type level (but constant across the 3 waves) in Table 16.

within-group-heterogeneity in parameter estimates, which we illustrate in Appendix B.4.

Evolution of preferences by demographic type We can also look at the evolution of consumer preferences over time—based on their parameter estimates—by demographic groups and by their location in rural or urban areas. We summarize our findings in Table 7, which reports the median estimates by wave and group. The analysis reveals that the broad patterns identified in the yearly analysis do not necessarily apply to all groups.[11] While we reaffirm the pattern of increasing individual withdrawal costs for most demographic groups, there are notable differences for both the cash elasticity and holding costs. Specifically, older low-income consumers in fact display an increased preference for cash over years. Concerning holding costs, older and poorer consumers similarly display the opposite behavior identified in the pooled yearly analysis in that their holding cost increases. These findings are largely reaffirmed when considering the wider distributional patterns in Appendix B.5.

Table 7: Evolution of parameter estimates by demographic type (median estimates)

	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural
(a) Cash elasticity, α								
2009	0.275	0.272	0.193	0.269	0.323	0.290	0.251	0.334
2013	0.276	0.216	0.102	0.297	0.229	0.635	0.255	0.333
2017	0.245	0.236	0.174	0.293	0.234	0.136	0.245	0.267
(b) Holding cost, γ								
2009	0.00156	0.00312	0.00092	0.00062	0.00150	0.00077	0.00106	0.00162
2013	0.00207	0.00148	0.00129	0.00074	0.00054	0.00009	0.00082	0.00235
2017	0.00154	0.00122	0.00020	0.00076	0.00043	0.00865	0.00082	0.00130
(c) Withdrawal cost, F								
2009	0.239	0.269	0.255	0.147	0.208	0.225	0.269	0.094
2013	0.322	0.275	0.203	0.252	0.248	0.092	0.293	0.105
2017	0.414	0.375	0.078	0.256	0.313	0.602	0.380	0.101
Observations	924	564	185	1189	435	127	2902	522

Notes: The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

3.2 Impact of Changes in the Access-to-Cash Infrastructure

The cash infrastructure in Canada continues to evolve, with the number of bank branches in Canada peaking around 2013; see Appendix A.1. Because our sample is a representative repeated cross-section of Canadian consumers and not a panel, we do not observe consumers from the same location in each survey wave. As such, it is important to consider the evolution of our distance measure for the consumers in our sample. Table 8 displays the distribution of distance measures across the waves. It reaffirms that consumers in our sample faced the

[11]Due to the comparatively small sample size for high-income consumers, we do not focus on the estimates for the two associated demographic groups with an average of around 50 consumers per sample wave.

worst access-to-cash infrastructure in 2009. However, the worsening of the infrastructure between 2013 and 2017 does not fully translate into the distance faced by consumers in our sample, as seen by the near-constant median.

Table 8: Evolution of distance measure by consumers, our sample

Year	Mean	p10	p25	Median	p75	p90	N-obs.
2009	288.14	0.71	1.67	6.35	111.66	573.90	973
2013	160.32	0.52	1.24	3.42	40.72	279.70	1408
2017	205.65	0.48	1.24	3.48	38.72	287.62	1043
All	210.50	0.57	1.38	3.95	55.62	349.48	3424

Notes: The distance measure is the natural logarithm of the geographic area of the forward sortation area (FSA) consumers are located in in square kilometers over the number of available bank branches.

Evaluation of Factual Changes The changing infrastructure naturally begets the question how it impacts consumers. Towards this, we conduct the following exercise. We take consumers' individually estimated preferences and evaluate outcomes for each of the three years from which our sample is drawn by supposing that consumers are facing the access-to-cash infrastructure from the year of the respective wave. For example, for a consumer from the 2009 wave, we evaluate their outcome not only under the actually observed infrastructure in 2009, but also under the infrastructure present in their FSA in 2013 and 2017 (while stipulating that their preferences are unaffected). We focus on two key metrics: consumers' use of cash and consumers' cash holdings. As before, we separately conduct the analysis by demographic group and by urban/rural status. In addition, we look at the impact on the subgroup of 232 consumers for whom the infrastructure worsened substantially between 2013 and 2017 in the form of a more than 25% increase of our distance measure. We summarize results in Table 9, which shows the average cash use and cash holdings by group, and provide an overview over the distributional impact in Appendix B.6.

There are several takeaways. First, the average impact on consumers is limited in terms of both their cash use and cash holdings. This applies to the overall sample as well as to the different subgroups by demographics and locality. Second, there is a much more pronounced impact on consumers who are substantially affected. Consumers whose access-to-cash infrastructure substantially deteriorated between 2013 and 2017 reduce their cash use by on average 11.3%. This reduction goes hand in hand with an average reduction in cash holdings of only 2.2%. Third, an analysis of the impact of infrastructure changes on the full distribution of consumers reveals additional insights. In particular, the median cash holdings by substantially affected consumers actually increase by 5.4%.

A key limitation of the above analysis is that the access-to-cash infrastructure has been mostly stable in the FSAs where consumers in our sample are present: 26.46% (906 of 3424) experienced a change in the infrastructure as proxied by our distance measure of more than 10% between two sample waves, and only 8.76% (300 out of 3424) experienced a change of more than 25% between 2009 and 2017. To further assess the validity of the findings for the substantially affected consumers, we therefore conduct a counterfactual analysis that considers hypothetical changes in the access-to-cash infrastructure *for all consumers.*

Table 9: Impact of Infrastructure Changes on Cash Use and Cash Holdings

(a) Average cash use by group

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	15.428	12.390	12.693	14.098	17.192	18.959	23.019	15.025	17.672	15.539
2013	15.580	12.553	12.987	14.487	17.308	18.957	22.974	15.209	17.646	15.489
2017	15.412	12.296	12.925	14.367	17.169	18.752	22.756	15.053	17.406	13.734
Observations	3424	924	564	185	1189	435	127	2902	522	232

(b) Average cash holdings by group

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	53.379	39.630	43.205	43.257	62.421	68.491	76.911	53.083	55.022	53.593
2013	53.585	40.181	43.618	42.915	62.544	68.287	76.676	53.342	54.936	54.666
2017	53.470	39.867	43.817	43.028	62.410	68.129	76.611	53.235	54.775	53.438
Observations	3424	924	564	185	1189	435	127	2902	522	232

The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually). **indicates that the distance measure capturing the access-to-cash infrastructure increased by more than 25% between 2013 and 2017.*

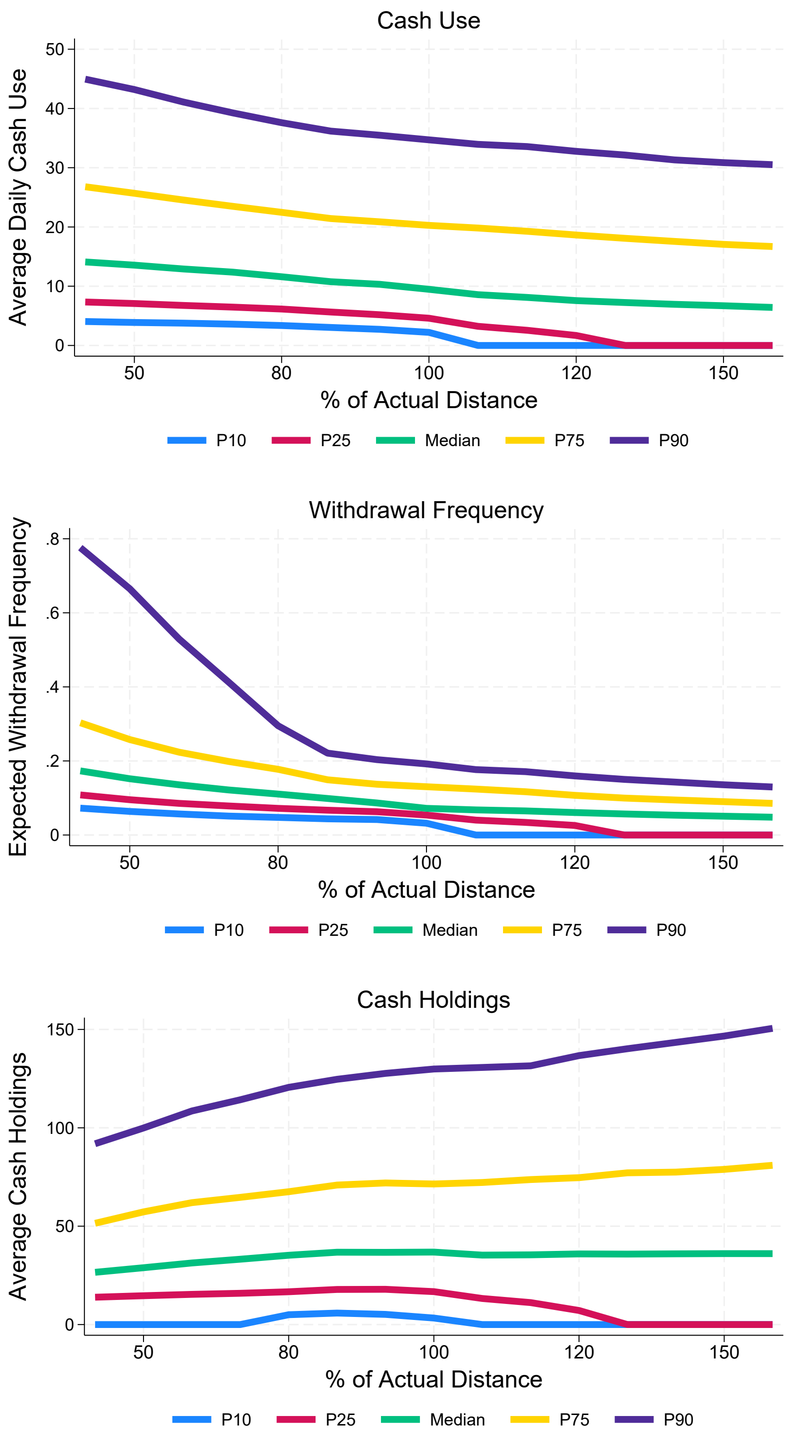
4 Counterfactual Analyses

We begin by tracing out the heterogeneous responses by consumers to changes in the access to cash infrastructure. Towards this, we conduct the following exercise. We fix consumers' preference parameters at the estimated consumer-specific values. We then vary the cost of a single withdrawal—equal to the estimated idiosyncratic withdrawal cost multiplied with the log of the distance measure—by allocating each consumer to a counterfactual setting in which this cost corresponds to $x\%$ of the actual cost, where $x \in \{0, 1, 5, 10, 20, \ldots, 200\}$. Formally, the utility penalty of a withdrawal in the counterfactual setting is given by $x \cdot F_i \cdot \ln(1 + d_i)$ instead of the factual $F_i \cdot \ln(1 + d_i)$.

For each such setting, we simulate forward consumers' behavior for 20 cycles of 183 periods each, which allows us to infer their average behavior. To capture the impact of the infrastructure changes on consumers and in particular their distributional impact, we plot the P10, P25, Median, P75 and P90 for the following three main outcomes: cash use, withdrawal frequency, and cash holdings. Figure 3 summarizes the results, focusing on the range for $x \in \{50, \ldots, 150\}$. Appendix B.7 shows the results for the full range of perturbations.

The analysis further underpins the findings from the evaluation of factual infrastructure changes and reveals several takeaways. First, as expected, cash use and withdrawal frequency decline for each of the considered percentiles of the distribution. This is naturally explained by the increase in realized withdrawal costs due to the increased distance to the access-to-cash infrastructure. Second, around a quarter of consumers would stop using cash even if obtaining cash becomes only moderately more cumbersome as proxied by a $\approx 25\%$ increase in the counterfactual distance. These consumers stop withdrawing cash and reduce their cash holdings and use to zero. More generally, cash holdings as a function of the distance are non-monotonic at the lower end of the distribution—if cash is easy to obtain, consumers

Figure 3: Effect of distance to A2C infrastructure



hold little and withdraw low amounts more frequently. They then increase their holdings to economize on withdrawals as it becomes more cumbersome but stop using cash entirely once it becomes too costly to obtain.

