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Low Response Rate from Merchants? Sample and Ask Consumers! An Application of Indirect Sampling Under a Consumer-Merchant Bipartite Network

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Abstract

Under the consumer-merchant bipartite network, we apply the indirect sampling approach to estimate merchant payment acceptance through a consumer payment diary. The records of in-person transactions in the consumer diary provide both the merchant sample via consumer-merchant linkages, and the merchant acceptance via consumers' responses. Among merchants receiving multiple transactions, we show that the derived payment acceptance from the consumer reporting is high quality in terms of very few conflicts between usage and perception, and within perceptions. Furthermore, we show the necessity of weight adjustment to correct for the non-recorded-merchant bias due to the shorter duration of the diary (i.e., constrained to maximum three days). Finally, we compare our indirect sampling estimates to the ones from a direct sampling survey, and we find the results align well, which supports our indirect sampling application in terms of alleviating merchant response burden and reducing survey operation cost.

Topics: Bank notes; Econometrics and statistical methods
JEL codes: C80, C83, E5

Résumé

Nous appliquons la méthode d'échantillonnage indirect dans un réseau bipartite consommateurs-commerçants afin d'estimer l'acceptation des modes de paiement par les commerçants à l'aide d'un journal de paiements tenu par des consommateurs. Les transactions en personne consignées dans le journal nous fournissent à la fois : 1) l'échantillon de commerçants, obtenu à partir des liens entre les consommateurs et les commerçants; et 2) l'acceptation des modes de paiement par les commerçants, obtenue à partir des réponses des consommateurs. Parmi les commerçants où plus d'une transaction est effectuée, nous montrons que l'acceptation des modes de paiement dérivée des journaux des consommateurs est très bonne, du fait qu'il y a très peu de conflits entre l'utilisation et la perception, et entre les perceptions. De plus, nous montrons la nécessité d'ajuster les pondérations pour corriger le biais induit par l'absence de certains commerçants dans l'échantillon en raison de la durée plus courte visée par le journal (limitée à un maximum de trois jours). Enfin, nous comparons les estimations tirées de notre méthode d'échantillonnage indirect à celles d'une enquête par échantillonnage direct, et constatons que les résultats concordent bien. Ce constat soutient notre utilisation de la méthode d'échantillonnage indirect, laquelle permet également de ne pas mettre le fardeau de réponse sur les commerçants et de réduire les coûts de production de l'enquête.

Sujets : Billets de banque ; Méthodes économétriques et statistiques
Codes JEL : C80, C83, E5

1. Introduction

The Bank of Canada conducts research that focuses on understanding the demand for and usage of cash, as well as the evolving landscape of digital currencies and fintech, paying particular attention to the Canadian payments landscape. The landscape consists of consumers and merchants, and the Bank of Canada conducts regular surveys to gain insights from both sides: consumer surveys in 2009 (Arango and Welte 2012), 2013 (Henry, Huynh, and Shen 2015), 2017 (Henry, Huynh, and Welte 2018), 2021 (Henry, Shimoda, and Zhu 2022), 2022 (Henry, Rusu, and Shimoda 2024), and 2023 (Henry, Shimoda, and Rusu 2024), and merchant surveys in 2015 (Kosse et al. 2017), 2018 (Huynh, Nicholls, and Nicholson 2019), 2021-22 (Welte and Wu 2023), and 2023 (Welte et al. 2024). These surveys provide data on consumer payment behaviors and merchant acceptance of various payment methods. When conducting merchant surveys, such as in the 2021-2022 Merchant Payment Acceptance Survey (2021-22 MAS), Welte and Wu (2023) sample units directly from a merchant frame and ask the sampled merchant to report its payment acceptance. Here, under the direct sampling approach, both the sampling and reporting units are merchants.

However, directly sampling and asking merchants about their payment acceptance incurs a high cost and low response rate. With respect to cost, we need to construct the merchant sampling frame, which is resource-intensive. Additionally, the 2021-22 MAS data is collected through an expensive mode called Computer Assisted Telephone Interview (CATI). Moreover, the 2021-22 MAS also suffers from low response rates (Welte and Wu, 2023) and usually requires non-response follow-ups, which further increases costs.

As an alternative, we apply the indirect sampling approach by leveraging our consumer surveys. Instead of directly asking merchants to report their payment acceptance, we ask consumers to report the payment acceptance of the merchants with which consumers conduct transactions. This approach reduces the cost and operational challenges associated with sampling merchants directly, because conducting consumer surveys involves a readily available consumer sampling frame. Additionally, the data is collected though the self-administered online survey questionnaire, which is less expensive than CATI, and consumer surveys generally have higher response rates (Henry, Huynh, and Welte 2018). In this paper, we leverage the 2022 Bank of Canada Methods-of-Payment (MOP) diary and use the consumer records of in-person transactions during a three-day period to map out the indirectly sampled merchants and estimate their payment acceptance rates.

Regarding the indirect sampling methodology, we make two innovations that differ from the existing literature: one concerns the survey design, and the other concerns the survey statistics. First, our new design feature chooses the consumer as both the sampling and reporting unit to reduce the merchant response burden, in contrast to the typical indirect sampling approach, where the consumer is the sampling unit, but the indirectly sampled merchant is the reporting unit. Although the typical indirect sampling approach avoids the cost and challenge of constructing the merchant sampling frame, the indirectly sampled merchant would still have to respond via the expensive CATI mode and the response rate would likely be low. Instead, we propose asking consumers to report their actual method-of-payment usages and perceived acceptances so that we can derive the merchant in-person payment acceptance from consumer reporting.[1] Here is an example of this novel design feature: a consumer reports that she used cash at a merchant to buy food; since she paid with cash, this implies cash was accepted at this merchant. At the same time, the survey questionnaire also prompted this consumer to *conjecture* whether a debit card or credit card could be accepted, which could be based on her observations of other customers' payment choices or of signs displayed at the merchant. One potential concern with deriving merchant payment acceptance from consumer responses is the reliability of these responses. Among merchants receiving multiple transactions, incidences of conflicts between usage and perception, and within perception, would raise concerns regarding the reliability of consumer responses. Fortunately, we show that both the incidence and intensity of conflict is low, indicating that consumer responses and the derived merchant acceptance are reliable and thus high quality.

Second, we show the necessity of weight adjustment to correct for non-recorded-merchant bias due to the shorter duration of the diary (i.e., constrained to maximum 3 days). In practice, some consumers may visit a specific merchant on only a bi-weekly or monthly basis. In this case, this merchant may not be recorded in our three-day diary, which could lead to potential missing merchants if the consumer could have recorded more transactions over a longer period. As a result, we need to adjust the generalized weight share method (GWSM) weights (Lavallee 2007) to correct for these missing merchants. Because we do not observe the missing merchants, our adjustment approach is to calibrate the GWSM weights to the population merchant characteristics from an administrative source (i.e., Statistics Canada). Here the calibration plays a similar role to correct for the non-response bias, as in Haziza and Lesage (2016). Notice that our non-recorded-merchant bias is connected to the link non-response studied in Xu and Lavallee (2009) but is different in one important aspect: the link non-response in Xu and Lavallee (2009) only biases downward the standardization factor (i.e., the population total of transactions received by a linked merchant), resulting in the overestimation of the GWSM total estimates. In our case, missing merchants could bias the composition of indirectly sampled merchants so that the GWSM total estimates, without accounting for the shorter diary duration, could be biased either upwards or downwards.

By integrating the above two innovations into the typical indirect sampling method, we compare our newly proposed indirect sampling estimates to the ones from a direct sampling survey, and we find these two results align well, which supports our indirect sampling application in terms of alleviating merchant response burden and reducing survey operation cost.

[1] In survey research, the practice where respondents answer questions on behalf of another individual, commonly referred to as "proxy reporting," is well-established (Tamborini and Kim, 2012, and Celhay et al. 2024).

While the theory of indirect sampling originated in the context of household panel studies (Ernst 1989), there have been proposals to extend the application of the GWSM to generate unbiased estimates for other target populations, as highlighted by Deville and Lavallée (2006) and Lavallée (2007). Indirect sampling has been applied to reach the tourism population (Deville and Maumy-Bertand 2006) and the kindergarten population (Kiesl, 2010). Moreover, the indirect sampling framework has been applied to multiple frame surveys (Maia, 2009 and Wolter, Smith and Blumberg, 2010). Additionally, from an efficiency perspective, Falorsi et al. (2019) propose an optimal sampling strategy to minimize the sampling cost while ensuring a pre-defined estimation precision, and Medous et al. (2023) study the impact of the link weights on the efficiency of the GWSM estimators.

The remainder of this paper proceeds as follows. Section 2 presents an overview of the indirect sampling method with notations connected to our empirical application. Section 3 offers details of our indirect sampling estimator with two innovations: (i) the derived merchant payment acceptance from consumer reporting and (ii) the calibrated GWSM weight that corrects for non-recorded-merchant bias. Section 4 provides our indirect sampling estimates with comparison to the ones from the 2021-22 MAS direct sampling approach (Welte and Wu, 2023). Section 5 concludes and suggests future research. All technical and supplementing tables and figures are included in the appendix.

2. Overview of indirect sampling and our empirical setup

In this section, we provide the notations for direct sampling, traditional indirect sampling and our newly proposed indirect sampling. We conclude the section with a summary of the key differences between the methodologies, as well as how our proposed application differs from traditional applications of indirect sampling (Table 1).

Suppose that the merchant target population $U_M = \{1,2,\dots,N_M\}$ consists of N_M merchant units. Associated with merchant unit m are values $\boldsymbol{x}_m$ (i.e., size, region, locality and industry) and the binary y_m^k, which takes a value of 1 if the merchant accepts $k \in \{cash, debit\ card, credit\ card\}$, and a value of 0 otherwise. Our parameters of interest are the average Canadian merchants' acceptance rates of cash, debit cards and credit cards at the point of sale (equation 1), as well as the subdomain estimates for some variables $\boldsymbol{x}_m$ taking values X:

$$\mu^k \equiv \frac{\sum_{m \in U_M} y_m^k}{N_M}, \tag{1}$$

$$\mu_X^k \equiv \frac{\sum_{m \in U_M} 1_{x_m \in X} y_m^k}{\sum_{m \in U_M} 1_{x_m \in X}}. \tag{2}$$

To ease the notation, we suppress the superscript k in the following sections and focus on the average cash acceptance rate where $k = cash$.

First, we will introduce the direct sampling method to estimate μ, and then present the indirect sampling counterpart. We estimate the in-person payment acceptance for merchants that:

- are small (0–5 employees, inclusive) and medium-sized (6–49 employees, inclusive)
- belong to the industries "Retail trade" (North American Industry Classification (NAICS) codes 44 and 45), "Food services and drinking places" (NAICS code 722), and "Other services" (NAICS codes 811 and 812).

Hence our target population falls within the same scope of the 2021-22 MAS, which can serve as a direct sampling benchmark to evaluate the performance of the indirect sampling estimates; see Section 4 for more details.

Estimation based on direct sampling: Let $\{(\pi_m, y_m), m \in S_M\}$ be the sample drawn from the target merchant population U_M through direct sampling using some sampling design with the inclusion probability $\pi_m > 0$ for every $m \in U_M$, where the inverse of π_m is weight w_m. To get a design-unbiased estimator for μ, the Horvitz-Thompson-estimator (HT-estimator) can be applied as:

$$\tilde{\mu} \equiv \frac{\sum_{m \in S_M} w_m y_m}{\sum_{m \in S_M} w_m}. \tag{3}$$

An example is the 2021-22 MAS (Welte and Wu 2023), where S_M is directly sampled from an in-house built sampling frame, U_M, w_m is computed based on the stratified random sample design, and y_m is directly reported by merchants based on whether they accept cash and other payment methods at the point of sale.

Estimation based on indirect sampling: We start from the consumer population U_C, whose consumer units are linked to the merchant units in the population U_M, and the linkage is built upon consumers' transactions at these linked merchants. Let v be a non-negative link function on $U_C \times U_M$, i.e., for every $c \in U_C$ and $m \in U_M$ we have $v_{cm} \equiv v(c,m) \geq 0$, such that a link exists between $c \in U_C$ and $m \in U_M$, if and only if $v_{cm} > 0$. We define $v_{cm} \geq 0$ as the number of transactions between consumer unit c and merchant unit m. Let $v_{+m} \equiv \sum_{c \in U_C} v_{cm}$ be the total number transactions received by merchant m. Our 2022 MOP payment diary satisfies this underlying data structure, where the consumers with the variables $\{(\pi_c, \boldsymbol{z}_{cm}), c \in S_C\}$ are sampled from the consumer population U_C with known selection probabilities $\pi_c > 0$, or the weight w_c, the inverse of π_c. And the variables $\boldsymbol{z}_{cm}$ consist of the name of the merchant, the actual method-of-payment use and perceived acceptances, when consumer c transacts at merchant m. Based on merchant names, we can construct the indirectly sampled merchant sample $\hat{S}_M$ which is defined as the set of all merchants in U_M that have a link to some element of S_C. More formally, $\hat{S}_M \equiv \{m \in U_M | v_{cm} > 0 \text{ for } c \in S_C\}$. In the end, we derive the merchant payment acceptance $\hat{y}_m$ from asking consumers to report their actual payment usages and perceived acceptances (details in Section 3.2). Then our baseline indirect sampling estimator based on $\hat{S}_M$ is:

$$\hat{\mu} \equiv \frac{\sum_{c \in S_C} w_c \left(\sum_{m \in \Omega_c} \frac{v_{cm}}{v_{+m}} \hat{y}_m \right)}{\sum_{c \in S_C} \sum_{m \in \Omega_c} w_c \frac{v_{cm}}{v_{+m}}} = \frac{\sum_{m \in \hat{S}_M} \hat{w}_m \hat{y}_m}{\sum_{m \in \hat{S}_M} \hat{w}_m}, \tag{4}$$

where $\Omega_c \equiv \{m \in U_M : v_{cm} > 0\}$ in the first equation is the set of all merchants in U_M being visited by consumer $c \in S_C$ and the weight $\hat{w}_m \equiv \sum_{c \in S_C} w_c \frac{v_{cm}}{v_{+m}}$ in the second equation is constructed following the GWSM (Lavallée 2007). Notice that the second equation is derived by the definition of $\hat{S}_M$ where we have $v_{cm} = 0$ for $c \in S_C$ and $m \neq \hat{S}_M$ (Kiesl, 2016).