However, this is only one of two response patterns identified by the analysis. The second group only moderately reduces their use of cash at the point of sale as withdrawing cash becomes more cumbersome. They also economize on withdrawals but consistently increase their cash holdings as the distance to the cash infrastructure increases.

Who responds how? The identified bi-modality in consumer responses begets the question which types of consumers exhibit which type of response. Towards this, we focus the analysis on the counterfactual exercise, which increases consumers' distance to access-to-cash infrastructure by 25%. This is motivated by the previous finding that such an increase is sufficient to induce a substantial fraction of consumers to no longer use cash. Moreover, it is in line with the magnitude of recently announced and implemented branch closure programs.[12] We report outcomes in the form of implied elasticities.[13]

Table 10: Elasticity of model predictions w.r.t. increase in distance (25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
average withdrawal amount	-0.65	-4.00	-0.06	0.03	0.47	0.94
expected withdrawal frequency	-1.42	-4.00	-3.10	-0.64	-0.33	-0.11
average cash holding	-0.49	-4.00	-0.19	-0.01	0.39	0.85
average cash use	-1.19	-4.00	-2.82	-0.28	-0.06	-0.01
expected payoff per period	-0.17	-0.42	-0.09	-0.01	-0.00	-0.00
Observations	3424					

(b) Cash users (post increase)	mean	p10	p25	p50	p75	p90
average withdrawal amount	0.43	-0.00	0.01	0.20	0.60	1.14
expected withdrawal frequency	-0.59	-1.12	-0.75	-0.49	-0.24	-0.09
average cash holding	0.23	-0.21	-0.07	0.01	0.52	0.97
average cash use	-0.29	-0.62	-0.39	-0.14	-0.04	-0.01
expected payoff per period	-0.08	-0.29	-0.04	-0.01	-0.00	-0.00
Observations	2592					

(c) Cash non-users (post increase)	mean	p10	p25	p50	p75	p90
expected payoff per period	-0.44	-1.29	-0.33	-0.06	-0.00	-0.00
Observations	832					

Table 10 reports the elasticities both for the entire consumer sample and then separately for consumers who continue to use cash following the counterfactual worsening of the access-to-cash infrastructure and consumers who no longer use cash. There are several takeaways. The average impact is much more sizeable on consumers' withdrawal frequency and cash use

[12] See, e.g., Journal de Québec (2022), CBC News (2024), CTV News (2016).

[13] For each outcome x with the counterfactual outcome x', we compute the elasticity defined as $\frac{x'-x}{x}/\frac{1.25d_i-d_i}{d_i} = 4\frac{x'-x}{x}$. This directly implies for consumers who stop using cash—$x' = 0$ for all but the expected value function—that the reported elasticity will be equal to -4. Appendix B.8 contains elasticities implied by smaller perturbations, where the maximal elasticity can naturally be larger.

than on consumers' average holding and withdrawal levels (see the first and fourth column in all panels for the average and median effects). Overall, this translates into a relatively minor effect on consumers in terms of their welfare (bottom row of Panel a).

By considering the full distribution of elasticities (columns 2 to 9), we are able to draw several important conclusions. First, the distribution confirms the bi-modality in the response behavior by consumers. Some consumers respond to a higher cost of withdrawing cash—which the increase in the distance corresponds to—by substituting away from cash for use at the point of sale and withdrawing less frequently and lower amounts, which leads to substantially lower cash holdings. In contrast, the second group of consumers only marginally adjusts their cash use at the point of sale. These consumers also adjust their withdrawal behavior, however, and respond to the increased withdrawal cost by withdrawing more cash less often, which also leads to a higher average cash holding. The overall modest negative impact in terms of the welfare of consumers is concentrated among less than a quarter of consumers.

These findings are reaffirmed when decomposing the analysis into the extensive and intensive margins. Consumers who continue to use cash (Panel b) indeed use less cash and withdraw less frequently. However, almost all of these consumers increase the withdrawal amount. While the median consumer barely adjusts their holdings, cash holdings on average increase. More generally, the welfare impact is even more muted for continued cash users. This is in sharp contrast to the consumers who decide not to use cash following the increased cost of withdrawals: about 24.3% (832/3424) of consumers fall into this group and exhibit a much more sizable reduction in welfare.

Welfare impact To further analyze this, we look not at the elasticity but at the absolute impact of a 25% increase in the cost to withdraw cash. We illustrate this using two approaches. First, we focus on the distribution of the percentage reduction in consumers' expected payoff, both across their response to the worsening infrastructure and by demographic group. These results are depicted in Table 11. Second, we translate this by considering the compensating variation required to keep consumers indifferent. Specifically, we express the payoff reduction as the share of withdrawals these consumers would have made at the original distance that would need to be free—i.e., where no utility penalty is incurred—to compensate them for the worsening infrastructure. Results are shown in Table 12.[14]

[14] We use the withdrawals at the original distance as almost a quarter of consumers no longer use cash following the deterioration. Appendix B.9 shows the absolute number of withdrawals instead of the share.

Table 11: Reduction in consumers' expected payoff in % (25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
Overall	4.13	0.03	0.09	0.25	2.30	10.43
Cash non-users	10.93	0.01	0.04	1.57	8.20	32.14
Cash users	1.95	0.04	0.09	0.20	0.94	7.25
Cash users with decreased holdings	2.23	0.04	0.08	0.21	1.19	8.90
Cash users with increased holdings	1.69	0.04	0.09	0.20	0.81	6.63
Young & Low Income	4.50	0.02	0.08	0.29	3.17	12.84
Young & Med. Income	4.40	0.03	0.08	0.27	2.99	11.14
Young & High Income	3.85	0.03	0.07	0.19	1.80	10.56
Old & Low Income	4.26	0.04	0.09	0.24	1.85	10.17
Old & Med. Income	2.85	0.03	0.09	0.23	1.62	7.35
Old & High Income	3.81	0.06	0.10	0.25	1.39	9.13
Observations	3424					

Table 12: Compensating variation in terms of share of withdrawals (25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
Overall	0.32	0.14	0.20	0.23	0.26	0.63
Cash non-users	0.60	0.03	0.06	0.54	0.75	1.16
Cash users	0.24	0.18	0.21	0.23	0.25	0.26
Cash users with decreased holdings	0.27	0.22	0.23	0.24	0.25	0.30
Cash users with increased holdings	0.21	0.17	0.19	0.21	0.23	0.25
Young & Low Income	0.37	0.10	0.20	0.24	0.33	0.70
Young & Med. Income	0.37	0.09	0.20	0.24	0.40	0.74
Young & High Income	0.28	0.13	0.20	0.23	0.25	0.57
Old & Low Income	0.30	0.16	0.21	0.23	0.25	0.56
Old & Med. Income	0.29	0.16	0.20	0.23	0.25	0.55
Old & High Income	0.25	0.17	0.21	0.23	0.24	0.29
Observations	3424					

The key takeaway is that the negative welfare impact is concentrated on consumers who stop using cash following the deteriorating infrastructure. On average, their expected payoff reduces by 10.93%, compared to a 4.13% reduction across the consumer sample and 1.95% reduction for continued cash users. This is a sizable reduction as it corresponds to 60% of withdrawals made under the factual infrastructure being required to be free in order to compensate them. Additionally, the decomposition by demographic group reveals that younger and lower-income consumers are comparatively more heavily affected.

Relationship to demographics To further investigate which demographic types of consumers are affected in which fashion, we assess both consumers' preferences and demographics as a function of the response behavior in Table 13. Table 13 depicts the average parameter estimates, averages for the demographic variables, and shares of the four main demographic

Table 13: Estimates and demographics by response to 25% increase in distance

Variable	**Cash non-users**	**Cash users**		
		all	decreased holdings	increased holdings
	(1)	(2)	(3)	(4)
Cash elasticity α	0.351	0.376	0.321	0.426
Cash holding cost γ	0.011	0.003	0.003	0.002
Withdrawal cost parameter F	2.306	1.107	1.151	1.067
Age	43.775	49.716	48.228	51.069
Income	46558.363	47980.695	46094.891	49694.178
Revolver	0.254	0.190	0.200	0.180
Urban	0.841	0.850	0.846	0.853
Young & Low Income	0.337	0.248	0.269	0.230
Young & Med. Income	0.219	0.147	0.161	0.135
Young & High Income	0.053	0.054	0.059	0.050
Old & Low Income	0.261	0.375	0.370	0.379
Old & Med. Income	0.107	0.133	0.111	0.154
Old & High Income	0.024	0.041	0.029	0.052
Observations	832	2592	1234	1358

groups by age and income by the consumer responses to a 25% increase in the distance to the access-to-cash infrastructure. Column (1) contains information for consumers who stop using cash following the increase, while columns (2) to (4) contain information for consumers who continue to use cash. The latter separately reports averages for all consumers in column (2), consumers who continue to use cash but decrease their cash holdings in column (3), and consumers who continue to use cash and increase their cash holdings in column (4).

The analysis reveals a striking pattern. First, there are no substantial differences in the intrinsic preferences for using cash between continued cash users and those who stop using cash. However, among continued cash users, it is those with a higher preference for the utilization of cash who increase their holdings. Second, continued cash users have significantly lower costs of holding cash as well as individual withdrawal costs. This suggests that heterogeneous consumer costs play an important role in determining the extensive margin response to changes in the access to cash infrastructure. At the same time, costs appear to play a limited role for the intensive margin response conditional on consumers continuing to use cash at the point of sale.

Third, consumers who continue to use cash tend to be older and more affluent, as evidenced by their higher age, income, and lower share of revolvers. However, continued cash users who decrease their holdings only exhibit a moderately different income or revolver shares than those who stop using cash. However, the analysis reveals that age is the predominant factor as older and lower-income consumers tend to continue to use cash.

Summary Overall, we find that accounting for consumer heterogeneity by estimating the model for broad demographic groups understates the heterogeneous impact of changes in the access to cash infrastructure even within these groups. The identified moderate average welfare effects thus do not paint the full picture. Instead, the analysis reveals two types of responses as access to cash becomes more cumbersome. Consumers either reduce the use of cash and withdrawals and potentially stop using cash entirely, or alternatively economize on withdrawals by increasing their cash holdings. This bi-modality in response behavior is important, particularly in light of the ongoing reduction in the number of bank branches in Canada and the concentrated impact on subgroups of consumers.

Specifically, we find that the most heavily affected consumers are those whose extensive margin response to a worsening infrastructure is to stop using cash. This consumer group in turn tends to be younger and less affluent and more likely to hold a revolving credit card balance. Importantly, their response is not driven by their intrinsic preference for cash use but instead by higher idiosyncratic cash holding costs and opportunity costs of withdrawal. This is potentially problematic from a public policy perspective as these consumers do not necessarily want to substitute away from cash but only do so because it becomes prohibitively costly.

5 Extensions

5.1 Discount factor β as a parameter

Our estimation uses 12 (4 moments x 3 instruments) moment conditions to estimate three underlying parameters. One avenue of extension is therefore to not assume a given fixed level of consumer discounting β but instead to treat β as a parameter to be estimated. This is motivated by and similar to Fulford and Schuh (2017), who find evidence for heterogeneous preferences when analyzing credit card utilization and consumption over the life and business cycle.

Towards this, it is important to note the role of the discount factor β in our theoretical model. As the consumer knows the realization of the random total expenditure innovation ϵ_{it} prior to making her withdrawal and cash usage decision, β reflects the forward-lookingness of consumers and how much they value potential future benefits (in the form of optimal cash holdings) relative to maximizing their flow utility. At the same time, it in part captures consumers' attitude towards risk given the inherent uncertainty in future outcomes.