Before applying the indirect sampling estimator of Equation 4 to our data, we discuss the assumptions required for $\hat{\mu}$ to be unbiased. In Section 3, we empirically test these assumptions in detail, and propose adjustments if some are violated. In general, there are three assumptions relating to the coverage of the indirectly sampled merchants, the quality of consumer reporting on behalf of merchants, and the bias of non-recorded-merchant driven by the shorter diary duration (i.e., maximum three days).

Assumption 1 (**Good coverage of $\boldsymbol{U_M}$):** For every $m \in U_M$, we have $v_{+m} \equiv \sum_{c \in U_C} v_{cm} > 0$.

Assumption 1 assumes that every merchant in U_M will have a chance to be visited by at least one consumer from U_C. In other words, the sum of all the links from U_C to $m \in U_M$ is bigger than zero, that is, $v_{+m} > 0$.

Assumption 2 (High quality of consumer reporting on behalf of merchant): For each merchant $m \in \hat{S}_M$, the derived $\hat{y}_m$ from consumer reporting on behalf of the merchant m has negligible measurement error, that is, $\hat{y}_m \approx y_m$ where y_m is the acceptance self-reported by the merchant m.

Assumption 2 exemplifies our design innovation of choosing the consumer as both the sampling and reporting unit to reduce merchant response burden. This is in contrast to the traditional indirect sampling approach where the consumer is the sampled unit, but the indirectly sampled merchant is the reporting unit. Assumption 2 argues that asking consumers is almost as good as asking merchants in terms of the negligible discrepancy between the $\hat{y}_m$ derived from consumer responses, and the y_m directly reported by merchants.

Assumption 3 (Few non-recorded merchants from the three-day diary): Indirectly sampled merchants $\hat{S}_M \equiv \{m \in U_M | v_{cm} > 0 \text{ for } c \in S_C\} \text{is equal to } \Omega_c$ where $\Omega_c \equiv \{m \in U_M : v_{cm} > 0\}$.

Following Deville and Lavallee (2006), the unbiasedness of the $\hat{\mu}$ requires Assumption 3: the set Ω_c consists of all merchants in U_M that are being visited by the consumer $c \in S_C$. However, due to the shorter duration of the diary (i.e., maximum three days), consumer c might not record merchants outside these three days. Let Ω_c^3 denote the set of merchants being visited by consumer c during the three-day period and define $\hat{S}_M^3 \equiv \cup_{c \in S_C} \Omega_c^3$ as set of all merchants visited by the consumer sample S_C in the three-day period. Since we do not observe all the merchants in $\hat{S}_M$ but only the merchants $\hat{S}_M^3$ from the three-day period, our feasible indirect sampling estimator based on $\hat{S}_M^3$ is then:

$$\hat{\mu}^3 \equiv \frac{\sum_{c \in S_C} w_c \left(\sum_{m \in \Omega_c^3} \frac{v_{cm}}{v_{+m}} \hat{y}_m \right)}{\sum_{c \in S_C} \sum_{m \in \Omega_c^3} w_c \frac{v_{cm}}{v_{+m}}} = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m} . \tag{5}$$

However, as shown in the next session, we find empirical evidence against Assumption 3 due to the discrepancy between $\hat{S}_M^3$ and $\cup_{c \in S_C} \Omega_c$. Hence, we propose a calibrated GWSM estimator

$$\hat{\mu}^{3,cal} = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal} \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal}} , \tag{6}$$

to account for the shorter diary duration by using non-response calibration technique (Haziza and Lesage 2016).

Table 1 summarizes the distinctions between three approaches of estimating merchant acceptance. Under direct sampling, merchants serve as both the sampling and response units, which often incurs high costs and low response rates. Traditional indirect sampling, by contrast, involves consumers as the sampling unit while retaining merchants as the response unit; however, we continue to face similar challenges in cost and response rate because of low merchant participation. Our newly proposed indirect sampling addresses these challenges through two innovations. First, consumers serve as both the sampling and response units (e.g., reporting on the payment acceptance of the merchants they visit over a three-day diary period). Second, we correct for potential biases resulting from the diary's short length through a non-response calibration of the GWSM weights.

Table 1: Summary of direct, traditional indirect sampling and our newly proposed indirect sampling for estimating merchant payment acceptance

	Direct sampling	**Traditional indirect sampling**	**Our proposed indirect sampling**
Sampling unit	Merchants	Consumers	Consumers
Response unit	Merchants	Merchants	**Key innovation 1:** Consumers to reduce cost and increase response rate
Merchant sample	Drawn from merchant sampling frame	Constructed from consumer-merchant transactional data (Section 3.1)	
Merchant payment acceptance	Reported by merchants		Inferred from high-quality consumer responses (Section 3.2)
Weights	Reciprocal of inclusion probability	Generalized Weight Share Method (GWSM)	**Key innovation 2:** Calibrated GWSM to account for shorter diary duration (Section 3.3)

3. Construction of indirect sample estimates

The consumer sample S_C comes from the 2022 MOP payment diary, which was collected in late 2022 over the course of a three-day period. During this time period, consumers were asked to track details of transactions that they made. For each transaction recorded, the consumer provided details including the merchant's name, the method of payment the consumer used for the transaction, and the perceived acceptance of other methods of payments that were not used for that transaction. These transaction and consumer-specific details are subsequently used to construct the three key components of $\hat{\mu}^3$.

Recall that:

$$\hat{\mu}^3 = \frac{\sum_{m\in\hat{S}_M^3} \hat{w}_m \hat{y}_m}{\sum_{m\in\hat{S}_M^3} \hat{w}_m}, \tag{5}$$

where $\hat{w}_m \equiv \sum_{c\in S_C} w_c \frac{v_{cm}}{v_{+m}}$. In the following subsections, we describe how to obtain the three key components of $\hat{\mu}^3$. Table A.4.1 in Appendix A.4 provides a detailed overview of how this is done:

- $\hat{S}_M^3$, the merchants indirectly sampled during the three-day diary (Section 3.1)

- $\hat{y}_m$, the merchant acceptance derived from consumer reporting (Section 3.2)
- $\widehat{w}_m$, the GWSM weights (Section 3.3).

Within each subsection, we empirically test Assumptions 1-3 to check whether $\hat{\mu}^3$ is unbiased or not under the existing weighting scheme of GWSM (Lavallée 2007). In the case where an assumption is violated, we propose weight adjustments to mitigate this bias.

3.1 Merchant sample $\hat{S}_M^3$

The merchant sample $\hat{S}_M^3$ is constructed from the merchant names reported by consumers. Over the course of the diary, each consumer c records the set of merchants that they visit during the three-day diary, Ω_c^3. The union of all these sets results in $\hat{S}_M^3 \equiv \cup_{c \in S_C} \Omega_c^3$. As with any dataset consisting of names, especially when reported by different consumers, it is common to encounter variations or duplicates due to typographical errors or inconsistencies. To account for this, we use a string-matching technique (see Appendix A.1 for details) to first identify, and then consolidate, these variations and duplicates. This process produces $\hat{S}_M^3$, the indirect sample of unique merchants. It consists of 595 merchants, recorded by a sample size of 826 consumers, who make a total of 1,445 transactions over the course of three days.

Next, Table 2 illustrates the process of constructing merchant-level data from a sample of consumer-level data. It demonstrates the many-to-many relationships observed in the consumer diary: the first consumer c_1 reports two transactions, one at merchant m_1 and the other one at merchant m_2. The second consumer, c_2, reports one transaction at merchant m_1. From these three transactions, two unique merchants are identified. The indirectly sampled merchant data can then be constructed so that each row corresponds to a unique merchant.

Table 2: Illustrative example of transforming the sample of consumers to the sample of indirectly sampled merchants

Illustrative example of consumer diary		
	Transaction 1	Transaction 2
Consumer ID	Merchant name	Merchant name
c_1	m_1	m_2
c_2	m_1	

Illustrative example of indirectly sampled merchants		
	Transaction 1	Transaction 2
Merchant name	Consumer ID	Consumer ID

m_1	c_1	c_2
m_2	c_1	

Recall Assumption 1 states that every merchant in U_M has a chance to be visited by at least one consumer from U_C. Ideally this assumption would be validated by repeatedly sampling consumers who then report the merchants where they make transactions. However, this is not feasible. Since the actual consumer survey was conducted only once, we can form only a single draw of the indirect sampling. Therefore, we study the necessary condition of Assumption 1 based on the multi-way tables from both directly sampled consumers and indirectly sampled merchants: if Assumption 1 holds, then the multi-way tables should have non-zero entries, or the observed range (or the support) of auxiliary variables should be comparable and close to those from the target population. This follows the diagnosis tool for deterministic undercoverage described in Chen et al. 2023.

First, we present evidence to show that the consumer sample S_C has good coverage for demographics of age, gender and income, which is the prerequisite for the indirectly sampled merchants to have good coverage. The presence of non-zero cells in the "Consumer count" column in Table 3 indicates that consumers in a particular stratum have the positive probability of being sampled. Next, we focus on the indirectly sampled merchants in $\hat{S}_M^3$, and show that all the cells in the multi-way table based on the $\hat{S}_M^3$ are non-zero. We observe that, similar to S_C, we find that the three-way sample count contains no instances of zero. Therefore, the non-zero cells in Table 4 indicate evidence that the merchant $\hat{S}_M^3$ has coverage of their respective populations. As discussed, Tables 3 and 4 provide only necessary conditions for our indirectly sampled $\hat{S}_M^3$ having full coverage. To reduce potential undercoverage bias, Section 3.4 implements weight calibration (Dever and Valliant 2016 and Haziza and Lesage 2016) to adjust the basic GWSM weight.

Table 3: Three-way count of consumers in S_C

		Consumer count		
Age	**Gender**	**Low income**	**Medium income**	**High income**
18-34	Female	11	17	17
	Male	13	19	24
35-54	Female	21	39	88
	Male	24	36	74
55+	Female	51	88	98
	Male	54	77	75
Sample size			826	

Table 4: Three-way count of merchants in $\hat{S}_M^3$

		Merchant count	
Industry	**Locality**	**Small**	**Medium**
Retail trade (44/45)	Rural	34	21
	Urban	170	95
Food services and drinking places (722)	Rural	11	23
	Urban	52	147
Other services (81)	Rural	3	1
	Urban	27	11
Sample size		595	

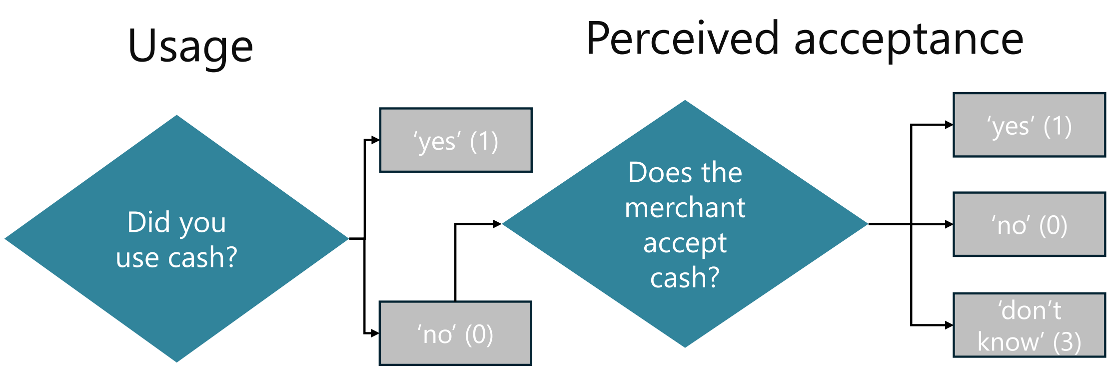
Note: This table presents the three-way count of merchants in $\hat{S}_M^3$ by industry, locality and size.

3.2 Merchant acceptance $\hat{y}_m$

In typical applications of indirect sampling, the target unit—in this case, merchants—would be asked to provide y_m. Doing so, however, would result in the same issues faced in the direct sampling of merchants, i.e., high costs and low response rates. We instead rely on consumers to act as both the sampling and reporting unit, eliminating the need to ask merchants directly. We construct $\hat{y}_m$ based on details of method of payment usage and perceived acceptance reported by consumers.

The consumer diary asks respondents to report the method of payment used for a transaction that is made in person, as well as their perceived acceptance of methods of payment not being used. The survey logic proceeds as follows (Figure 1): as an example, a consumer recording a transaction is first asked about cash usage, to which they can respond 'yes' (1) or 'no' (0). If they respond no, they are then asked about their perceived acceptance of cash, to which they can respond 'yes,' 'no,' or 'don't know' (3). If they respond 'yes' to usage, then perceived acceptance takes an empty value because if it is used then it must be accepted. The survey logic is the same for debit card and credit card transactions.

Figure 1: Survey logic for cash usage and perceived acceptance



Note: Consumers are first asked '*What payment method did you use for this purchase?*'. Cash, debit card and credit card are presented as options, and consumers select 'yes' (1) or 'no' (2) with respect to each. For the method(s) of payment that the consumer did not use, consumers are then asked, '*Did the business accept any of the following method(s) of payment?*', and consumers can select 'yes,' 'no,' or 'don't know' (3).