Identification Identification of β obtains because it directly affects the value of precautionary cash holdings, which are one of the moments we target in our estimation. All else given, a higher β_i implies that a given consumer values precautionary cash holdings more than a consumer with a lower β_j, who discounts the future more heavily. Because the cost of holding cash, γ_i, is incurred immediately and negatively impacts consumer utility, the model associates more patient consumers with on average larger cash holdings.

Estimation For the representative approach, we use the regular two-step GMM approach, which yields the optimal weighting matrix endogenously. For the heterogeneous approach, we extend the candidate parameter tuples by considering 13 discrete values for $\beta \in \{0, 0.1, \ldots, 0.9, 1\} \cap \{0.05, 0.950652901\}$; that is, we consider evenly spaced grid points as well as the original $\beta \approx 0.95$ and its counterpart 0.05.[15]

[15]While $\beta = 1$ may violate certain technical conditions in an infinite horizon setup, we approximate consumer decisions via a finite horizon problem solved by backward induction in our implementation. This allows the use of such a high value as an upper bound on the consumer time preference parameter value.

When weighting the individual moments, we continue to use the optimal two-stage weighting matrix from the representative approach *with a fixed discount factor*. This setup ensures that estimates are comparable and that treating β as a parameter to be estimated strictly improves the model fit.

Estimation We here focus on results obtained from the heterogeneous approach and relegate results derived from the representative approach to Appendix C.1. In Table 14, we summarize the results by sample wave.

Table 14: Heterogeneous consumers: estimation results by year

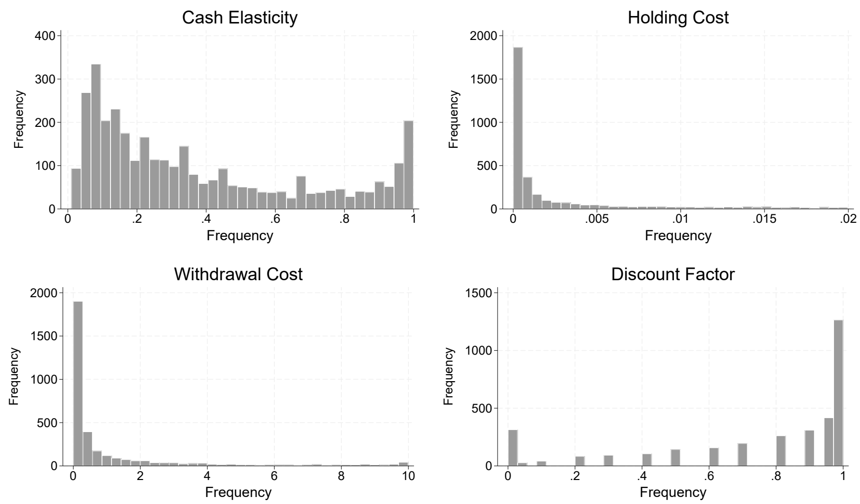
Parameter	(1) Overall	(2) 2009	(3) 2013	(4) 2017
Preference for cash, α				
Mean	0.376	0.379	0.372	0.377
Median	0.268	0.269	0.269	0.251
S.d.	0.307	0.305	0.303	0.315
Holding cost, γ				
Mean	0.0027	0.0028	0.0028	0.0026
Median	0.0005	0.0005	0.0004	0.0004
S.d.	0.0047	0.0046	0.0047	0.0047
Withdrawal cost, F				
Mean	1.220	1.056	1.210	1.388
Median	0.220	0.182	0.223	0.264
S.d.	2.239	2.079	2.237	2.371
Discount factor, β				
Mean	0.744	0.757	0.730	0.751
Median	0.900	0.900	0.900	0.900
S.d.	0.334	0.322	0.345	0.331
Average daily cash use	15.62	16.60	16.55	13.44
Average cash withdrawal	164.96	162.02	161.40	172.51
Probability of withdrawal	0.10	0.11	0.11	0.08
Average cash holding	52.72	51.05	52.76	54.23
N-obs.	3424	973	1,408	1,043

Notes: Results are obtained from matching each consumer to the parameter value which minimizes the weighted squared distance between the predicted moments and those observed in the data. Specification (1) reports averages, median, and standard deviation for each parameter across all years. Specifications (2), (3), and (4) report the same for individual waves. Moments for matching are obtained by interacting 4 errors with 3 instrumental variables. The weighting matrix is the optimal 2-step weighting matrix from the representative approach with β fixed to 0.9506529.

There are two key takeaways. First, the key patterns from the main specification carry over: the median preference for cash and individual holding cost decline over time, while the idiosyncratic withdrawal cost increases. Second, the median discount factor is high at 0.9, and there is no discernible pattern as to how the level of consumer patience evolves over time. This is in marked contrast to the representative approach, which estimates a low

β of 0.486; see Appendix C.1. Third, the additional model flexibility leads to an intuitive finding in terms of the level of the parameter estimates for the individual holding cost γ, which decline markedly. While the model with the fixed β attributed limited cash holdings to a high individual holding cost, the flexible model is able to distinguish between said high holding cost and limited patience as driving forces. We document the heterogeneity of the estimates in Figure 4.

Figure 4: Distribution of parameter estimates including β, full sample



Relationship to Demographics In terms of demographics, patterns derived from the main specification are reaffirmed. When decomposing the results by demographic groups, we find that older and less affluent consumers display a higher preference for cash. Older consumers also have a lower idiosyncratic withdrawal and holding costs than younger consumers. Detailed results are reported in Appendix C.2.

Counterfactual response to infrastructure changes The key result is that, even when accounting for heterogeneity in consumers' discount factors, the main takeaways of our analysis carry over. Specifically, we continue to find a bi-modality in consumer responses to a worsening cash infrastructure and relationship to consumer demographics. The detailed counterfactual analysis can be found in Appendix C.3. Comparing the results with those using the main specification in Section 4, it is notable that the intrinsic cash preference of consumers who stop using cash in response to the increased withdrawal cost is even larger.

5.2 Other extensions

Robustness Our results are robust to perturbations in consumers' planning horizon when numerically approximating the value function for a given parameter tuple. This numerical solution also relies on interpolation from a finite set of discrete points but is robust to the use of finer grids. Results are also robust to alternative definitions—both in terms of number and scope—of consumer spending types.

Deposits We can extend the baseline version of the model to allow consumers to deposit cash as well as withdraw it. This extension is conceptually straightforward as the per-period behavior by consumers remains uniquely defined for any given target change in cash inventories; see Appendix A.3. However, consumers would never have an incentive to deposit cash on the equilibrium path unless there are random shocks to their cash inventories. Incorporating deposits is an interesting avenue for future work but therefore contingent on obtaining additional data, e.g., about cash gifts during seasonal holidays.

Withdrawal Costs In the baseline version of the model, we assume that consumers withdraw cash at a cost which is proportional to the distance to the bank branch network. In reality, consumers may often withdraw cash while commuting to work or shopping. This type of behavior has been incorporated into the literature in various ways. For example, Alvarez and Lippi (2017) allow consumers to face free withdrawal opportunities with some positive probability, while Chen et al. (2021) explicitly classify consumers into groups who do and do not incur free/low-cost withdrawal opportunities.

Within our framework, there are natural extensions which allow for a non-deterministic withdrawal cost. The first follows Alvarez and Lippi (2017) by allowing for free withdrawal opportunities, where a consumer receives an opportunity to withdraw cash at no cost with probability p^f. This augments the set of parameters to be estimated by the parameter p^f. The second alternative assumes that consumers face stochastic withdrawal costs. In particular, we can allow consumers to face withdrawal costs given by

$$C^w_{it} = F \times d_{it}, \quad d_{it} = \max\left\{\underline{d},\ d_i + \nu_{it}\right\}, \quad \nu_{it} \overset{iid}{\sim} N\left(0, \sigma_d^2\right),$$

where the level of truncation (currently mass-point) $\underline{d}$ determines the lowest attainable withdrawal cost and where ν_{it} is a random innovation to the consumer-specific average withdrawal cost. In estimation, we define $\underline{d}$ to be either zero (representing a free withdrawal opportunity) or the smallest distance in the sample.

There are additional considerations which warrant different specifications of withdrawal costs experienced by consumers. Chen et al. (2021) document a discontinuity in consumers' withdrawal behavior around a distance of 1.6 km to the nearest branch of their affiliated institution. We can account for this, e.g., by allowing for a non-linear effect of the FSA-specific distance measure. Doing so is particularly interesting for future work that is able to leverage better data on consumer locations or travel behavior.

6 Conclusion

We propose and estimate a structural model of dynamic cash inventory management that accounts for payment choice when making transactions at the point of sale. For estimation, we leverage detailed diary and survey data from three waves of the Method of Payments (MOP) survey of Canadian consumers conducted in 2009, 2013, and 2017.

Our key findings are twofold. First, accounting for individual-level consumer heterogeneity is crucial for matching the data and assessing counterfactual responses by consumers to changes in the access-to-cash infrastructure. While average responses are muted, the underlying individual consumer responses exhibit a bi-modality. As access to cash becomes more cumbersome, only some consumers substantially reduce—or altogether avoid—using cash to pay for transactions at the point of sale. The remainder only moderately reduce their use of cash and facilitate this by withdrawing and holding larger amounts of cash.

The second main finding relates to the welfare impact of these changes. We show that the negative impact in terms of consumer surplus is concentrated on those consumers who display an extensive margin response and stop using cash at the point of sale. Importantly, this response is triggered not due to an intrinsically lower preference for the use of cash but because these consumers tend to have higher cash holding and withdrawal costs. Demographically, these consumers are predominantly younger, less affluent, and more likely to carry a revolving credit card balance. Given ongoing programs by Canadian banks to consolidate the number of bank branches, our findings have important implications for the accessibility of cash for the Canadian populace.

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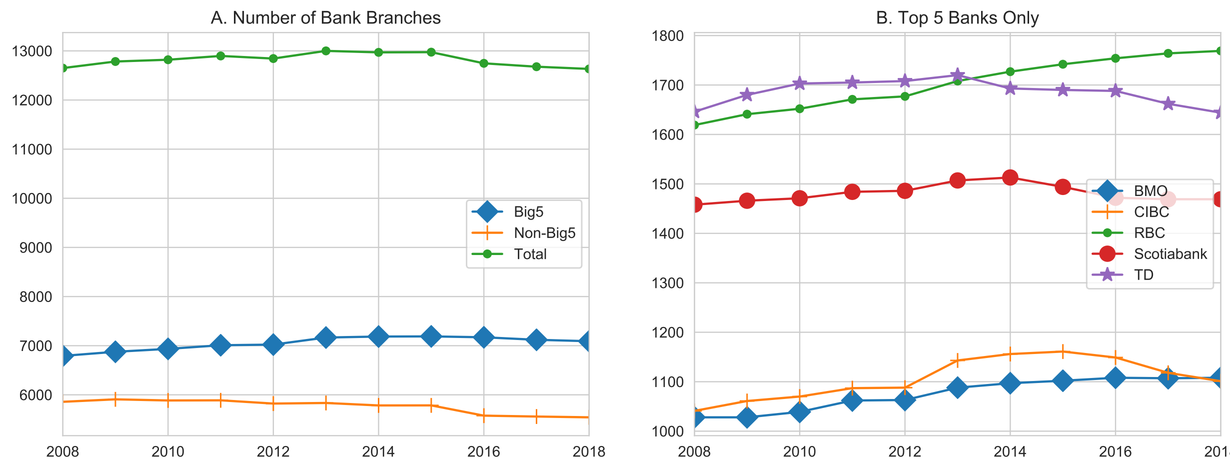
A Appendix

A.1 Evolution of Access-to-Cash Infrastructure

Evolution of Bank Branches Figure 5.A plots the number of bank branches over time. Compared with the automated banking machines, bank networks are much smaller, with approximately 13,000 branches in 2018. The total number of bank branches increases steadily and peaks in 2013 before slowly decreasing. We also plot the trend of Big Five vs. non–Big Five branches.[16] This reveals that the closure of bank branches in the past few years is concentrated on non–Big Five banks. Finally, we plot the trends for each of the Big Five banks individually in Figure 5, which reveals heterogeneity across the Big Five: while RBC and BMO have steadily expanded the number of branches, TD, RBC, and Scotiabank have seen a reduction in recent years.