The logic in Figure 1 can be generalized to all v_{+m} transactions that a merchant $m \in \hat{S}_M^3$ receives. Recall $v_{+m} \equiv \sum_{c \in U_C} v_{cm}$, where v_{cm} is the number of transactions conducted by consumer c at merchant m. Thus, for each merchant $m \in \hat{S}_M^3$, we can consolidate its set of usage and perceived acceptance values from all v_{+m} transactions as $\boldsymbol{u}_m = \{u_{m,1}, \dots, u_{m,v_{+m}}\}$ and $\boldsymbol{p}_m = \{p_{m,1}, \dots, p_{m,v_{+m}}\}$. We define $\hat{y}_m = f(\boldsymbol{u}_m, \boldsymbol{p}_m)$ where the function f generates the derived cash acceptance $\hat{y}_m$ from sets usage $\boldsymbol{u}_m$ and perception $\boldsymbol{p}_m$. We present three different mapping rules f, where $\hat{y}_m$ is determined by the majority response (Rule 1), the weighted average (Rule 2), or usage is always correct when it occurs (Rule 3). We note that Rules 1 and 2 place an equal amount of emphasis on $\boldsymbol{u}_m$ and $\boldsymbol{p}_m$ in determining $\hat{y}_m$, whereas Rule 3 places a relatively larger emphasis on $\boldsymbol{u}_m$.

Rule 1 Majority rules: Here $\hat{y}_m$ is determined by the most frequently occurring reported value among $\boldsymbol{u}_m$ and $\boldsymbol{p}_m$.

Let $v_{+m}^{u=Y}$ represent the count of transactions where usage was Y. Similarly, let $v_{+m}^{p=Y}$, $v_{+m}^{p=N}$ and $v_{+m}^{p=DK}$ represent the count of transactions where perceived acceptance was yes (Y), no (N) and don't know (DK), respectively:

$$v_{+m}^{u=Y} = \sum_{v=1}^{v_{+m}} 1_{u_{m,v}=Y} ,$$

$$v_{+m}^{p=Y} = \sum_{v=1}^{v_{+m}} 1_{p_{m,v}=Y} ,$$

$$v_{+m}^{p=N} = \sum_{v=1}^{v_{+m}} 1_{p_{m,v}=N} ,$$

$$v_{+m}^{p=DK} = \sum_{v=1}^{v_{+m}} 1_{p_{m,v}=DK} .$$

By the survey logic, these values are mutually exclusive, so

$$v_{+m} = v_{+m}^{u=Y} + v_{+m}^{p=Y} + v_{+m}^{p=N} + v_{+m}^{p=DK} . \tag{7}$$

As noted previously, we treat usage and perceived acceptance equally under Rule 1. Then, $\hat{y}_m$ is determined by the most frequently occurring value of: $v_{+m}^{u=Y} + v_{+m}^{p=Y}$, $v_{+m}^{p=N}$ and $v_{+m}^{p=DK}$.

Under Rule 1, we obtain $f_1(\boldsymbol{u}_m, \boldsymbol{p}_m)$:

$$\hat{y}_m \in \{0,1,3\} = f_1(\boldsymbol{u}_m, \boldsymbol{p}_m) = \begin{cases} 1 \text{ if } \max\left(v_{+m}^{u=Y} + v_{+m}^{p=Y}, v_{+m}^{p=N}, v_{+m}^{p=DK}\right) = v_{+m}^{u=Y} + v_{+m}^{p=Y} \\ 3 \text{ if } \max\left(v_{+m}^{u=Y} + v_{+m}^{p=Y}, v_{+m}^{p=N}, v_{+m}^{p=DK}\right) = v_{+m}^{p=DK} \\ 0 \qquad \text{Otherwise} \end{cases} . \tag{8}$$

where `Otherwise' includes instances where $\max\left(v_{+m}^{u=Y} + v_{+m}^{p=Y}, v_{+m}^{p=N}, v_{+m}^{p=DK}\right) = v_{+m}^{p=N}$ as well as instances where the maximum value cannot be determined due to ties occurring.

Rule 2 Weighted average: Here $\hat{y}_m$ is determined as the weighted average of all values across $\boldsymbol{u}_m$ and $\boldsymbol{p}_m$. Note that Rule 2, like Rule 1, places an equal amount of emphasis on usage and perceived acceptance.

Under Rule 2, we obtain $f_2(\boldsymbol{u}_m, \boldsymbol{p}_m)$:

$$\hat{y}_m \in \{[0,1], 3\} = f_2(\boldsymbol{u}_m, \boldsymbol{p}_m) = \begin{cases} \frac{v_{+m}^{u=Y} + v_{+m}^{p=Y}}{v_{+m} - v_{+m}^{p=DK}} \text{ if } v_{+m} \neq v_{+m}^{p=DK} \\ 3 \qquad \text{if } v_{+m} = v_{+m}^{p=DK} \end{cases} , \tag{9}$$

where $\hat{y}_m$ is a percentage between zero and one, calculated as the number of times $u_{m,v}$ or $p_{m,v}$ is reported as 'yes,' divided by the number of visits, excluding visits where $p_{m,v}$ is reported as 'don't know.'

Rule 3 Usage is always correct: Here $\hat{y}_m$ is mapped to 1 if usage occurs at least once; otherwise $\hat{y}_m$ is determined by Rule 1. Rule 3 differs from Rules 1 and 2 in that it places the great emphasis on usage: if usage is reported on at least one transaction, then merchant m must accept it; as long as $v_{+m}^{u=Y} \geq 1$ for at least one transaction, then $\hat{y}_m = 1$. If $v_{+m}^{u=Y} = 0$ (i.e., $u_{m,v} = 0$ for all transactions), then $\hat{y}_m$ needs to be derived from $\boldsymbol{p}_m$. In these cases, we can apply Rule 1.

Under Rule 3, we obtain $f_3(\boldsymbol{u}_m, \boldsymbol{p}_m)$:

$$\hat{y}_m \in \{0,1,3\} = \begin{cases} 1 & \text{if } v_{+m}^{u=Y} \geq 1 \\ f_1(\boldsymbol{u}_m, \boldsymbol{p}_m) & \text{if } v_{+m}^{u=Y} = 0 \end{cases}. \tag{10}$$

Notice that from Table 5 the majority of $\hat{y}_m$ produced from the above three rules are the same, so that we should expect minimal effects of different rules on the indirect payment acceptance estimates.

Table 5: Proportion (%) $\hat{S}_M^3$ with consistency of $\hat{y}_m$ across the three mapping rules

	$\hat{y}_m$ is the same across all three mapping rules	**$\hat{y}_m$ is different at least under one mapping rule**
Cash	98.66	1.34
Debit card	97.82	2.18
Credit card	98.32	1.68

Note: Here, '$\hat{y}_m$ is the same under all three mapping rules' corresponds to $f_1(\boldsymbol{u}_m, \boldsymbol{p}_m) = f_2(\boldsymbol{u}_m, \boldsymbol{p}_m) = f_3(\boldsymbol{u}_m, \boldsymbol{p}_m)$. '$\hat{y}_m$ is different at least under one mapping rule' corresponds to at least one mapping's value is different from the other two's.

From the mapping rules, it is shown that the derivation of $\hat{y}_m$ depends on both consumer usage and perceived acceptance. Thus, both $\boldsymbol{u}_m$ and $\boldsymbol{p}_m$ should be of high quality to ensure the estimated $\hat{y}_m$ and true y_m have negligible differences (evidence for Assumption 2). However, we do not observe y_m in the consumer diary. So, in lieu of comparing $\hat{y}_m$ to y_m, we rely on evidence observed in the usage and perceived acceptance found in the consumer diary. In particular, our quality check will focus on the merchants who receive multiple transactions so that we can examine the consistency between usage and perception, or within perceptions.

We partition merchants into two sets: those receiving one visit $\{m \in \hat{S}_M^3 | v_{+m} = 1\}$ and those receiving multiple visits $\{m \in \hat{S}_M^3 | v_{+m} > 1\}$. Within each set, we determine the proportion of merchants for which:

- usage occurs at least once: $v_{+m}^{u=Y} \geq 1$.
- usage does not occur, and the method of payment is perceived to be accepted or not accepted at least once: $v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} + v_{+m}^{p=N} > 0$.
- usage does not occur, and the method of payment's perceived acceptance is reported as 'don't know' for all transactions: $v_{+m}^{u=Y} = 0, v_{+m}^{p=DK} = v_{+m}$.

Table 6: $\hat{S}_M^3$ broken down by frequency of transactions where usage and perceived acceptance occurs

		% of merchants	
	Different types of merchants grouped by usages and perceptions	Merchant has only single visit $\{m \in \hat{S}_M^3 \vert v_{+m} = 1\}$	Merchant has multiple visits $\{m \in \hat{S}_M^3 \vert v_{+m} > 1\}$
Cash	At least one usage	27.77	63.27
	No usage, ALL perception	65.59	35.71
	No usage, no perception (perceived acceptance all DK)	6.64	1.02
	Total	100.00	100.00
Debit card	At least one usage	19.72	52.04
	No usage, ALL perception	71.83	44.9
	No usage, no perception (perceived acceptance all DK)	8.45	3.06
	Total	100.00	100.00
Credit card	At least one usage	50.7	73.47
	No usage, ALL perception	43.06	25.51
	No usage, no perception (perceived acceptance all DK)	6.24	1.02
	Total	100.00	100.00

Note: '*At least one usage*' indicates merchants for which usage occurs at least once: $v_{+m}^{u=Y} \geq 1$.
'*No usage, ALL perception*' indicates merchants for which usage does not occur and the method of payment is perceived to be accepted or not accepted at least once: $v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} + v_{+m}^{p=N} > 0$. '*No usage, no perception (perceived acceptance all DK)*' indicates merchants for which usage does not occur, and the method of payment's perceived acceptance is reported as 'don't know' for all transactions: $v_{+m}^{u=Y} = 0, v_{+m}^{p=DK} = v_{+m}$.

In Table 6, of the merchants receiving one visit, $\{m \in \hat{S}_M^3 \vert v_{+m} = 1\}$, usage of cash occurs for 27.77% of them. This means that for the remaining 72.23% of merchants, $\hat{y}_m$ needs to be inferred using only $\boldsymbol{p}_m$. In this case, $\boldsymbol{p}_m = \{p_{m,1}\}$, that is $\boldsymbol{p}_m$ degenerates to a scalar. Then $\hat{y}_m = f(\boldsymbol{u}_m, \boldsymbol{p}_m) = f(p_{m,1})$, since $v_{+m}^{u=Y} = 0$. Of the merchants receiving more than one visit

$\{m \in \hat{S}_M^3 | v_{+m} > 1\}$, usage of cash occurs on at least one visit for 63.27%, meaning that for the remaining 36.73% of merchants, $\hat{y}_m$ needs to be inferred using only $\boldsymbol{p}_m$, where $\boldsymbol{p}_m = \{p_{m,1}, \dots, p_{m,v_{+m}}\}$. Then $\hat{y}_m = f(\boldsymbol{u}_m, \boldsymbol{p}_m) = f(p_{m,1}, \dots, p_{m,v_{+m}})$ since again, $v_{+m}^{u=Y} = 0$. Therefore, for the merchants receiving no usage, the values of $\hat{y}_m$ have to depend entirely on perceived acceptance $\boldsymbol{p}_m$. Hence the quality of $\boldsymbol{p}_m$ is crucial. In the following two sections, we consider two measures of the quality for $\hat{y}_m$ by examining the consistency of perceived acceptance: the incidence of 'conflict merchants' (i.e., the proportion of merchants with inconsistent usage and perceived acceptance across transactions (see Section 3.2.1.), as well as the intensity of conflict (i.e., the degree of the inconsistency between usage and perceived acceptance across merchants; see Section 3.2.2).

3.2.1 Low incidence of conflict

While it is impossible to evaluate the quality of an individual transaction, it is possible to evaluate the consistency of responses among all the transactions from a given merchant. Among merchants receiving more than one transaction, we can identify the 'conflict merchants' by comparing consumers' usage with consumers' perceptions or comparing among consumers' perceptions. This allows us to define three mutually exclusive types of conflicts:

- **between usage and perceived acceptance**. That is, usage occurs at least once, but the method of payment is perceived to be not accepted at least once:
$$\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$$

- **within perceived acceptance only**.[2] That is, usage does not occur. The method of payment is perceived to be accepted at least once, but is also perceived to be not accepted at least once:
$$\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$$

- **Both between usage and perceived acceptance, and within perceived acceptance.** That is, conflicts exist both between usage and perceived acceptance, as well as within perceived acceptance:
$$\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}.$$

Examples of all three conflict types are illustrated in Table 7. Merchants exhibiting one of these three types of conflict are classified as 'conflict' merchants, whereas those who do not are classified as 'no conflict' merchants. Using this classification, we can evaluate the incidence of conflict in terms of the proportion of merchants in $\hat{S}_M^3$ for all three methods of payment. Table 8 shows that the proportion of conflict merchants is low for cash, debit card, and credit card transactions, which indicates that the consumer responses are of good quality: only 1.35%

[2] In the context of our data, conflicts within usage $\boldsymbol{u}_m$ only do not exist, as non-usage does not imply non-acceptance. We also note that conflict is possible only for merchants receiving more than one visit, i.e., $m \in \hat{S}_M^3 | v_{+m} > 1\}$.