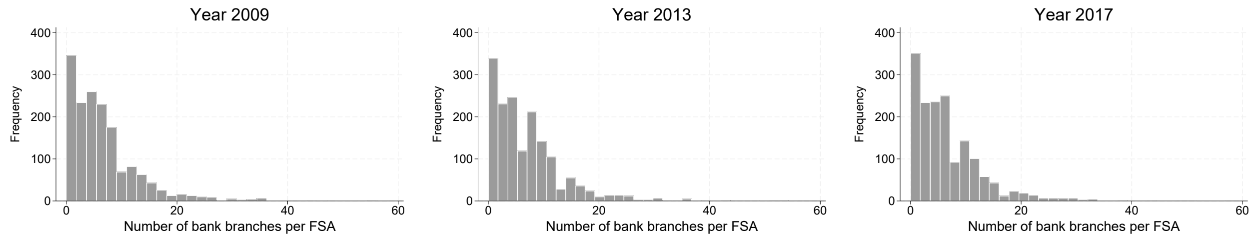
Figure 5: Number of Bank Branches



The dynamics of the bank branch distribution across forward sortation areas (FSAs) for the consumers in our sample is illustrated in Figure 6, where the unit of observation is the branch count in an FSA and the sample are the 1148 FSAs from which we observe at least one consumer in at least one of the three survey waves. In line with the peak of the number of branches in 2013, the average number of branches across the sample was largest in that wave (8.39, compared to 8.25 in 2009 and 8.09 in 2017).

[16]Big Five is the name colloquially given to the five largest banks that dominate the banking industry of Canada: Bank of Montreal (BMO), Bank of Nova Scotia (Scotiabank), Canadian Imperial Bank of Commerce (CIBC), Royal Bank of Canada (RBC), and TD Canada Trust (TD; formerly Toronto-Dominion Bank).

Figure 6: Dynamics of bank branch distribution across FSAs.



A.2 Proof of Lemma 1

Proof. For ease of exposition, we omit subscripts and denote $s = s_{it}$. The unconstrained solution to $\max_c\{\alpha \ln(1+c) + (1-\alpha)\ln(1+s-c)\}$ is given by $\hat{c} = (2+s)\alpha - 1$. However, we need to account for the bounds that cash usage is restricted to be nonnegative ($\hat{c} \geq 0 \iff s \geq \frac{1}{\alpha} - 2$) and capped by the total expenditure s ($\hat{c} \leq s \iff s \geq \frac{2\alpha-1}{1-\alpha}$). Defining $\tilde{c}$ as in the Lemma to be the resulting optimal cash usage absent inventory concerns, it follows directly that for any $\Delta h \leq -\tilde{c}$, the optimal (c^*, w^*) is given by $(-\Delta h, 0)$.

- For $\Delta h = -\tilde{c}$, this is clear because $c = \tilde{c}$ implies $w = 0$.
- For $\Delta h < -\tilde{c}$, we can rule out any solution that is not $(-\Delta h, 0)$. If there were such a candidate solution $(\hat{c}, \hat{w})$, it would involve $\hat{c} > -\Delta h > \tilde{c}$ and $\hat{w} > 0$. By virtue of $\tilde{c}$ being the unique maximizer of the unconstrained problem, we know that $\alpha\ln(1-\Delta h) + (1-\alpha)\ln(1+s+\Delta h) > \alpha\ln(1+\hat{c}) + (1-\alpha)\ln(1+s-\hat{c})$. But this directly implies that $\hat{u}(\hat{c},\hat{w}) = \alpha\ln(1+\hat{c}) + (1-\alpha)\ln(1+s-\hat{c}) - F\ln(1+d_{it}) < \alpha\ln(1-\Delta h) + (1-\alpha)\ln(1+s+\Delta h) = \hat{u}(-\Delta h, 0)$.

For $\Delta h > 0$, $w > 0$ is necessary due to $c \geq 0$. But that implies that the withdrawal cost is incurred irrespective of the choice of c and hence that the consumer will choose $c = \tilde{c}$ which implies $w = \tilde{c} + \Delta h$.

This leaves the region $\Delta h \in (-\tilde{c}, 0]$. Given that $\tilde{c}$ is the unique solution to the problem absent inventory concerns, any positive withdrawal amount would be associated with $c = \tilde{c}$. We therefore need to compare two policies. Either the consumer chooses the optimal cash usage level $c = \tilde{c}$ and incurs the withdrawal cost, $(c_1, w_1) = (\tilde{c}, \tilde{c} + \Delta h)$, or she adjusts her cash usage to avoid the costly withdrawal, $(c_2, w_2) = (-\Delta h, 0)$. Given the associated utilities

$$u_w = \alpha\ln[1+\tilde{c}] + (1-\alpha)\ln[1+s-\tilde{c}] - F\ln(1+d) \tag{22}$$
$$u_n = \alpha\ln(1-\Delta h) + (1-\alpha)\ln(1+s+\Delta h), \tag{23}$$

we obtain that she prefers to withdraw if and only if $u_w > u_n$ which is equivalent to

$$F\ln(1+d) < \alpha\ln[1+\tilde{c}] + (1-\alpha)\ln[1+s-\tilde{c}] - \alpha\ln[1-\Delta h] - (1-\alpha)\ln[1+s_{it}+\Delta h]\,. \tag{24}$$

This implicitly defines $\bar{d}$ and collecting these results yields the Lemma. ■

A.3 Appendix: Model with Deposit Option

Lemma 2 *For a given* $(h_{it-1}, \epsilon_{it})$ *and a target* h_{it} *which translates into* $\Delta h = h_{it} - h_{it-1}$*, and which satisfies* $\Delta h \geq -h_{it-1}$*, there is a unique* (c^*, w^*) *which solves*

$$\max_{(c,w)}\{\alpha \ln(1+c) + (1-\alpha)\ln(1+s_i+\epsilon_{it}-c) - F \times \mathbb{1}_{w>0}\ln(1+d_{it})\} \quad s.t. \quad s_{it} \geq c \geq 0 \qquad (25)$$
$$w - c = \Delta h.$$

Denoting $\tilde{c} = \min\{\max\{(2+s_{it})\alpha - 1, 0\}, s_{it}\}$ *the desired level of cash usage absent inventory constraints and* $\bar{d}(\tilde{c}, \Delta h)$ *the solution to*

$$F \ln\left[1+\bar{d}\right] = \alpha \ln[1+\tilde{c}] + (1-\alpha)\ln[1+s_{it}-\tilde{c}] - \alpha \ln[1-\Delta h] - (1-\alpha)\ln[1+s_{it}+\Delta h], \qquad (26)$$

which is relevant and well-behaved only for $\Delta h \in [-s_{it}, 0]$*, we obtain*

$$(c^*, w^*) = \begin{cases} (\tilde{c}, \Delta h + \tilde{c}) & \text{if} \quad -h_{it-1} \leq \Delta h < -s_{it} \wedge h_{it-1} > s_{it} \\ (-\Delta h, 0) & \text{if} \quad \Delta h \in [\max\{-h_{it-1}, -s_{it}\}, 0] \wedge d_{it} \geq \bar{d} \\ (\tilde{c}, \Delta h + \tilde{c}) & \text{if} \quad \Delta h \in [\max\{-h_{it-1}, -s_{it}\}, 0] \wedge d_{it} < \bar{d} \\ (\tilde{c}, \Delta h + \tilde{c}) & \text{if} \quad \Delta h > 0 \end{cases}. \qquad (27)$$

Proof. The proof is analogous to the one for Lemma 1. ∎

B Additional Estimation Results and Illustrations

B.1 Representative 2-Step Estimation

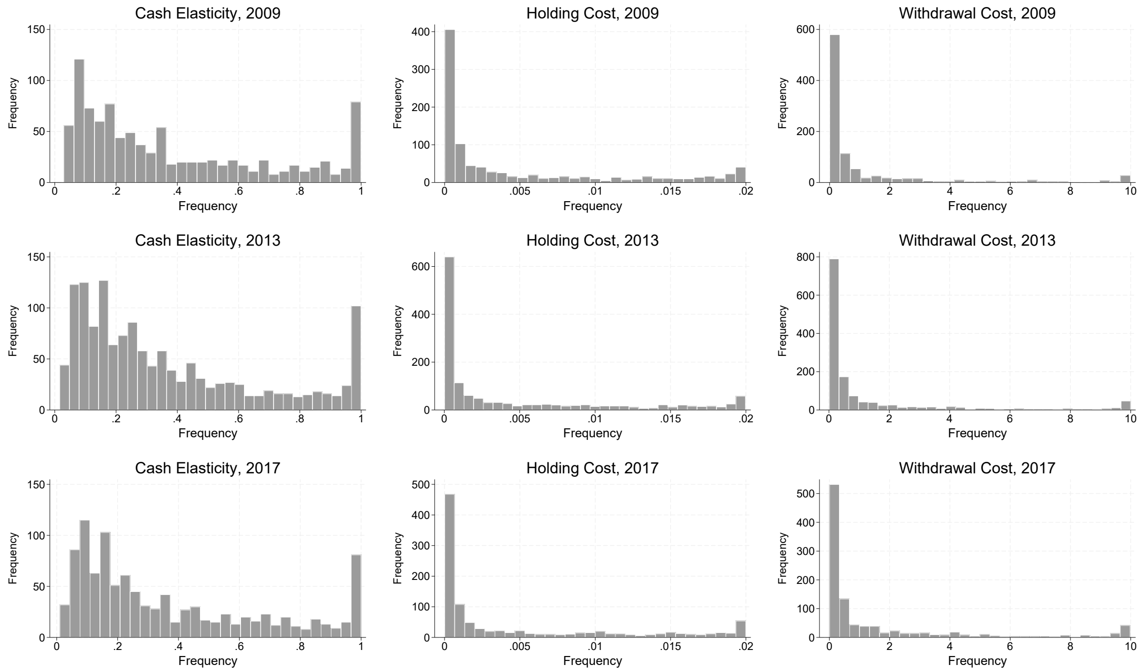
Table 15: Representative consumer: first and second (optimal) gmm, 3,424 obs.

Parameter	Starting	First stage	Second stage
Preference for cash, α	0.149	0.185	0.189
(s.e.)		(0.0004)	(0.002)
Holding cost, γ	0.0003	0.0004	0.0004
(s.e.)		(0.00001)	(0.00002)
Withdrawal cost, F	0.167	0.203	0.204
(s.e.)		(0.003)	(0.007)
Expected cash use			14.15
Expected withdrawal level			147.04
Probability of withdrawal			0.11
Expected holding level			56.26

Notes: Starting values are obtained by grid search. Moments for estimation are obtained by interacting 4 errors with 3 instrumental variables.

B.2 Distributions of Estimated Parameters by Wave

Figure 7: Estimated parameters (α, γ, F) per wave.



B.3 Estimation and Model Fit by Demographic Group

We begin by dividing consumers into six demographic groups along the two dimensions of age and income. Specifically, we classify consumers into *young* and *old* based on the sample average age and into three income brackets corresponding to the ones used by Statistics Canada. Specifically, we consider "Low Income (LI)" consumers to be those earning weakly less than CAD 45,000 per year, "Medium Income (MI)" consumers to be those earning between CAD 45,000 and 85,000, and "High Income (HI)" consumers those earning more than CAD 85,000. Table 16 reports the results from estimating the model using the representative consumer approach by imposing that parameters are identical at the type level (but constant across the 3 waves).

Table 16: Representative consumer: by demographic type, second (optimal) gmm

Parameter	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI
Preference for cash, α	0.201	0.186	0.167	0.207	0.162	0.173
(s.e.)	(0.007)	(0.009)	(0.008)	(0.002)	(0.007)	(0.001)
Holding cost, γ	0.00060	0.00058	0.00029	0.00030	0.00022	0.00033
(s.e.)	(0.00002)	(0.00008)	(0.00001)	(0.00002)	(0.00002)	(0.00002)
Withdrawal cost, F	0.305	0.352	0.121	0.127	0.116	0.149
(s.e.)	(0.019)	(0.031)	(0.006)	(0.006)	(0.029)	(0.004)
Expected cash use	11.70	11.76	14.68	16.86	17.20	18.04
Expected withdrawal level	127.72	143.85	130.87	158.92	164.78	176.39
Probability of withdrawal	0.11	0.09	0.12	0.12	0.12	0.11
Expected holding level	46.90	51.53	51.89	64.53	66.19	67.30
N-obs.	924	564	185	1189	435	127

Notes: Starting values are taken from the representative consumer model. Moments for estimation are obtained by interacting 4 errors with 3 instrumental variables. The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as three income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

There are three main takeaways. First, being younger and less affluent is associated with a higher preference for using cash, but only older consumers actually use more cash. This is because a lower income reduces overall expenditures. Second, older consumers have lower withdrawal and holding costs, with the exception of the high-income group in the respective age brackets. This can be explained by a lower opportunity cost of time to make withdrawals (withdrawal cost) and a lower opportunity cost of holding cash instead of, e.g., investing it. Third, because older consumers use more cash than young consumers, it is important to account for this when considering the welfare impact of changes in the access to cash infrastructure.

However, it needs to be noted that the model fit by demographic group is still substantially poorer than that obtained from the heterogeneous approach. This can be seen by repeating the exercise from Table 5, i.e., by comparing the differences in the distributions between the data and the model-implied moments for each of the demographic groups. We report the results below. Additional comparisons (e.g., fit comparison by survey wave, or by survey wave and demographic groups) reveal comparable patterns and are not reported here for expositional purposes. They are available upon request.

Table 17: Model fit (data vs prediction) data, prediction, differences, type Young&LI

	p10	p25	p50	p75	p90
			Data		
Cash Use	1.42	2.83	6.67	14.16	28.32
Withdrawal Level	21.24	42.48	84.95	136.78	294.00
Withdrawal Frequency	0.03	0.03	0.07	0.13	0.20
Average Holding	2.00	11.40	28.84	63.71	113.99
			Representative prediction		
Cash Use	2.11	4.67	8.53	14.65	23.56
Withdrawal Level	35.32	64.58	105.83	168.83	248.34
Withdrawal Frequency	0.03	0.04	0.08	0.13	0.19
Average Holding	12.55	26.26	42.49	64.22	87.54
			Heterogeneous prediction		
Cash Use	1.75	3.35	7.30	14.99	29.52
Withdrawal Level	33.27	50.24	94.49	172.09	294.99
Withdrawal Frequency	0.03	0.05	0.07	0.13	0.20
Average Holding	0.00	12.25	26.91	51.58	91.40
			Differences Data-Representative prediction		
Cash Use	-0.69	-1.84	-1.86	-0.49	4.76
Withdrawal Level	-14.08	-22.10	-20.88	-32.05	45.66
Withdrawal Frequency	0.00	-0.01	-0.01	0.00	0.01
Average Holding	-10.55	-14.86	-13.65	-0.51	26.45
			Differences Data-Heterogeneous prediction		
Cash Use	-0.33	-0.52	-0.63	-0.83	-1.20
Withdrawal Level	-12.03	-7.76	-9.54	-35.31	-0.99
Withdrawal Frequency	0.00	-0.02	0.00	0.00	0.00
Average Holding	2.00	-0.85	1.93	12.13	22.59
	p10	p25	p50	p75	p90

Table 18: Model fit (data vs prediction) data, prediction, differences, type Young&MI

	p10	p25	p50	p75	p90
			Data		
Cash Use	1.52	3.04	6.67	15.20	30.40
Withdrawal Level	22.80	45.59	100.00	200.00	284.96
Withdrawal Frequency	0.03	0.03	0.07	0.13	0.17
Average Holding	3.19	10.62	29.37	74.33	127.43
			Representative prediction		
Cash Use	1.93	4.73	9.09	15.30	25.34
Withdrawal Level	40.32	77.10	127.88	189.45	263.96
Withdrawal Frequency	0.03	0.04	0.07	0.11	0.17
Average Holding	14.70	31.03	50.69	67.80	90.32
			Heterogeneous prediction		
Cash Use	1.94	3.69	7.36	16.61	30.22
Withdrawal Level	38.26	58.09	104.19	196.60	291.30
Withdrawal Frequency	0.03	0.05	0.07	0.12	0.17
Average Holding	0.00	12.81	27.13	59.84	108.65
			Differences Data-Representative prediction		
Cash Use	-0.41	-1.69	-2.42	-0.10	5.06
Withdrawal Level	-17.52	-31.51	-27.88	10.55	21.00
Withdrawal Frequency	0.00	-0.01	0.00	0.02	0.00
Average Holding	-11.51	-20.41	-21.32	6.53	37.11
			Differences Data-Heterogeneous prediction		
Cash Use	-0.42	-0.65	-0.69	-1.41	0.18
Withdrawal Level	-15.46	-12.50	-4.19	3.40	-6.34
Withdrawal Frequency	0.00	-0.02	0.00	0.01	0.00
Average Holding	3.19	-2.19	2.24	14.49	18.78
	p10	p25	p50	p75	p90

Table 19: Model fit (data vs prediction) data, prediction, differences, type Young&HI

	p10	p25	p50	p75	p90
		Data			
Cash Use	2.28	3.80	7.60	15.20	30.40
Withdrawal Level	45.59	45.59	91.19	136.78	227.97
Withdrawal Frequency	0.07	0.07	0.07	0.13	0.20
Average Holding	3.42	13.68	39.90	68.39	113.99
		Representative prediction			
Cash Use	2.92	5.21	10.51	18.29	29.12
Withdrawal Level	37.95	69.54	110.82	168.93	266.51
Withdrawal Frequency	0.04	0.06	0.09	0.14	0.20
Average Holding	15.75	29.07	46.42	66.59	100.48
		Heterogeneous prediction			
Cash Use	2.49	4.57	8.76	15.43	34.33
Withdrawal Level	37.95	56.81	107.84	166.53	270.98
Withdrawal Frequency	0.05	0.07	0.08	0.12	0.20
Average Holding	0.00	13.45	31.27	57.73	100.78
		Differences Data-Representative prediction			
Cash Use	-0.64	-1.41	-2.91	-3.09	1.28
Withdrawal Level	7.64	-23.95	-19.63	-32.15	-38.54
Withdrawal Frequency	0.03	0.01	-0.02	-0.01	0.00
Average Holding	-12.33	-15.39	-6.52	1.80	13.51
		Differences Data-Heterogeneous prediction			
Cash Use	-0.21	-0.77	-1.16	-0.23	-3.93
Withdrawal Level	7.64	-11.22	-16.65	-29.75	-43.01
Withdrawal Frequency	0.02	0.00	-0.01	0.01	0.00
Average Holding	3.42	0.23	8.63	10.66	13.21
	p10	p25	p50	p75	p90

Table 20: Model fit (data vs prediction) data, prediction, differences, type Old&LI

	p10	p25	p50	p75	p90
		Data			
Cash Use	2.12	4.56	10.00	21.24	38.00
Withdrawal Level	40.00	60.00	106.19	212.38	341.96
Withdrawal Frequency	0.03	0.07	0.07	0.13	0.20
Average Holding	10.00	25.00	56.28	113.99	192.00
		Representative prediction			
Cash Use	3.83	6.94	12.08	20.06	32.63
Withdrawal Level	50.02	83.07	137.86	205.88	298.18
Withdrawal Frequency	0.04	0.06	0.09	0.14	0.20
Average Holding	22.85	35.76	59.47	85.74	118.35
		Heterogeneous prediction			
Cash Use	2.87	5.94	11.64	23.45	38.51
Withdrawal Level	42.84	74.95	133.37	240.04	379.16
Withdrawal Frequency	0.03	0.06	0.08	0.13	0.20
Average Holding	7.70	22.22	43.81	87.47	142.16
		Differences Data-Representative prediction			
Cash Use	-1.71	-2.38	-2.08	1.18	5.37
Withdrawal Level	-10.02	-23.07	-31.67	6.50	43.78
Withdrawal Frequency	-0.01	0.01	-0.02	-0.01	0.00
Average Holding	-12.85	-10.76	-3.19	28.25	73.65
		Differences Data-Heterogeneous prediction			
Cash Use	-0.75	-1.38	-1.64	-2.21	-0.51
Withdrawal Level	-2.84	-14.95	-27.18	-27.66	-37.20
Withdrawal Frequency	0.00	0.01	-0.01	0.00	0.00
Average Holding	2.30	2.78	12.47	26.52	49.84
	p10	p25	p50	p75	p90

Table 21: Model fit (data vs prediction) data, prediction, differences, type Old&MI

	p10	p25	p50	p75	p90
			Data		
Cash Use	2.67	4.56	12.74	21.24	38.00
Withdrawal Level	42.48	68.39	113.99	212.38	350.00
Withdrawal Frequency	0.03	0.07	0.07	0.13	0.17
Average Holding	10.00	25.49	61.59	129.55	237.86
			Representative prediction		
Cash Use	3.48	6.55	11.60	21.51	38.74
Withdrawal Level	48.09	91.87	138.09	213.30	312.82
Withdrawal Frequency	0.04	0.05	0.08	0.13	0.21
Average Holding	20.75	38.74	59.20	86.46	118.92
			Heterogeneous prediction		
Cash Use	2.96	6.08	13.57	24.14	42.17
Withdrawal Level	48.97	88.40	147.48	256.05	421.34
Withdrawal Frequency	0.04	0.06	0.08	0.13	0.17
Average Holding	7.02	22.96	47.55	98.57	177.19
			Differences Data-Representative prediction		
Cash Use	-0.81	-1.99	1.14	-0.27	-0.74
Withdrawal Level	-5.61	-23.48	-24.10	-0.92	37.18
Withdrawal Frequency	-0.01	0.02	-0.01	0.00	-0.04
Average Holding	-10.75	-13.25	2.39	43.09	118.94
			Differences Data-Heterogeneous prediction		
Cash Use	-0.29	-1.52	-0.83	-2.90	-4.17
Withdrawal Level	-6.49	-20.01	-33.49	-43.67	-71.34
Withdrawal Frequency	-0.01	0.01	-0.01	0.00	0.00
Average Holding	2.98	2.53	14.04	30.98	60.67
	p10	p25	p50	p75	p90

Table 22: Model fit (data vs prediction) data, prediction, differences, type Old&HI

	p10	p25	p50	p75	p90
		Data			
Cash Use	4.56	7.60	15.20	30.40	45.59
Withdrawal Level	45.59	68.39	170.98	227.97	455.94
Withdrawal Frequency	0.07	0.07	0.10	0.13	0.20
Average Holding	17.10	22.80	79.79	142.48	227.97
		Representative prediction			
Cash Use	4.15	7.92	13.19	24.06	36.14
Withdrawal Level	69.25	95.67	145.35	227.49	332.08
Withdrawal Frequency	0.04	0.06	0.09	0.13	0.20
Average Holding	29.38	39.21	57.95	87.94	123.15
		Heterogeneous prediction			
Cash Use	5.77	8.82	16.16	31.09	46.01
Withdrawal Level	51.82	106.30	207.70	290.57	462.41
Withdrawal Frequency	0.05	0.07	0.09	0.13	0.22
Average Holding	8.39	24.72	59.97	107.73	183.17
		Differences Data-Representative prediction			
Cash Use	0.41	-0.32	2.01	6.34	9.45
Withdrawal Level	-23.66	-27.28	25.63	0.48	123.86
Withdrawal Frequency	0.03	0.01	0.01	0.00	0.00
Average Holding	-12.28	-16.41	21.84	54.54	104.82
		Differences Data-Heterogeneous prediction			
Cash Use	-1.21	-1.22	-0.96	-0.69	-0.42
Withdrawal Level	-6.23	-37.91	-36.72	-62.60	-6.47
Withdrawal Frequency	0.02	0.00	0.01	0.00	-0.02
Average Holding	8.71	-1.92	19.82	34.75	44.80
	p10	p25	p50	p75	p90