(0.17%+1.18%) of $\hat{S}_M^3$ is a conflict with respect to cash; this value is low for debit card (2.01%) and credit card (1.52%) as well.[3]

Table 7: Types of conflict merchants that exist in $\hat{S}_M^3$

Conflict	$\boldsymbol{m}$	$u_{m,v}$	$p_{m,v}$
Between usage and perception	m_i	Y	-
	m_i	N	N
	m_i	N	N
Within perceived acceptance only	m_j	N	Y
	m_j	N	N
Both between usage and perceived acceptance, and within perceived acceptance	m_k	Y	-
	m_k	N	Y
	m_k	N	N

Note: "Between usage and perception" refers to merchants for which usage occurs at least once, but the method of payment is perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$. "Within perceived acceptance only" refers to merchants for which usage does not occur. The method of payment is perceived to be accepted at least once, but is also perceived to be not accepted at least once: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. "Both between usage and perceived acceptance, and within perceived acceptance" refers to merchants for conflicts exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

[3] When conflict does occur, it does not appear to be systematically related to the merchant characteristics $\boldsymbol{x}_m$ (size, industry, locality and region). For cash, debit card and credit card, we fit a separate logistic regression model in which we regress the incidence of conflict, modeled as a binary variable on merchant characteristics $\boldsymbol{x}_m$. At the 0.05 significance level, there is no statistical significance for any coefficient in the fitted models, indicating $\boldsymbol{x}_m$ are not predictive of conflicts for cash, debit card or credit card. Refer to Appendix B, Tables B.4, B.5 and B.6 for the regression summaries.

Table 8: Incidence of conflict types based on $u_{m,v}$ and $p_{m,v}$ (% of $\hat{S}_M^3$)

	Cash		Debit card		Credit card	
	$\boldsymbol{v_{+m} = 1}$	$\boldsymbol{v_{+m} > 1}$	$\boldsymbol{v_{+m} = 1}$	$\boldsymbol{v_{+m} > 1}$	$\boldsymbol{v_{+m} = 1}$	$\boldsymbol{v_{+m} > 1}$
No conflict	83.53	15.13	83.53	14.45	83.53	14.96
Conflict						
Between usage and perception		0.17		0.00		0.34
Within perceived acceptance only		1.18		1.34		1.01
Both between usage and perceived acceptance, and within perceived acceptance		0.00		0.67		0.17
Total	100		100		100	

Note: "No conflict" refers to merchants who do not exhibit any of the three types of conflict, and also includes merchants for which perceived acceptance was reported as 'don't know' for all transactions, i.e., $v_{+m} = v_{+m}^{p=DK}$. "Between usage and perception" refers to merchants for which usage occurs at least once, and the method of payment is perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$. "Within perceived acceptance only" refers to merchants for which usage does not occur. The method of payment is perceived to be accepted at least once, but is also perceived to be not accepted at least once: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. "Both between usage and perceived acceptance, and within perceived acceptance" refers to merchants for conflicts exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

3.2.2 Low intensity of conflict

In order to assess the intensity of conflict, we define $\hat{S}_M^* = \{m \in \hat{S}_M^3 | v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\} \subset \hat{S}_M^3$ to be the subset of merchants that receive more than one visit, and where method of payment usage occurred at least once.

Since usage implies true acceptance according to Rule 3, conditioning on usage occurring at least once, $v_{+m}^{u=Y} \geq 1$ provides a benchmark against which perceived acceptance can be evaluated. For each $m \in \hat{S}_M^*$, we consider the conditional distribution of $\boldsymbol{p}_m$

$$R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=Y}}{v_{+m}-v_{+m}^{u=Y}} \in [0,1] , \tag{11}$$

$$R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=N}}{v_{+m}-v_{+m}^{u=Y}} \in [0,1] , \tag{12}$$

$$R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=DK}}{v_{+m}-v_{+m}^{u=Y}} \in [0,1] . \tag{13}$$

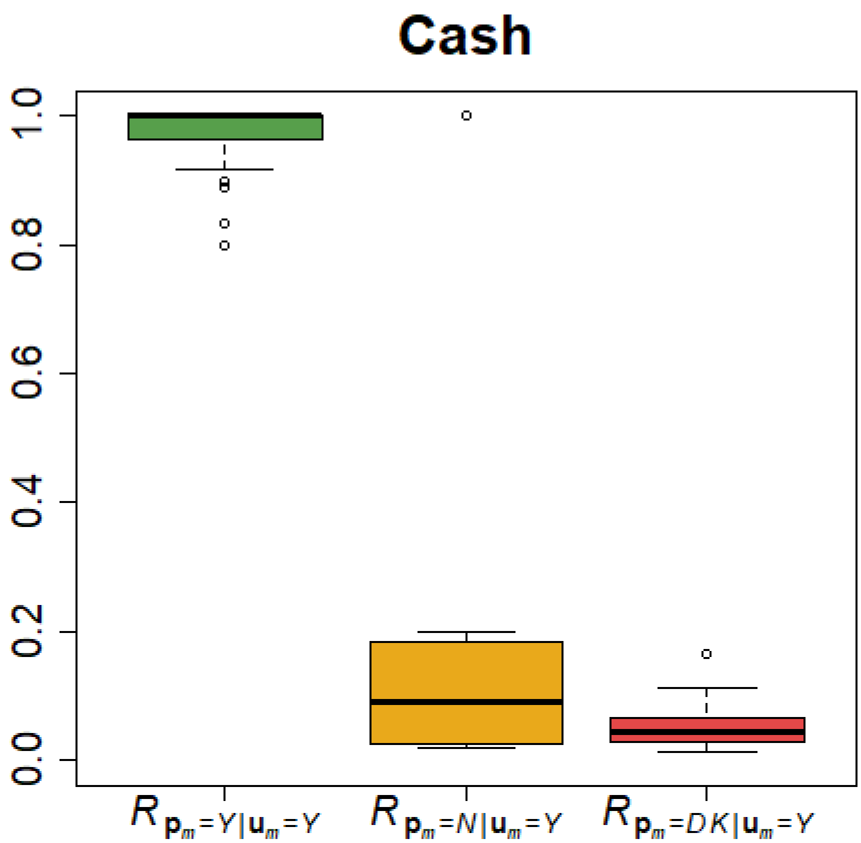
Note that:

$$R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y} + R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y} + R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y} = 1 . \tag{14}$$

Specifically, for each $m \in \hat{S}_M^*$, the frequency of perceived acceptance being 0 (a.k.a., the method of payment is perceived to be not accepted), $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, quantifies the intensity of conflict, because perceived as being not-accepted contradicts the fact of cash being used and thus must be accepted. Furthermore, notice that two extreme cases: one is when $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$=1, this implies all the perceived acceptance aligns with the actual usage so that this merchant unit m has perceived acceptance of perfect quality. On the other hand, when $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$=0, this implies there are extreme conflicts between the actual usage and all the perceptions so that for the merchant unit m we should seriously doubt its perceived acceptances.

Calculating $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y}$ for $m \in \hat{S}_M^*$, and plotting the distribution of each allows us to evaluate the intensity of conflict for all relevant merchants (Figures 2.1, 2.2, 2.3). For a low intensity of conflict and thus a high quality of responses, we would expect to see the distribution of $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$ to be centered close to one, which is indeed the case for cash, debit card, and credit card transactions.

Figure 2.1: Conditional distribution $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y}$, for $m \in \hat{S}_M^*$ where $\hat{S}_M^* \equiv \{m \in \hat{S}_M^3 | v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\}$



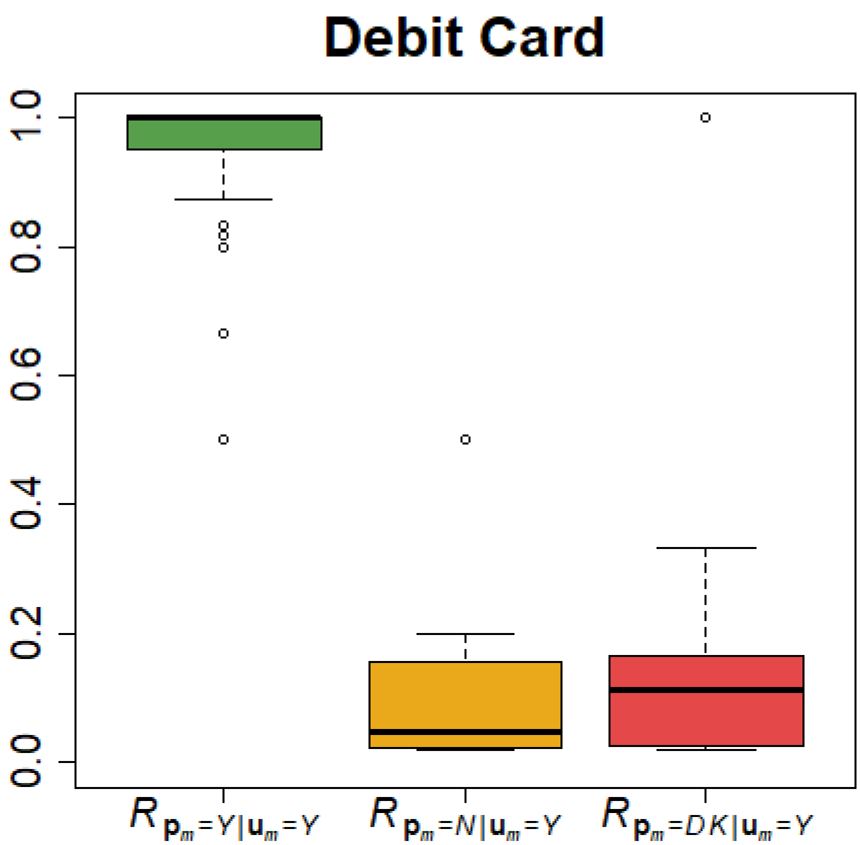
Note: This plot shows the distribution of $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y}$ for cash transactions, calculated for $m \in \hat{S}_M^* = \{m \in \hat{S}_M^3 | v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\}$. In other words, we only consider merchants receiving multiple transactions where cash is used at least once:

$R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=Y}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where cash was perceived to be accepted.

$R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=N}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where cash was perceived to be not accepted.

$R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=DK}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where the consumer reported ‘don’t know’ to cash perception.

Figure 2.2: Conditional distribution $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y}$, for $m \in \hat{S}_M^*$ where $\hat{S}_M^* \equiv \{m \in \hat{S}_M^3 | v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\}$



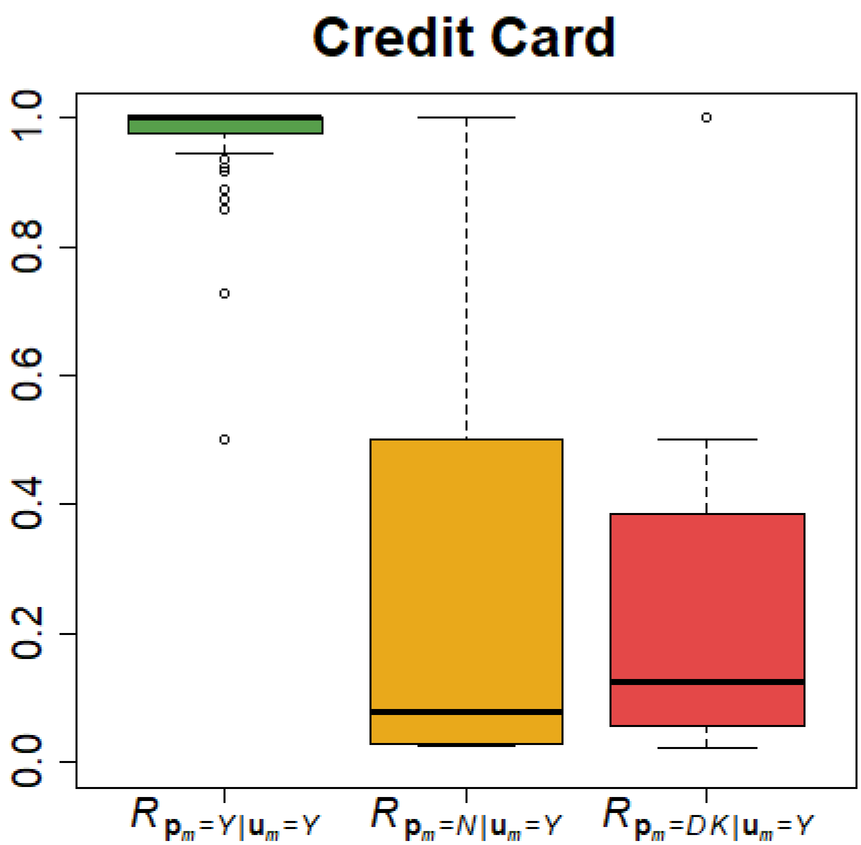
Note: This plot shows the distribution of $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|u_m=Y}$, and $R_{p_m=DK|u_m=Y}$ for debit card transactions, calculated for $m \in \hat{S}_M^* = \{m \in \hat{S}_M^3 | v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\}$, in other words, conditioning on there being at least one usage among multiple transactions:

$R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=Y}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where debit card was perceived to be accepted.

$R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=N}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where debit card was perceived to be not accepted.

$R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=DK}}{v_{+m} - v_{+m}^{u=Y}}$ is the proportion of transactions where the consumer reported ‘don’t know’ to debit card perception.

Figure 2.3: Conditional distribution $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{p_m=DK|u_m=Y}$, for $m \in \hat{S}_M^*$ where $\hat{S}_M^* \equiv \left\{m \in \hat{S}_M^3 \middle| v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\right\}$



Note: This plot shows the distribution of $R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y}$, $R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y}$, and $R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y}$ for credit card transactions, calculated for $\hat{S}_M^* = \left\{m \in \hat{S}_M^3 \middle| v_{+m} > 1,\ v_{+m}^{u=Y} \geq 1\right\}$, in other words, conditioning on there being at least one usage among multiple transactions.

$R_{\boldsymbol{p}_m=Y|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=Y}}{v_{+m}-v_{+m}^{u=Y}}$ is the proportion of transactions where credit card was perceived to be accepted.

$R_{\boldsymbol{p}_m=N|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=N}}{v_{+m}-v_{+m}^{u=Y}}$ is the proportion of transactions where credit card was perceived to be not accepted.

$R_{\boldsymbol{p}_m=DK|\boldsymbol{u}_m=Y} = \frac{v_{+m}^{p=DK}}{v_{+m}-v_{+m}^{u=Y}}$ is the proportion of transactions the consumer reported 'don't know' to credit card perception.

Evaluating the quality of $\boldsymbol{p}_m$ conditional on usage occurring at least once has provided evidence that the consumer's perception is reliable. So, it is reasonable that perceived acceptance can be used to help infer $\hat{y}_m$. While this analysis is restricted to $m \in \hat{S}_M^*$ we might reasonably infer that the results extend to the remaining merchants in $\hat{S}_M^3$, specifically, $m \in \hat{S}_M^3 \backslash \hat{S}_M^*$, the merchants who receive only one transaction, or those receiving multiple transactions for which no usage occurred.

To summarize, we evaluate the quality of consumer responses by considering how much conflict there is across usage and perceived acceptance and find that the incidence of conflict in $\hat{S}_M^3$ is low for cash, debit card, and credit card transactions. For the merchants receiving more than one transaction, where usage occurs at least once, we consider the conditional distribution of perceived acceptance, and find that p_m is, in general, consistent with u_m, indicating that the intensity of conflict is also low. This evidence affirms Assumption 2: the low incident and low intensity of conflicts indicate a high quality of consumer responses, which implies the reliability of derived $\hat{y}_m$.

3.3 Merchant weights $\widehat{w}_m$

To calculate each merchant weight, $\widehat{w}_m \equiv \sum_{c \in S_C} w_c \frac{v_{cm}}{v_{+m}}$, we require:

- w_c: the weights of the consumers who conduct a transaction at this merchant
- v_{cm}: the number of transactions each consumer $c \in S_C$ conducts at the merchant m
- v_{+m}: the total number of transactions that the merchant receives, which is $v_{+m} \equiv \sum_{c \in U_C} v_{cm}$.

So, the merchant's GWSM weight $\widehat{w}_m$ can be interpreted as the average of the weights of the consumers that conduct transactions at it. A consumer c who conducts more transactions at merchant m contributes a larger share of their weight, w_c, to this merchant's GWSM weight. For details on construction of v_{cm} and v_{+m} refer to Appendix A.3.

However, as discussed in Section 2, Assumption 3 is likely to be violated due to potential non-recorded merchants driven by the shorter duration of the three-day diary, that is, Ω_c^3 being the subset of Ω_C. In other words, the merchants that are visited less frequently by consumers may not be recorded in the three-day diary, leading to bias. In the following sections, we present empirical evidence against Assumption 3 and we provide the solution as the non-response calibration following Haziza and Lesage (2016).

3.3.1 Test for Assumption 3 and weight adjustment

Since $\hat{S}_M^3 \subseteq \hat{S}_M$ is due to non-recorded merchants outside of our three-day diary, then it is expected that the $\widehat{w}_m$ weighted composition of $\hat{S}_M^3$ would be different from the population composition of merchants from U_M. In the following we will compare the composition of $\hat{S}_M^3$ weighted by $\widehat{w}_m$ to that of the population, obtained from administrative data in the form of Statistics Canada's June 2021 Business Registrar (Statistics Canada BR) (Table 9). We observe that the discrepancies for size and industry are especially large. Specifically, small merchants

(0-5 employees) are underrepresented, as are merchants operating in the "Other services" industry (Table 9). Conversely, medium-sized merchants are overrepresented, as are merchants operating in the "Retail trade" and "Food services and drinking places" industries. We see that, by locality as well as region, there are instances where the composition of $\hat{S}_M^3$ and the Statistics Canada BR are more closely aligned. Discrepancies do persist by region, however; Ontario is underrepresented, and British Columbia and the Atlantic region are overrepresented.

Table 9: Composition of the Statistics Canada Business Register compared with the sample composition of $\hat{S}_M^3$ weighted using $\widehat{w}_m$

	Statistics Canada BR	$\hat{S}_M^3$ **weighted by** $\widehat{w}_m$
Size		
Small (0 to 5)	74	51
Medium (6 to 49)	26	49
Industry		
Retail trade (44/45)	47	56
Food services and drinking places (722)	19	38
Other services (811, 812)	34	6
Locality		
Rural	15	15
Urban	85	85
Region		
British Columbia	14	22
Prairies	18	15
Ontario	38	31
Quebec	24	21
Atlantic	6	11

Note: The column Statistics Canada BR indicates the composition obtained from the Statistics Canada's Business Register (June 2021). The column $\hat{S}_M^3$ indicates the sample composition weighted by $\widehat{w}_m$.

So, the discrepancy between the composition of the population and indirect samples weighted by $\widehat{w}_m$ indicate that the current weights $\widehat{w}_m$ from the GWSM are not sufficient to restore the representativeness of the indirect sample. We present potential root causes of the composition discrepancy from the perspective of the shorter duration of our three-day diary. Due to its relatively short length, consumers may not be able to record all the merchants that they could if they were given a longer time frame. These missing merchants in the three-day diary can be explained by the number of days for which consumers completed the diary (i.e., diary length). Because consumers are not required to complete all three days, some consumers complete only one or two days, and these consumers might record fewer merchants than the consumers who complete all three days.

Table 10: Relationship between number of days the diary was completed and the average number of merchants recorded

Diary status	**# Consumers**	**# Merchants**	**Average number**

			merchants for the completed period
One day completed	33	44	1.33
Two days completed	132	191	1.45
Three days completed	661	1,073	1.62

Note: The consumers in each row are mutually exclusive, but the merchants in each row may not be. The average number of merchants for the completed period is calculated as the number of merchants divided by the number of consumers.

Most consumers completed three days of the survey (Row 3 in Table 10), and we observe that the average number of merchants recorded is higher for these consumers compared with those who completed only one or two days. This strictly increasing pattern suggests that the more days of the diary that are completed, the more merchants are recorded. A longer diary gives consumers more opportunities to record transactions at less frequently visited merchants. Industries such as "Other services," which consists of merchants providing personal care or home maintenance, may be visited on only a bi-weekly or monthly basis, explaining their underrepresentation in $\hat{S}_M^3$ relative to the Statistics Canada BR (Table 9).

These patterns observed in the consumer survey data, specifically that a longer diary results in a large cardinality of Ω_c^3, indicate that there is some degree of non-recorded-merchant bias, necessitating an adjustment to the GWSM weights to account for it.

3.3.2 Non-response calibration to account for the shorter diary length

The sampled merchants in the three-day diary are $\hat{S}_M^3 \equiv \cup_{c \in S_C} \Omega_c^3$, while the merchants not recorded in the three-day diary are denoted as $\hat{S}_M \backslash \hat{S}_M^3$. Therefore, we can treat these merchants in $\hat{S}_M \backslash \hat{S}_M^3$ as unit non-respondents, allowing us to employ the tools under the unit non-response framework. Since our diary only lasts a maximum of three days, in practice we are unable to observe these non-recorded merchants $\hat{S}_M \backslash \hat{S}_M^3$. So, we employ non-response calibration outlined in Haziza and Lesage (2016).[4]

The general procedure of Haziza and Lesage (2016) is to adjust the $\hat{w}_m$ by some adjustment factor $F(\boldsymbol{\lambda}^{\mathrm{T}}\boldsymbol{x_m})$, so that the new weight $\hat{w}_m^{cal}$ corrects for the non-recorded merchants from $\hat{S}_M \backslash \hat{S}_M^3$. The calibrated GWSM weight will be:

$$\hat{w}_m^{cal} = \hat{w}_m F\left(\hat{\boldsymbol{\lambda}}^{\mathrm{T}}\boldsymbol{x_m}\right),$$

[4] Here we apply the non-response calibration to correct for the unit nonresponse, where the other alternative could be the imputation method. For example, we could potentially employ Graham (2020) to predict the purchase decision/visit under the sparse network asymptotics. In terms of imputing the consumer-merchant linkage (purchase decision/visit) in the more than three-day duration, the imputation model should consider not only consumer and merchant characteristics, but also the two-sided nature of the payment network (Bounie, François and Van Hove, 2017) and consumer awareness of merchant payment (Huynh, Nicholls and Shcherbakov, 2022).

where the function F is specified according to some calibration objective function.[5] In order to estimate $\hat{\lambda}^{\mathrm{T}}$, we use the below calibration equation:

$$\sum_{m\in\hat{S}_M^3} \widehat{w}_m F\left(\hat{\boldsymbol{\lambda}}^{\mathbf{T}}\boldsymbol{x_m}\right)\boldsymbol{x_m} = \sum_{m\in U_M} \boldsymbol{x_m},$$

where $\boldsymbol{x_m}$ correspond to the business size, industry, locality, and region of merchant m and $\sum_{m\in U_M}\boldsymbol{x_m}$ is obtained from the Statistics Canada BR. The choice of auxiliary variables follows the methodology in Chen and Shen (2017).

By substituting ${\widehat{w}_m}^{cal}$ into the estimate for $\hat{\mu}^3$, we obtain the non-response calibrated indirect estimate:

$$\hat{\mu}^{3,cal} = \frac{\sum_{m\in\hat{S}_M^3}\widehat{w}_m^{cal}\hat{y}_m}{\sum_{m\in\hat{S}_M^3}\widehat{w}_m^{cal}}. \tag{6}$$

4. Comparing indirect sample estimates to direct sample estimates

In this section, we compare two versions of indirect estimates with their direct estimate benchmarks and find that the indirect estimates calculated under our proposed methodology align well. We show this alignment by comparing the absolute difference between estimates, as well as showing where the two versions of indirect estimates fall within their corresponding direct estimates' confidence intervals.

To evaluate the performance of indirect sampling, we first establish a benchmark, $\tilde{\mu}$, which is obtained through direct sampling and reported in the 2021-22 MAS:

$$\tilde{\mu} \equiv \frac{\sum_{m\in S_M} w_m y_m}{\sum_{m\in S_M} w_m}, \tag{3}$$

where the weight w_m follows Chen and Shen (2017). Moreover, we have indirect sample estimates $\hat{\mu}^3$ calculated using the uncalibrated GWSM weights $\widehat{w}_m$, as well as indirect sample estimates $\hat{\mu}^{3,cal}$ calculated using calibrated GWSM weights $\widehat{w}_m^{cal}$ to account for potential non-recorded merchants:

$$\hat{\mu}^3 = \frac{\sum_{m\in\hat{S}_M^3}\widehat{w}_m\hat{y}_m}{\sum_{m\in\hat{S}_M^3}\widehat{w}_m}, \tag{5}$$

$$\hat{\mu}^{3,cal} = \frac{\sum_{m\in\hat{S}_M^3}\widehat{w}_m^{cal}\hat{y}_m}{\sum_{m\in\hat{S}_M^3}\widehat{w}_m^{cal}}. \tag{6}$$

[5] Note that such calibration approach to calibrate is equivalent to the inverse probability weighting (IPW) estimator; see Wu (2022).

Additionally, we also experiment with three sets of mapping rules (Section 3.2) to generate $\hat{y}_m$ from consumer-reported usage $\boldsymbol{u}_m$ and perceived acceptance $\boldsymbol{p}_m$.

Firstly, we note that the impact of the different mapping rules on the final results are negligible, as we can see in Tables 11.1, 11.2 and 11.3, for all three methods of payment. They produce similar indirect estimates of cash, debit card and credit card acceptance. This can be explained by Table 5 where the above three mapping rules produce the identical value of $\hat{y}_m$ for most $m \in \hat{S}_M^3$.

Next, to assess the performance of $\hat{\mu}^3$ and $\hat{\mu}^{3,cal}$, we first compare their point estimates with respect to $\tilde{\mu}$. Since the direct sampling $\tilde{\mu}$ is subject to the sampling variability, we also check whether the point estimates of $\hat{\mu}^3$ and $\hat{\mu}^{3,cal}$ are within in the confidence interval of $\tilde{\mu}$. At the overall level, we observe that with respect to the absolute difference between direct estimate $\tilde{\mu}$ and our indirect estimates, $\hat{\mu}^3$ aligns well with respect to cash, and the absolute percentage point (PP) difference is between 1.51pp–1.76pp, depending on the mapping rule. With respect to debit card and credit card $\hat{\mu}^3$ performs moderately: with absolute PP difference between 8.91pp–9.40pp and 5.73pp–6.37pp, respectively. We observe a significant improvement in the indirect estimates calculated using $\hat{\mu}^{3,cal}$, especially with respect to debit and credit cards. The statistically calibrated GWSM estimates reduce the absolute PP difference to be between 0.20pp–0.36pp, 4.15pp–4.97pp, and 1.80pp–2.92pp for cash, debit card and credit card, respectively, indicating that calibration improves indirect sample estimates.