B.4 Heterogeneity by Group

Figure 8: Cash elasticity by consumer type

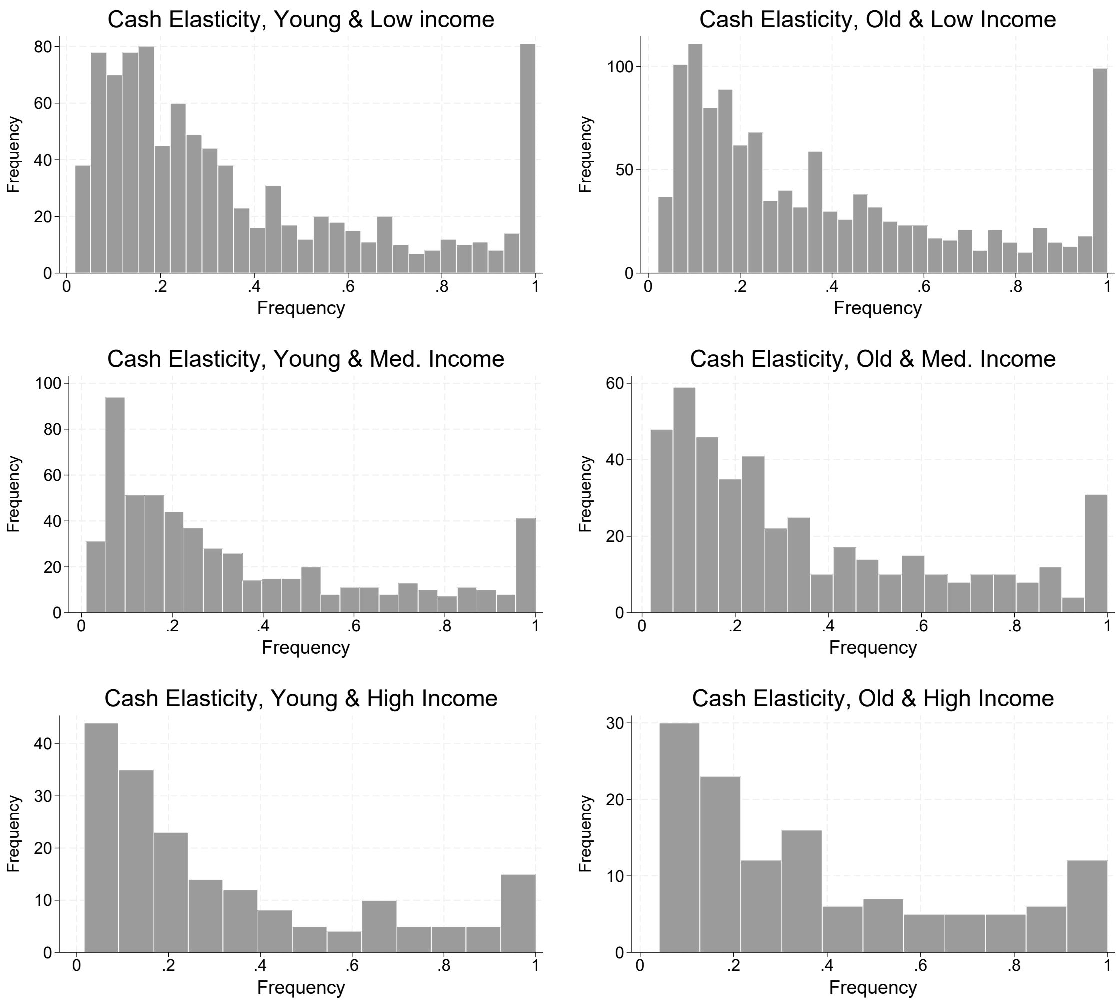


Figure 9: Holding cost by consumer type

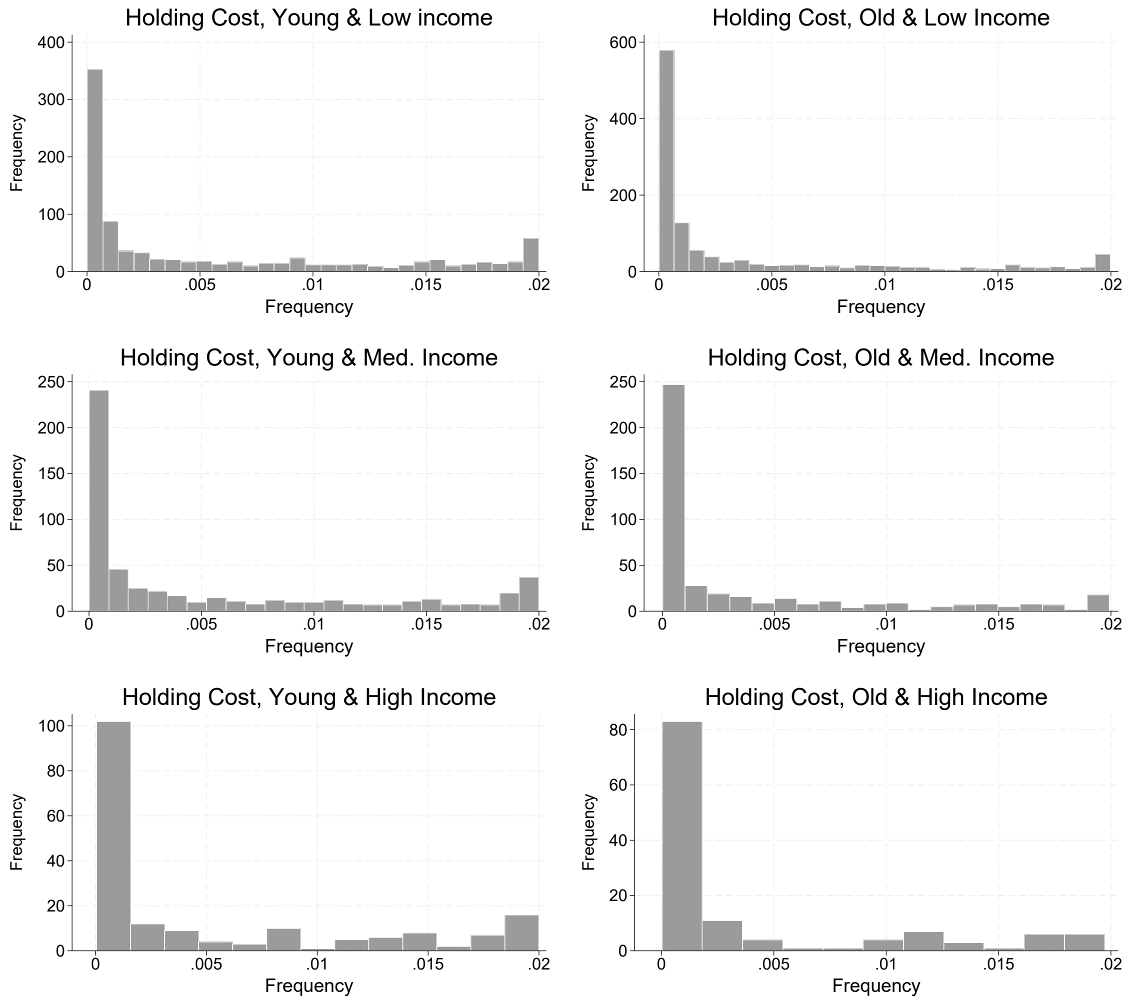
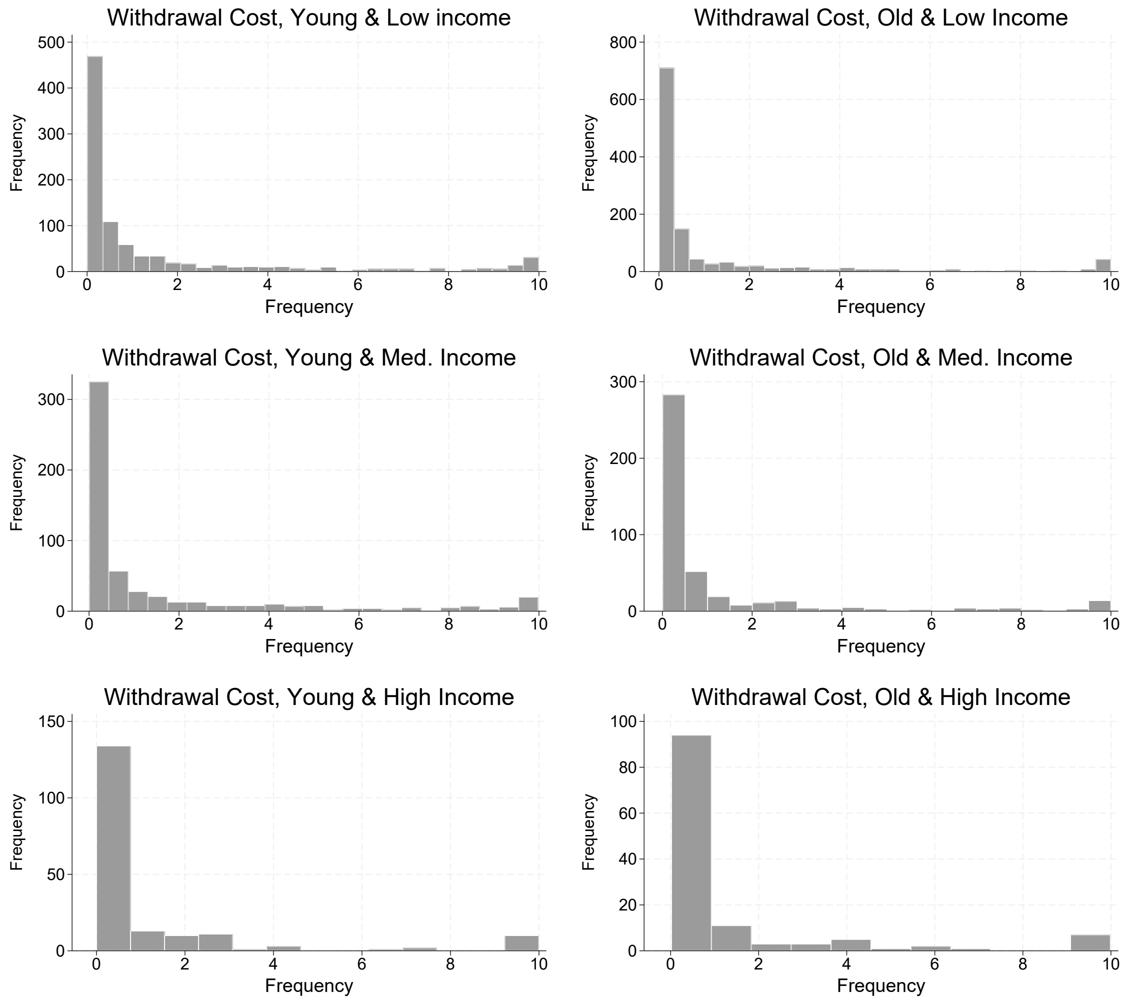


Figure 10: Withdrawal cost by consumer type



B.5 Evolution of Parameter Estimates by Type

Table 23: Evolution of parameter estimates by demographic type (p25 estimates)

(a) Cash elasticity, α								
2009	0.140	0.145	0.095	0.140	0.119	0.145	0.119	0.157
2013	0.145	0.115	0.016	0.148	0.115	0.087	0.133	0.135
2017	0.138	0.088	0.174	0.130	0.119	0.063	0.119	0.135