The discrepancies between the benchmark $\tilde{\mu}$ and uncalibrated indirect estimates $\hat{\mu}^3$ are even larger at the subdomain level, especially for debit card and credit card. The largest discrepancy occurs for debit card, Quebec[6]: the absolute difference between $\tilde{\mu}$ and $\hat{\mu}^3$ is 19.28pp. This value is similarly large for debit card acceptance with respect to merchants who are small (9.74pp-10.59pp), and merchants operating in "Other services" industries (6.94pp–9.73pp). These observations are also consistent for credit card, with the absolute difference between the direct sample benchmark and the uncalibrated indirect sample ranging between 5.59pp–6.80pp, 8.98pp–12.13pp, and 11.27pp–13.25pp for small merchants, merchants operating in "Other services" industries, and merchants located in Quebec, respectively. Like the overall estimates, the discrepancy is considerably reduced when using the calibrated GWSM estimate $\hat{\mu}^{3,cal}$. For debit card, the absolute PP difference between the benchmark estimate $\tilde{\mu}$ and the calibrated GWSM estimate $\hat{\mu}^{3,cal}$ is reduced to as little as 4.41 under Rule 2 for small merchants, and 2.12

[6] The 2021-22 MAS was in the field in mid to late 2021 and early 2022. Figure B.1 of Appendix B shows that during this time, Quebec was subject to stricter stringency measures relative to the other regions. Petrunia et al. (forthcoming) documented a negative relationship between stringency measures and both the volume of visits as well the duration of these visits. So, when the merchants in Quebec were subject to heightened restrictions, it is plausible that they reduced their store hours to account for the reduced visits, thus making it more difficult for them to be contacted for the 2021-22 MAS. As a result of this, these merchants were underrepresented in the 2021-22 MAS relative to the Statistics Canada benchmark, and we observe very wide confidence intervals for these estimates (Figures 3.1, 3.2, 3.3) relative to other subdomain estimates

under Rule 2 for merchants operating in "Other services." We note improvements of similar magnitude for the same subdomain estimates with respect to credit card.

We noted in Section 3.3.1 that these three strata (small, operating in "Other services," located in Quebec) are underrepresented in $\hat{S}_M^3$ relative to the Statistics Canada Business Register (Table 9). Specifically, small merchants and merchants operating in the "Other services" industries are severely underrepresented, while merchants in Quebec are moderately underrepresented. This underrepresentation, documented in Section 3.3.1, can be attributed to the relatively short duration of the consumer diary. Industries such as "Other services" tend to be visited less frequently and are thus more likely to be missing in $\hat{S}_M^3$ relative to merchants that belong to industries that are visited more frequently. We also know from direct sampling that merchants who are small (0-5 employees) and merchants who operate in the "Other services" industries tend to accept debit cards and credit cards at a lower rate relative to merchants who are large (6-49 employees) and to merchants operating in the other two in-scope industries ("Retail trade" and "Food services and drinking places"), respectively. To address this underrepresentation, we treat these 'missing' merchants as unit non-respondents and apply non-response calibration following Haziza and Lesage (2016), obtaining the calibrated GWSM estimates of indirect sampling, $\hat{\mu}^{3,\text{cal}}$. These calibrated estimates exhibit a notably smaller difference from the direct sampling benchmark, particularly for debit card and credit card acceptances, and improve upon on the uncalibrated GWSM estimates at both the overall and subdomain levels.

Lastly, it is not enough to just produce unbiased estimates relative to $\tilde{\mu}$; it is also important to provide indicators of the quality of those estimates. Therefore, we visualize the improvement of $\hat{\mu}^{3,\text{cal}}$ over $\hat{\mu}^3$ by considering where they fall with respect to confidence intervals calculated for $\tilde{\mu}$ (Figures 3.1, 3.2, 3.3).[7] Here we use pseudo-population bootstrap resampling (Chen and Tsang, forthcoming) to generate bootstrap estimates, then calculate the 95% confidence interval using the empirical cumulative distribution function (CDF). In the majority of instances (both overall and subdomain estimates) for cash, debit card and credit card, $\hat{\mu}^{3,\text{cal}}$ not only lies more frequently within the confidence interval of $\tilde{\mu}$ than $\hat{\mu}^3$, but also $\hat{\mu}^{3,\text{cal}}$ is more centered around $\tilde{\mu}$ than $\hat{\mu}^3$. Therefore, by benchmarking to the point estimate $\tilde{\mu}$ of the direct sample and its sampling variability, our proposed calibrated GWSM estimate $\hat{\mu}^{3,\text{cal}}$ performs better than the uncalibrated GWSM estimate $\hat{\mu}^3$.

[7] We also provide the confidence intervals for $\hat{\mu}^{3,\text{cal}}$ using Rule 1 for $\hat{y}_m$ in Appendix B (Figures B.2, B.3 and B.4). Here the confidence interval of $\hat{\mu}^{3,\text{cal}}$ is computed by using the empirical CDF of estimates generated through the pseudo-population bootstrap for single-phase survey (Chen and Tsang, forthcoming). In particular, we first generated the b=1000 resampled consumer data from the consumer pseudo-population based on the consumer sample S_C and the associated weight w_C, and then we re-computed the b^{th} resampling version of $\hat{\mu}^{3,cal\,(b)}$ along with the resampled data $\hat{S}_M^{3\,(b)}$, $\hat{w}_m^{cal\,(b)}$ and $\hat{y}_m^{(b)}$(generated under mapping Rule 1).

Table 11.1: Indirect estimates of cash acceptance (percentage)

	$\tilde{\mu}$	Rule 1: Majority rules $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 1: Majority rules $\lvert\tilde{\mu}-\hat{\mu}^{3,\mathrm{cal}}\rvert$	Rule 2: Weighted average $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 2: Weighted average $\lvert\tilde{\mu}-\hat{\mu}^{3,\mathrm{cal}}\rvert$	Rule 3: Usage is always correct $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 3: Usage is always correct $\lvert\tilde{\mu}-\hat{\mu}^{3,\mathrm{cal}}\rvert$
General	97	1.76	0.34	1.51	0.20	1.76	0.36
Size							
0 to 5	97	1.67	1.78	1.20	1.05	1.68	1.79
6 to 49	96	2.61	4.06	2.58	4.09	2.61	4.06
Industry							
Retail trade (44/45)	97	2.43	2.66	2.28	2.45	2.43	2.66
Food services and drinking places (722)	98	0.26	1.36	0.25	1.38	0.26	1.36
Other services (811, 812)	96	0.55	2.34	3.24	3.62	0.31	2.16
Region							
British Columbia	100	1.47	6.41	1.47	6.41	1.47	6.41
Prairies	96	0.84	2.23	0.60	1.99	0.84	2.23
Ontario	96	2.14	0.07	2.01	0.18	2.14	0.07
Quebec	96	3.90	3.86	3.00	1.88	3.90	3.87
Atlantic	100	0.13	0.04	0.13	0.04	0.13	0.04

Note 1: $\tilde{\mu}$ (equation 3) corresponds to estimates from direct sampling (2021-22 MAS), $\hat{\mu}^3$ (equation 5) corresponds to estimates from uncalibrated indirect sampling, $\hat{\mu}^{3,cal}$ (equation 6) corresponds to estimates from calibrated direct sampling. $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$ corresponds to the absolute difference between estimates from direct sampling and uncalibrated indirect sampling. $\lvert\tilde{\mu}-\hat{\mu}^{3,\mathrm{cal}}\rvert$ measures the absolute difference between estimates from direct sampling and calibrated indirect sampling.

Note 2: Merchant industry and region are obtained from the consumer diary, merchant size is obtained through linkage to an external commercial data source, and details on the construction of all merchant characteristics x_m can be found in Appendix A.2.

Note 3: The formatting follows a three-colour scale based on percentile values. In Tables 11.1, 11.2, and 11.3, the smallest values are shaded in the darkest green, the largest value in the darkest red, and the midpoint (50th percentile) in yellow. All other values are coloured according to their percentile position along this scale. So, indirect estimates that align well with direct estimates are indicated by green.

Table 11.2: Indirect estimates of debit card acceptance (percentage)

	$\tilde{\mu}$	Rule 1: Majority rules		Rule 2: Weighted average		Rule 3: Usage is always correct	
		$\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	$\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$	$\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	$\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$	$\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	$\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$
General	88	9.39	4.97	8.91	4.15	9.40	4.97
Size							
0 to 5	86	10.59	5.44	9.74	4.41	10.59	5.44
6 to 49	94	4.42	4.04	4.36	3.98	4.43	4.04
Industry							
Retail trade (44/45)	91	6.56	6.25	6.03	5.38	6.56	6.25
Food services and drinking places (722)	94	4.25	2.92	4.18	2.87	4.26	2.93
Other services (811, 812)	81	9.73	3.12	6.94	2.12	9.73	3.12
Region							
British Columbia	92	5.66	0.44	5.68	0.46	5.68	0.46
Prairies	91	3.34	2.47	3.25	2.55	3.34	2.47
Ontario	89	9.42	4.44	8.49	3.44	9.42	4.44
Quebec	79	19.28	15.28	18.27	13.44	19.28	15.28
Atlantic	100	3.38	1.41	3.38	1.41	3.38	1.41

Note 1: $\tilde{\mu}$ (equation 3) corresponds to estimates from direct sampling (2021-22 MAS), $\hat{\mu}^3$ (equation 5) corresponds to estimates from uncalibrated indirect sampling, $\hat{\mu}^{3,cal}$ (equation 6) corresponds to estimates from calibrated direct sampling. $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$ corresponds to the absolute difference between estimates from direct sampling and uncalibrated indirect sampling. $\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$ measures the absolute difference between estimates from direct sampling and calibrated indirect sampling.

Note 2: Merchant industry and region are obtained from the consumer diary, merchant size is obtained through linkage to an external commercial data source, and details on the construction of all merchant characteristics x_m can be found in Appendix A.2.

Note 3: The formatting follows a three-colour scale based on percentile values. In Tables 11.1, 11.2, and 11.3, the smallest values are shaded in the darkest green, the largest value in the darkest red, and the midpoint (50th percentile) in yellow. All other values are coloured according to their percentile position along this scale. So, indirect estimates that align well with direct estimates are indicated by green.

Table 11.3: Indirect estimates of credit card acceptancepercentage)

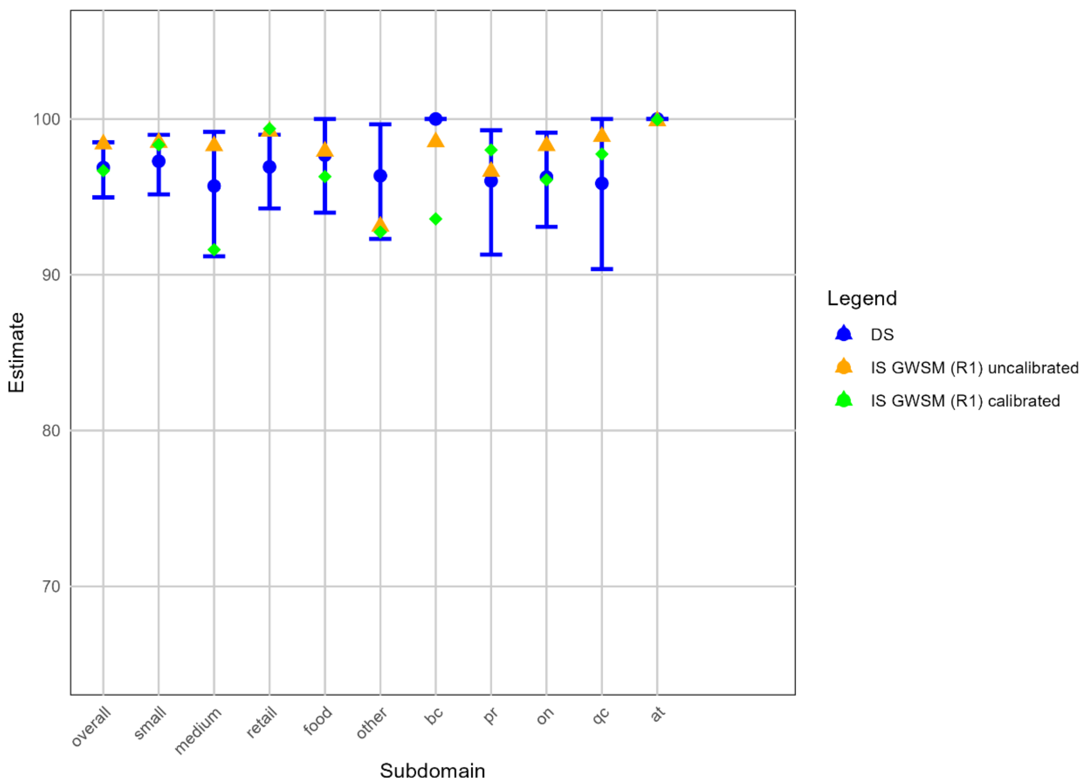
	$\tilde{\mu}$	Rule 1: Majority rules $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 1: Majority rules $\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$	Rule 2: Weighted average $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 2: Weighted average $\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$	Rule 3: Usage is always correct $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$	Rule 3: Usage is always correct $\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$
General	88	6.33	2.78	5.73	1.80	6.37	2.91
Size							
0 to 5	87	6.72	3.53	5.59	2.23	6.80	3.71
6 to 49	92	3.22	0.66	3.22	0.65	3.24	0.67
Industry							
Retail trade (44/45)	91	3.22	4.19	2.40	2.86	3.25	4.23
Food services and drinking places (722)	92	5.54	3.84	5.55	3.84	5.55	3.84
Other services (811, 812)	82	10.81	1.41	12.13	2.32	8.98	0.81
Region							
British Columbia	93	0.08	3.14	0.15	3.10	0.15	3.10
Prairies	92	3.10	1.99	3.10	1.99	3.10	1.99
Ontario	88	8.50	2.13	7.65	1.22	8.54	2.24
Quebec	80	13.12	9.55	11.27	6.81	13.25	9.98
Atlantic	100	6.28	4.45	6.28	4.45	6.28	4.45

Note 1: $\tilde{\mu}$ (equation 3) corresponds to estimates from direct sampling (2021-22 MAS), $\hat{\mu}^3$ (equation 5) corresponds to estimates from uncalibrated indirect sampling, $\hat{\mu}^{3,cal}$ (equation 6) corresponds to estimates from calibrated direct sampling. $\lvert\tilde{\mu}-\hat{\mu}^3\rvert$ corresponds to the absolute difference between estimates from direct sampling and uncalibrated indirect sampling. $\lvert\tilde{\mu}-\hat{\mu}^{3,\text{cal}}\rvert$ measures the absolute difference between estimates from direct sampling and calibrated indirect sampling.