(b) Holding cost, γ								
2009	0.00046	0.00051	0.00033	0.00024	0.00033	0.00020	0.00029	0.00048
2013	0.00029	0.00026	0.00019	0.00024	0.00017	0.00004	0.00021	0.00049
2017	0.00029	0.00027	0.00020	0.00020	0.00017	0.00036	0.00020	0.00038

(c) Withdrawal cost, F								
2009	0.083	0.082	0.083	0.061	0.110	0.078	0.097	0.046
2013	0.097	0.114	0.045	0.092	0.097	0.061	0.118	0.046
2017	0.145	0.118	0.078	0.083	0.127	0.083	0.135	0.050

	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural
Observations	924	564	185	1189	435	127	2902	522

Notes: The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

Table 24: Evolution of parameter estimates by demographic type (p75 estimates)

(a) Cash elasticity, α								
2009	0.576	0.605	0.539	0.546	0.645	0.571	0.574	0.617
2013	0.528	0.448	0.188	0.574	0.485	0.720	0.520	0.606
2017	0.569	0.541	0.174	0.619	0.478	0.209	0.568	0.561

(b) Holding cost, γ								
2009	0.00939	0.01375	0.00879	0.00359	0.00758	0.00404	0.00770	0.00930
2013	0.01063	0.00866	0.00240	0.00588	0.00354	0.00081	0.00704	0.01058
2017	0.01038	0.00964	0.00020	0.00558	0.00511	0.01694	0.00864	0.00815

(c) Withdrawal cost, F								
2009	0.975	1.880	0.980	0.545	0.822	1.007	1.369	0.325
2013	1.525	1.031	0.360	0.931	0.777	0.119	1.424	0.476
2017	2.346	2.117	0.078	1.471	1.065	1.121	2.085	0.387

	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural
Observations	924	564	185	1189	435	127	2902	522

Notes: The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

B.6 Evaluation of factual infrastructure changes

Table 25: Impact of Infrastructure Changes on Cash Use and Cash Holdings (p25)

(a) Cash use by group (p25)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	4.430	3.061	3.288	4.401	5.795	5.889	8.554	4.249	5.532	5.209
2013	4.684	3.328	3.460	4.405	5.843	5.963	8.382	4.535	5.551	5.209
2017	4.555	3.063	3.611	4.681	5.639	5.659	8.503	4.426	5.162	3.630
Observations	3424	924	564	185	1189	435	127	2902	522	232

(b) Cash holdings by group (p25)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	15.816	11.319	12.305	13.208	21.928	23.037	24.797	15.388	19.178	17.487
2013	16.378	12.202	13.017	14.128	21.826	23.038	24.798	15.850	18.683	17.326
2017	15.730	11.777	12.493	13.785	21.764	22.504	24.250	15.467	18.005	14.907
Observations	3424	924	564	185	1189	435	127	2902	522	232

*The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually). *indicates that the distance measure capturing the access-to-cash infrastructure increased by more than 25% between 2013 and 2017.*

Table 26: Impact of Infrastructure Changes on Cash Use and Cash Holdings (p50)

(a) Cash use by group (p50)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	9.484	7.120	7.233	8.663	11.365	13.523	16.337	9.284	10.805	9.776
2013	9.668	7.299	7.313	9.343	11.421	13.514	16.929	9.429	10.815	9.806
2017	9.464	7.116	7.269	9.316	11.267	13.280	16.929	9.321	10.604	7.800
Observations	3424	924	564	185	1189	435	127	2902	522	232

(b) Cash holdings by group (p50)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	36.609	26.702	27.109	30.919	43.806	47.395	60.176	36.266	38.025	38.966
2013	36.809	26.990	27.109	30.734	43.275	47.823	60.510	36.601	38.025	37.721
2017	36.775	26.952	27.158	28.793	43.215	47.180	61.110	36.614	37.305	39.763
Observations	3424	924	564	185	1189	435	127	2902	522	232

*The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually). *indicates that the distance measure capturing the access-to-cash infrastructure increased by more than 25% between 2013 and 2017.*

Table 27: Impact of Infrastructure Changes on Cash Use & Cash Holdings (p75)

(a) Cash use by group (p75)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	20.248	14.912	16.063	15.502	23.163	23.615	30.573	19.873	22.478	21.162
2013	20.357	14.855	16.178	16.084	23.163	23.752	30.573	19.898	22.478	20.734
2017	20.182	14.669	16.260	15.329	23.150	23.887	30.568	19.598	22.478	19.279
Observations	3424	924	564	185	1189	435	127	2902	522	232

(b) Cash holdings by group (p75)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	71.583	51.626	59.555	57.515	87.585	98.760	107.331	70.898	75.389	65.940
2013	71.359	51.833	60.701	56.442	87.863	97.525	115.478	70.364	75.388	68.983
2017	71.372	51.730	60.000	58.323	88.342	97.010	117.775	70.577	75.888	72.303
Observations	3424	924	564	185	1189	435	127	2902	522	232

*The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually). *indicates that the distance measure capturing the access-to-cash infrastructure increased by more than 25% between 2013 and 2017.*

Table 28: Impact of Infrastructure Changes on Withdrawal Frequency

(a) Average withdrawal frequency by group

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	0.101	0.100	0.090	0.103	0.104	0.101	0.114	0.100	0.103	0.110
2013	0.102	0.101	0.092	0.114	0.105	0.101	0.114	0.102	0.103	0.110
2017	0.100	0.095	0.093	0.112	0.104	0.098	0.113	0.100	0.100	0.083
Observations	3424	924	564	185	1189	435	127	2902	522	232

(b) Withdrawal frequency by group (p25)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	0.053	0.047	0.043	0.063	0.055	0.055	0.065	0.053	0.055	0.058
2013	0.055	0.048	0.048	0.066	0.056	0.058	0.065	0.054	0.055	0.058
2017	0.052	0.045	0.046	0.065	0.054	0.057	0.063	0.053	0.052	0.040
Observations	3424	924	564	185	1189	435	127	2902	522	232

(c) Withdrawal frequency by group (median)

Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	0.074	0.071	0.068	0.076	0.079	0.075	0.080	0.074	0.078	0.078
2013	0.075	0.071	0.069	0.081	0.081	0.078	0.080	0.075	0.077	0.078
2017	0.074	0.070	0.070	0.080	0.078	0.075	0.083	0.074	0.073	0.064
Observations	3424	924	564	185	1189	435	127	2902	522	232

(d) Withdrawal frequency by group (p75)

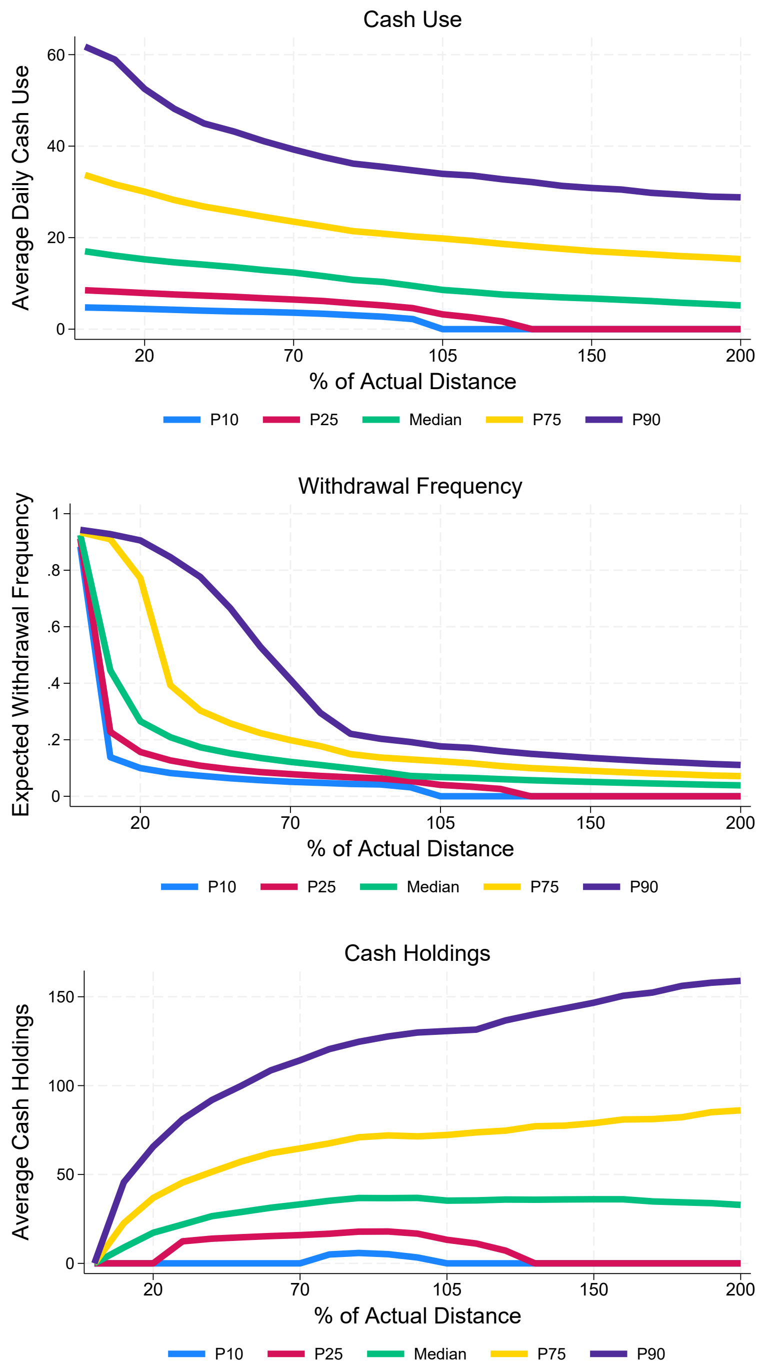
Infr.	All	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI	Urban	Rural	Subst.*
2009	0.131	0.131	0.123	0.113	0.133	0.129	0.134	0.131	0.132	0.132
2013	0.132	0.131	0.126	0.129	0.133	0.129	0.134	0.132	0.131	0.130
2017	0.130	0.128	0.127	0.126	0.132	0.128	0.130	0.130	0.130	0.103
Observations	3424	924	564	185	1189	435	127	2902	522	232

*The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually). *indicates that the distance measure capturing the access-to-cash infrastructure increased by more than 25% between 2013 and 2017.*

B.7 Response to Counterfactual Infrastructure Changes

One interpretation of the counterfactual with very low costs of withdrawal due to distance is that it is a proxy for a "perfect" frictionless CBDC that (i) is completely free to withdraw and access at any time and (ii) replaces cash for use at the point of sale. Even such an idealized CBDC would be faced with only a limited use at the point of sale, as indicated by Figure 11. We refer to our work in Engert et al. (2024b) for a detailed investigation into the impact of CBDC on the market for payments. In line with our findings here, the market penetration of even an "ideal CBDC" is limited and would invite a response by incumbent players further inhibiting its success.