Note 2: Merchant industry and region are obtained from the consumer diary, merchant size is obtained through linkage to an external commercial data source, and details on the construction of all merchant characteristics x_m can be found in Appendix A.2.

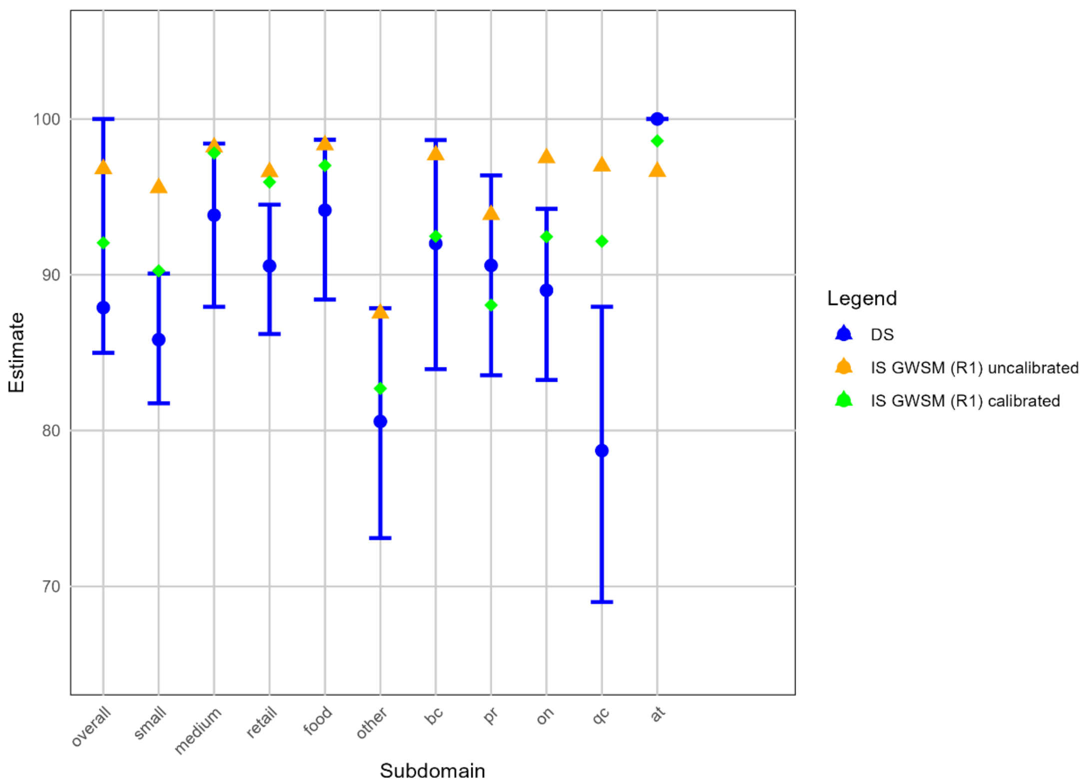
Note 3: The formatting follows a three-colour scale based on percentile values. In Tables 11.1, 11.2, and 11.3, the smallest values are shaded in the darkest green, the largest value in the darkest red, and the midpoint (50th percentile) in yellow. All other values are coloured according to their percentile position along this scale. So, indirect estimates that align well with direct estimates are indicated by green.

Figure 3.1: Comparing direct sample estimates $\tilde{\mu}$, their confidence intervals with indirect sample estimates $\hat{\mu}^3$ and $\hat{\mu}^{3,\mathrm{cal}}$ for cash acceptance



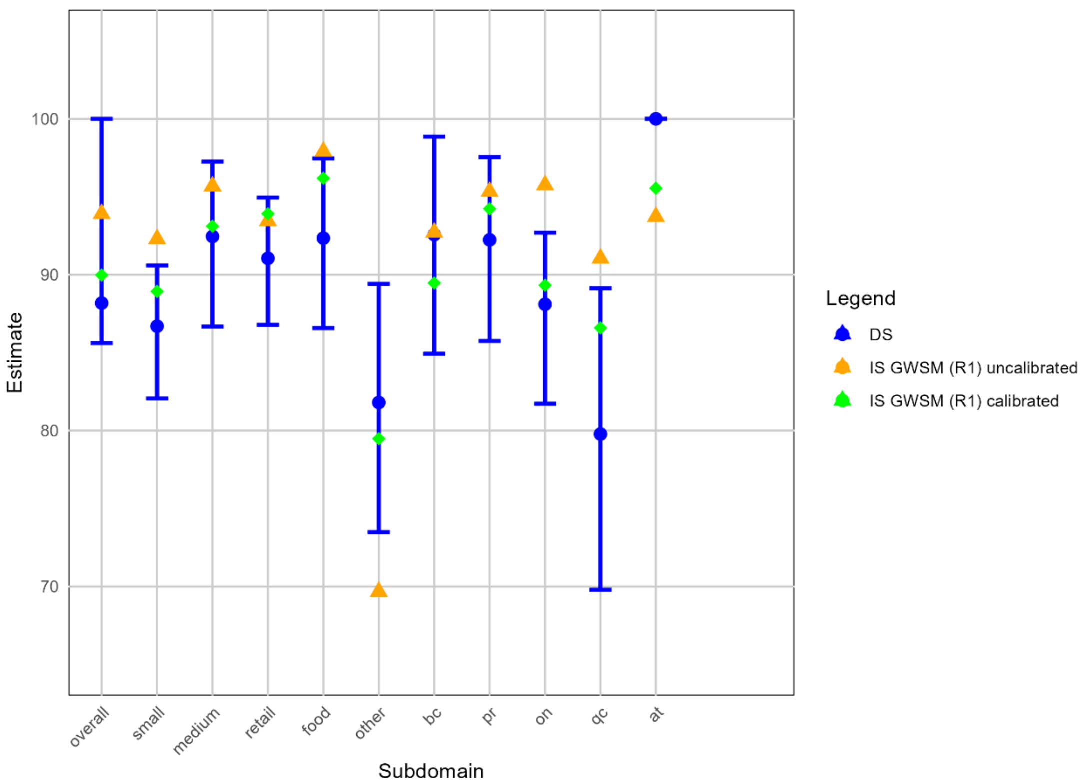
Note: Confidence intervals for direct estimates $\tilde{\mu}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling (Chen and Tsang, forthcoming). DS represents direct estimates $\tilde{\mu}$ from the 2021-22 MAS, IS GWSM (R1) uncalibrated represents uncalibrated indirect estimates $\hat{\mu}^3$ under mapping Rule 1, and IS GWSM (R1) calibrated represents calibrated indirect estimates $\hat{\mu}^{3,cal}$ under mapping Rule 1.

Figure 3.2: Comparing direct sample estimates $\tilde{\mu}$, their confidence intervals with indirect sample estimates $\hat{\mu}^3$ and $\hat{\mu}^{3,\mathrm{cal}}$ for debit card acceptance



Note: Confidence intervals for direct estimates $\tilde{\mu}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling (Chen and Tsang, forthcoming). DS represents direct estimates $\tilde{\mu}$ from the 2021-22 MAS, IS GWSM (R1) uncalibrated represents uncalibrated indirect estimates $\hat{\mu}^3$ under mapping Rule 1, and IS GWSM (R1) calibrated represents calibrated indirect estimates $\hat{\mu}^{3,cal}$ under mapping Rule 1. Quebec's confidence intervals are relatively wider than other regions' due to reasons discussed in Section 4.

Figure 3.3: Comparing direct sample estimates $\tilde{\mu}$, their confidence intervals with indirect sample estimates $\hat{\mu}^3$ and $\hat{\mu}^{3,\mathrm{cal}}$ for credit card acceptance



Note: Confidence intervals for direct estimates $\tilde{\mu}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling (Chen and Tsang, forthcoming). DS represents direct estimates $\tilde{\mu}$ from the 2021-22 MAS, IS GWSM (R1) uncalibrated represents uncalibrated indirect estimates $\hat{\mu}^3$ under mapping Rule 1, and IS GWSM (R1) calibrated represents calibrated indirect estimates $\hat{\mu}^{3,cal}$ under mapping Rule 1. Quebec's confidence intervals are relatively wider than other regions' due to reasons discussed in Section 4.

5. Discussion and future research

Compared with the direct sampling approach, where merchants are sampled and asked about their payment acceptance, we apply the indirect sampling approach to sample and ask consumers about the acceptance of the merchants that they visit. This not only results in higher response rates than directly sampling merchants, but also reduces the response burden placed on them. When comparing to the benchmark estimates from the 2021-22 MAS results based on the direct sampling approach, our proposed indirect sampling estimates align well with the ones from the direct sampling.

One of two innovations for our indirect sampling approach is to ask consumers to report their actual payment use and perceptions of acceptance at the merchant where they conduct their in-person transactions. As we document in Section 3, there are very few conflicts of payment acceptances between usage and perceptions, or within perceptions. This means that the perceived acceptance by consumer reporting is high quality, and we can rely on it to construct the merchant acceptance. However, note that such high-quality consumer perception is context-specific. In our application, we conjecture that the mechanisms behind consumers perceiving merchant acceptance could be that consumers see merchant signs, or observe other consumers' payment choices, or recall their previous shopping experiences at that merchant. Thus, it would be interesting for future work to disentangle the exact informational channel of how consumers form their perceptions.

The second innovation of the paper is related to adjusting the GWSM weights to correct for potential non-recorded-merchant bias due to the shorter duration of the diary. We show that such adjustment is crucial for our indirect sampling application because our current three-day diary does not allow consumers to record merchants that they visit outside of these three days. Instead of adjusting the GWSM weights through non-response calibration as we implement in the paper, one alternative is to use the propensity-score weighting estimator by computing the probability of being selected into the indirectly sampled merchants $\hat{S}_M^3$. Under the data integration framework between the probabilistic and non-probabilistic samples, we can treat the merchants in $\hat{S}_M^3$ as the non-probabilistic sample while treating the direct sampled merchants in the 2021-22 MAS as the probabilistic sample, and then employ the pseudo-maximum likelihood to estimate the above inclusion probability, following Chen, Li, and Wu (2020). We leave such data integration approach on the indirect sample for future investigation.

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Appendix A: Data processing to obtain $\hat{S}_M^3$, x_m and $\widehat{w}_m$

This section is broken down into four components: details on how $\hat{S}_M^3$ is obtained (Appendix A.1), how merchant characteristics x_m are obtained (Appendix A.2), and how the GWSM weight $\widehat{w}_m$ is computed (Appendix A.3), as well as an illustrative example of how these three components are obtained from the consumer diary (Appendix A.4).

A.1 Obtaining unique merchant sample $\hat{S}_M^3$

On each transaction, consumers are asked the following open-ended question:

"What was the name of the business where you made this purchase?"

The responses to this question serve as the source for obtaining $\hat{S}_M^3$, as discussed in Section 3.1 and illustrated in Table 1. To identify the unique merchants across all transactions, we perform string matching across all consumer-reported merchant names using the *tidytext* package in R.[8] Consumer-reported merchant names with a similarity score above a pre-defined threshold are treated as the same merchant.

A.2: Obtaining merchant characteristics x_m

Once $\hat{S}_M^3$ is established, we need to obtain x_m for each $m \in \hat{S}_M^3$. Both tasks are achieved through modal or mean assignment, depending on if x is discrete or continuous. Industry, locality and region (Appendix A.2.1) are available in the consumer survey, whereas size (Appendix A.2.2) is obtained by linking $\hat{S}_M^3$ to a commercial dataset. Lastly, we also discuss how we filter the indirect sample so that it focuses on the same scope as the direct sample (Appendix A.2.3).

A.2.1: Obtaining merchant's industry, locality and region

Industry is obtained from consumer responses, whereas locality and region are associated with the reporting consumer and are thus known. For each transaction that $m \in \hat{S}_M^3$ receives, consumers are asked the following question:

"What was the main type of good or service purchased during this transaction?"

Consumers can then select from a list (Table A.2.1), and their selection is mapped to a two- or three-digit NAICs code according to Statistics Canada's 2017 North American Industry Classification System (1.0).[9]

[8] https://www.tidytextmining.com/tfidf

[9] Statistics Canada 2017 NAICs codes

Table A.2.1: Map consumer response to NAICS

Original selection made by consumer	Mapped NAICs Code
Groceries or drugs: e.g., food, alcohol, tobacco, cleaning products, prescriptions	44
Personal attire: e.g., clothing accessories, cosmetics	44
Entertainment: e.g., movies, outings, concerts, admission for swimming pools, museums, zoos, galleries	71
Meals: e.g., restaurants, cafeterias, bars, coffee shops	72
Gasoline: gasoline	44
Hobby or sporting goods: e.g., craft supplies, toys, tools, sports equipment, books, newspaper	45
Health care: e.g., doctor, dentist, hospital bills	62
Professional or personal services: e.g., lawyer, mechanic, spa services, haircut	811/812
Durable goods: e.g., electronics, furniture, appliances, motor vehicles, household accessories	44
Travel/parking: e.g., hotel, taxi or ride sharing services, plane, train, paid parking, public transit	72
Other (please specify)	Dropped

Note: while this question does offer consumers the option to specify their purchase as open-ended text, we omit these transactions in this analysis.[10]

For $m \in \hat{S}_M^3$ receiving more than one visit, these merchants could have multiple values of (a total of v_{+m}) industry, locality and region. To consolidate these multiple values for a given merchant, we assign each $m \in \hat{S}_M^3$ their respective modal x value.