Figure 11: Effect of distance to A2C infrastructure



B.8 Elasticities — small perturbations

Table 29: Elasticity of model predictions w.r.t. increase in distance (+1% change)

All consumers	mean	p10	p25	p50	p75	p90
average withdrawal amount	-0.97	-0.28	-0.07	0.07	0.58	1.40
expected withdrawal frequency	-4.94	-15.00	-2.10	-0.43	0.00	0.00
average cash holding	-2.90	-7.41	-0.69	-0.04	0.08	0.49
average cash use	-4.46	-12.93	-1.55	-0.28	-0.05	0.00
expected payoff per period	-0.81	-0.59	-0.10	-0.01	-0.00	-0.00
Observations	3424					

Table 30: Elasticity of model predictions w.r.t. increase in distance (+5% change)

All consumers	mean	p10	p25	p50	p75	p90
average withdrawal amount	-1.48	-20.00	-0.04	0.03	0.32	1.71
expected withdrawal frequency	-3.65	-20.00	-3.08	-0.51	-0.16	-0.04
average cash holding	-1.73	-10.15	-0.31	-0.05	0.04	0.38
average cash use	-3.26	-20.00	-1.22	-0.30	-0.08	-0.01
expected payoff per period	-0.44	-0.56	-0.12	-0.01	-0.00	-0.00
Observations	3424					

B.9 Compensating variation

Table 31: Compensating variation in terms of number of withdrawals (25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
Overall	0.78	0.22	0.40	0.62	1.01	1.54
Cash non-users	0.82	0.03	0.16	0.68	1.18	1.69
Cash users	0.76	0.28	0.42	0.62	0.95	1.46
Cash users with decreased holdings	0.84	0.31	0.46	0.67	1.06	1.65
Cash users with increased holdings	0.69	0.25	0.40	0.57	0.88	1.27
Young & Low Income	0.81	0.20	0.40	0.63	1.04	1.62
Young & Med. Income	0.78	0.17	0.35	0.62	1.01	1.56
Young & High Income	0.81	0.23	0.41	0.59	1.01	1.70
Old & Low Income	0.77	0.23	0.40	0.64	0.98	1.50
Old & Med. Income	0.72	0.22	0.41	0.58	0.97	1.40
Old & High Income	0.81	0.29	0.44	0.59	0.99	1.63
Observations	3424					

C β as a preference parameter

C.1 Estimation results: representative approach

Table 32: Representative consumer with heterogeneous time preferences

Parameter	Starting	First stage	Second stage
Preference for cash, α	0.189	0.176	0.186
(s.e.)		(0.003)	(0.002)
Holding cost, γ	0.0004	0.00001	0.00001
(s.e.)		(0.000001)	(0.000001)
Withdrawal cost, F	0.204	0.039	0.045
(s.e.)		(0.005)	(0.003)
Discount factor, β	0.9507	0.578	0.486
(s.e.)		(0.023)	(0.032)
Expected cash use			17.74
Expected withdrawal level			157.78
Probability of withdrawal			0.10
Expected holding level			67.69

Notes: Starting values are obtained by grid search. Moments for estimation are obtained by interacting 4 errors with 3 instrumental variables.

C.2 Estimates by demographic type

Table 33: Estimates by demographic type (β as parameter)

Parameter	Y&LI	Y&MI	Y&HI	O&LI	O&MI	O&HI
Preference for cash, α						
Mean	0.39	0.36	0.34	0.39	0.36	0.38
Median	0.27	0.24	0.19	0.30	0.25	0.28
Std. Dev.	0.31	0.31	0.31	0.31	0.30	0.30
Holding cost, γ						
Mean	0.0032	0.0032	0.0029	0.0023	0.0024	0.0021
Median	0.0006	0.0006	0.0005	0.0004	0.0003	0.0004
Std. Dev.	0.0049	0.0051	0.0049	0.0044	0.0044	0.0041
Withdrawal cost, F						
Mean	1.42	1.37	1.08	1.08	1.07	1.09
Median	0.28	0.27	0.18	0.17	0.21	0.17
Std. Dev.	2.37	2.38	2.18	2.12	2.10	2.13
Discount factor, β						
Mean	0.69	0.71	0.74	0.78	0.78	0.79
Median	0.90	0.90	0.90	0.95	0.90	0.95
Std. Dev.	0.37	0.36	0.32	0.30	0.31	0.29
Average daily cash use	12.64	13.00	14.51	17.37	18.80	23.18
Average cash withdrawal	134.82	147.23	138.69	182.85	198.06	220.26
Probability of withdrawal	0.10	0.09	0.10	0.10	0.10	0.12
Average cash holding	38.32	42.62	42.69	61.75	68.93	76.91
N-Obs.	924	564	185	1189	435	127

Notes: Results are obtained from matching each consumer to the parameter value which minimizes the weighted squared distance between the predicted moments and those observed in the data. Weights are obtained from the representative consumer approach with fixed β and averages are reported by demographic types. The 6 demographic groups are constructed by splitting the sample into young (Y, below median sample age) and old (O, weakly above), as well as 3 income groups based on Statistics Canada income brackets: low income (LI, below CAD 45k annually), medium income (MI, CAD 45k to 85k annually), and high income (HI, above CAD 85k annually).

C.3 Counterfactual analysis with β as parameter

We repeat the analysis in Section 4, but using the heterogeneous estimates allowing for a flexible discount factor β. Tracing out the effect of distance in the form of costlier withdrawals yields Figure 12 and reaffirms the findings from Figure 3. We also repeat the decomposition of elasticities of model predictions into continued cash users and cash non-users and reaffirm the findings from Table 10 in Table 34. We then relate the response to consumer demographics in Table 35 and reaffirm findings from Table 13. Finally, we assess the welfare impact in terms of consumer surplus in Table 36.

Figure 12: Effect of distance to A2C infrastructure (β as parameter)

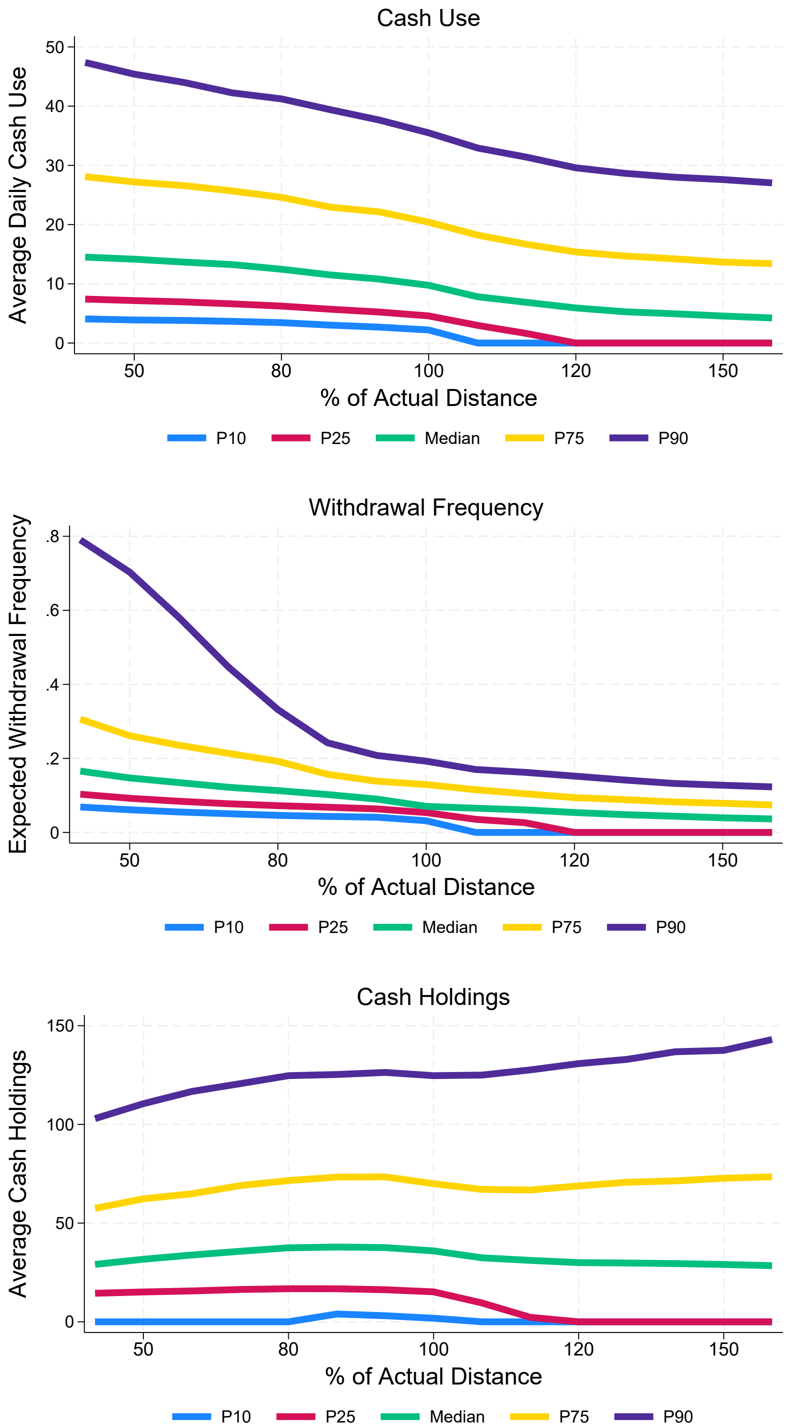


Table 34: Elasticity of model predictions (β as parameter, 25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
average withdrawal amount	-0.91	-4.00	-4.00	0.02	0.54	1.20
expected withdrawal frequency	-1.70	-4.00	-4.00	-0.80	-0.34	-0.10
average cash holding	-0.73	-4.00	-2.41	-0.01	0.45	1.02
average cash use	-1.44	-4.00	-4.00	-0.23	-0.04	-0.00
expected payoff per period	-0.41	-1.80	-0.09	-0.01	-0.00	-0.00
Observations	3424					

(b) Cash users (post increase)	mean	p10	p25	p50	p75	p90
average withdrawal amount	0.55	-0.00	0.01	0.35	0.79	1.48
expected withdrawal frequency	-0.63	-1.21	-0.85	-0.48	-0.19	-0.07
average cash holding	0.31	-0.20	-0.05	0.04	0.67	1.28
average cash use	-0.24	-0.52	-0.25	-0.07	-0.01	0.00
expected payoff per period	-0.06	-0.10	-0.02	-0.01	-0.00	-0.00
Observations	2329					

(c) Cash non-users (post increase)	mean	p10	p25	p50	p75	p90
expected payoff per period	-1.17	-3.77	-2.63	-0.18	-0.01	-0.00
Observations	1095					

Table 35: Estimates and demographics by response to 25% increase (β as parameter)

Variable	**Cash non-users**	**Cash users**		
		all	decreased holdings	increased holdings
	(1)	(2)	(3)	(4)
Cash elasticity α	0.507	0.314	0.292	0.330
Cash holding cost γ	0.006	0.001	0.002	0.001
Withdrawal cost parameter F	2.456	0.639	0.757	0.552
Discount factor β	0.450	0.883	0.813	0.934
Age	44.636	49.983	48.008	51.443
Income	46622.486	48111.302	47535.354	48537.771
Revolver	0.261	0.179	0.191	0.170
Urban	0.854	0.845	0.839	0.848
Young & Low Income	0.328	0.243	0.260	0.230
Young & Med. Income	0.214	0.142	0.170	0.121
Young & High Income	0.052	0.055	0.058	0.053
Old & Low Income	0.278	0.380	0.362	0.394
Old & Med. Income	0.101	0.139	0.113	0.158
Old & High Income	0.027	0.042	0.038	0.044
Observations	1095	2329	990	1339

Table 36: Reduction in consumers' expected payoff in % (β as parameter; 25% change)

(a) All consumers	mean	p10	p25	p50	p75	p90
Overall	10.35	0.03	0.07	0.20	2.34	44.93
Cash non-users	29.23	0.01	0.25	4.51	65.76	94.16
Cash users	1.48	0.03	0.06	0.13	0.41	2.53
Cash users with decreased holdings	2.48	0.03	0.07	0.16	0.64	4.14
Cash users with increased holdings	0.74	0.03	0.06	0.12	0.29	1.56
Young & Low Income	12.24	0.02	0.07	0.24	3.64	64.27
Young & Med. Income	10.89	0.02	0.07	0.22	3.30	46.43
Young & High Income	9.75	0.03	0.06	0.19	1.66	44.16
Old & Low Income	10.20	0.03	0.07	0.19	1.65	42.02
Old & Med. Income	6.46	0.03	0.06	0.17	1.45	14.27
Old & High Income	9.82	0.06	0.11	0.26	1.24	44.93
Observations	3424					