A.2.2: Merchant size

Merchant size is not available in the consumer diary and requires an external commercial dataset that contains employee count data. Similar to how $\hat{S}_M^3$ is established, we construct the link between the indirect merchant sample and the commercial dataset through string matching, using the same R package as before.[11]

For instances where $m \in \hat{S}_M^3$ is matched to more than one unit in the external commercial dataset, we assign m the average employee count, which is then mapped to either the small or medium size.

[10] Future work could involve categorizing that open-ended text to one of these pre-existing categories, where possible, to include the set of transactions from "Other services."

[11] https://www.tidytextmining.com/tfidf

A.2.3. Identifying in-scope merchants

Now that each merchant in the indirect sample has been assigned x_m, then we are able to filter them so that only merchants in the same scope as the 2021-22 MAS are considered. Specifically, this means focusing on merchants that:

- are small (0 to 5 employees, inclusive) and medium-sized (6 to 49 employees, inclusive)
- are independently owned and operated, not part of a chain or franchise
- operate in industries with NAICs codes “Retail trade” (codes 44 and 45), “Food services and drinking places” (code 722), and “Other services (except public administration)” (codes 811 and 812).

Doing so allows for comparability between the direct estimates and the indirect estimates, as both samples focus on the same scope of merchants.

A.3 Matrix representation of the consumer-merchant relationship to generate v_{cm} and v_{+m}

Once $\hat{S}_M^3$ is established we can express the transactions in the consumer-merchant matrix, where rows correspond to unique $c \in S_C$ and columns correspond to unique $m \in \hat{S}_M^3$.

Table A.3.1: Consumer-merchant transaction matrix

	$\boldsymbol{m_1}$	$\boldsymbol{m_2}$	$\boldsymbol{m_3}$	$\boldsymbol{m_4}$	$\boldsymbol{m_5}$	…	$\boldsymbol{m_{\hat{S}_M^3}}$
$\boldsymbol{c_1}$	1	1		2			1
$\boldsymbol{c_2}$		2			1		
$\boldsymbol{c_3}$			1				
$\boldsymbol{c_4}$				2			
$\boldsymbol{c_5}$		3			2		
$\vdots$						$\ddots$	
$\boldsymbol{c_{S_C}}$							4

v_{+m}	1	6	1	4	3	$\cdots$	5

The GWSM weight is defined as $\hat{w}_m \equiv \sum_{c \in S_C} w_c \frac{v_{cm}}{v_{+m}}$.

The consumer weights, w_c, are known by sampling design. The remaining two components, v_{cm} and v_{+m}, are obtained from the consumer-merchant transaction data, or the above transaction matrix. We can see that:

- v_{cm}, the number of transactions between consumer unit c and merchant unit m, is cell (c, m) in the above matrix
- $v_{+m} \equiv \sum_{c \in U_C} v_{cm}$, the total number of transactions that the merchant m receives, is the total of v_{cm} in the corresponding column m.

A.4 Illustrative example of constructing indirectly sampled merchants with their corresponding x_m, $\hat{y}_m$, $\hat{w}_m$ and $\hat{w}_m^{cal}$

Table A.4.1: Obtaining merchant-level data from consumer-level transaction data

Illustrative example of consumer diary							
Consumer-specific details		Transaction 1			Transaction 2		
Consumer S_c	Consumer weight w_c	Merchant name	Usage and perceived acceptance	Purchase Type	Merchant name	Usage and perceived acceptance	Purchase Type
c_1	w_1	m_1	Cash perceived being accepted	Grocery	m_2	Cash used	Meal
c_2	w_2	m_1	Cash used	Grocery			

Illustrative example of indirectly sampled merchants				
Merchant	Characteristic x_m	Merchant payment acceptance $\hat{y}_m$	Merchant weight $\hat{w}_m$	Calibrated merchant weight $\hat{w}_m^{cal}$
m_1	$\mathbf{x_1}$(i.e., Grocery)	Cash is accepted	$\hat{w}_1 = \frac{1}{2}w_1 + \frac{1}{2}w_2$	$\hat{w}_1 F(\hat{\boldsymbol{\lambda}}^{\mathbf{T}}\mathbf{x_1})$
m_2	$\mathbf{x_2}$ (i.e., Meal)	Cash is accepted	$\hat{w}_2 = w_1$	$\hat{w}_2 F(\hat{\boldsymbol{\lambda}}^{\mathbf{T}}\mathbf{x_2})$

Note: For example, for merchant m_1, x_1, $\hat{y}_1$, and $\hat{w}_1$ are constructed as follows: m_1 is in the Grocery category because purchase types reported by both c_1 and c_2 are Grocery. m_1 accepts cash because cash is perceived to be accepted by c_1 and is used by c_2. $\hat{w}_1$ is calculated using the GWSM formula $\hat{w}_1 \equiv \sum_{c\in S_C} w_c \frac{v_{c1}}{v_{+1}}$, where $v_{11} = 1, v_{12} = 1$ and $v_{+1} = v_{11} + v_{12} = 2$. $\hat{w}_1^{cal}$ is computed by calibrating to the external source (Section 3.3.2). For simplicity, the table is constructed based on merchants that do not have conflicting usage and perceived acceptance. For details on how conflicts in x_m are addressed, refer to Appendix A.2. For details on how conflicts in y_m are addressed, refer to Section 3.2.

Appendix B Supplementary Tables

Table B.1: Applicability of our proposed methodology to previous Bank of Canada's Method of Payment surveys

Year	Merchant name	Purchase type	Usage u_m	Perceived acceptance p_m	Available direct sample benchmark for comparison	Can apply our proposed methodology
2009	No	Yes	Yes	Consumers report their perception of whether "*the merchant **refuses** to accept **cash/debit card/credit card***"	✕	✕
2013	Yes	Yes	Yes	Consumers report their perception of whether the merchant accepts only cash	✕	✕
2017	Yes	Yes	Yes	Consumers report their perception of whether the merchant accepts only cash	✕	✕
2021	Yes	Yes	Yes	Consumers report their perception of whether "*the merchant **refuses** to accept **cash/debit/credit***"	✕	✓
2022	Yes	Yes	Yes	Consumers report their perception of whether "*the merchant accepts **cash/debit/credit***"	✓*	✓

Note: The 2021-22 Merchant Acceptance Survey serves as a benchmark, as it was in the field in both late 2021 and early 2022.

Table B.2: Four-way counts of consumer's characteristics

Age	Gender	Region	Low income	Medium income	High income
18-34	Male	Atlantic	0	1	1
18-34	Male	Quebec	1	3	4
18-34	Male	Ontario	8	8	6
18-34	Male	Prairies	2	2	5
18-34	Male	British Columbia	0	3	1
18-34	Female	Atlantic	3	4	0
18-34	Female	Quebec	2	3	7
18-34	Female	Ontario	4	6	10
18-34	Female	Prairies	1	3	5
18-34	Female	British Columbia	3	3	2
35-54	Male	Atlantic	2	3	6
35-54	Male	Quebec	6	9	18
35-54	Male	Ontario	7	14	36
35-54	Male	Prairies	4	8	18
35-54	Male	British Columbia	2	5	10
35-54	Female	Atlantic	2	2	7
35-54	Female	Quebec	2	4	11
35-54	Female	Ontario	7	16	34
35-54	Female	Prairies	8	7	12
35-54	Female	British Columbia	5	7	10
55+	Male	Atlantic	6	12	13
55+	Male	Quebec	10	9	4
55+	Male	Ontario	18	33	47
55+	Male	Prairies	10	19	18
55+	Male	British Columbia	7	15	16
55+	Female	Atlantic	6	7	6
55+	Female	Quebec	14	11	2
55+	Female	Ontario	16	34	40
55+	Female	Prairies	13	12	16
55+	Female	British Columbia	5	13	11
		Sample size		826	

Note: Here, we are considering only the consumers who report visiting at least one merchant in $\hat{S}_M^3$. Specifically, these are $c \in S_C$ such that $v_{cm} > 0$ for at least one $m \in \hat{S}_M^3$. In instances where consumer demographic information is missing, we impute them by using the relevant modal value.

Table B.3: Counts of different conflict-merchant types based on $u_{m,v}$ and $p_{m,v}$

	Cash		Debit card		Credit card	
	$v_{+m} = 1$	$v_{+m} > 1$	$v_{+m} = 1$	$v_{+m} > 1$	$v_{+m} = 1$	$v_{+m} > 1$
No conflict	497	90	497	86	497	89
Conflict						
Between usage and perception		1		0		2
Within perceived acceptance only		7		8		6
Both between usage and perceived acceptance, **and** within perceived acceptance		0		4		1
Total	595		595		595	

Note: "No Conflict" refers to merchants who did not exhibit any of the three types of conflict, and includes merchants for which perceived acceptance were reported as 'don't know' for all transactions, i.e., $v_{+m} = v_{+m}^{p=DK}$. "Between usage and perception" refers to merchants for which usage occurred at least once, but the method of payment was perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$. "Within perceived acceptance only" refers to merchants for which usage did not occur, while the method of payment was perceived to be accepted at least once, but was also perceived to be not accepted at least once: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. "Both between usage and perceived acceptance, *and* within perceived acceptance" refers to merchants for conflicts exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

Table B.4 Logistic regression of cash conflict on merchant characteristics

Variable	Estimate	SE	p-value
(Intercept)	-39.36	4,401.82	0.99
Small (0 to 5 employees)	0.04	0.78	0.96
Other services (811, 812)	1.50	1.48	0.31
Food services and drinking places (722)	1.48	1.13	0.19
Urban	17.10	2,780.57	1.00
British Columbia	-0.14	4,328.40	1.00
Ontario	17.25	3,412.40	1.00
Prairies	17.40	3,412.40	1.00
Quebec	17.42	3,412.40	1.00

Note: Logistic regression coefficients are presented as log-odds. Here, the dependent variable is a binary indicator of whether a merchant is a conflict merchant with respect to cash transactions. 'No Conflict' refers to merchants who do not exhibit any of the three types of conflict, and includes merchants for which perceived acceptance was reported as 'don't know' for all transactions, i.e., $v_{+m} = v_{+m}^{p=DK}$. 'Between usage and perception' refers to merchants for which cash was used at least once, and cash is perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$.

'Within perceived acceptance only' refers to merchants for which cash usage does not occur. Cash is perceived to be accepted at least once, but is also perceived to be not accepted at least once: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. 'Both between usage and perceived acceptance, and within perceived acceptance' refers to merchants for conflicts that exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

Table B.5: Logistic regression of debit card conflict on merchant characteristics

Term	Estimate	SE	p-value
(Intercept)	-21.41	2,200.03	0.99
Small (0 to 5 employees)	0.02	0.64	0.97
Other services (811, 812)	0.50	1.21	0.68
Food services and drinking places (722)	0.74	0.74	0.31
Urban	0.41	1.07	0.70
British Columbia	0.02	2,766.51	1.00
Ontario	17.24	2,200.03	0.99
Prairies	15.91	2200.03	0.99
Quebec	17.20	2,200.03	0.99

Note: Logistic regression coefficients are presented as log-odds. Here, the dependent variable is a binary indicator of whether a merchant is a conflict merchant with respect to debit card transactions. 'No Conflict' refers to merchants who do not exhibit any of the three types of conflict, and includes merchants for which perceived acceptance was reported as 'don't know' for all transactions, i.e., $v_{+m} = v_{+m}^{p=DK}$. 'Between usage and perception' refers to merchants for which debit card was used at least once, and debit card is perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$. 'Within perceived acceptance only' refers to merchants for which debit card usage does not occur. Debit card is perceived to be accepted at least once, but is also perceived to be not accepted at least once: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. 'Both between usage and perceived acceptance, and within perceived acceptance' refers to merchants for conflicts that exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

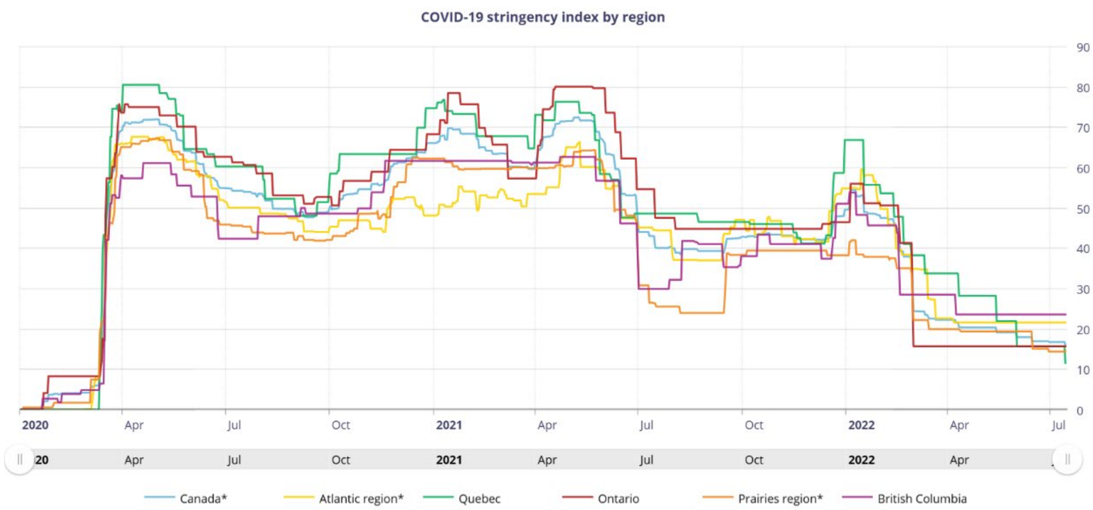
Table B.6: Logistic regression of credit card conflict on merchant characteristics

Term	Estimate	SE	p-value
(Intercept)	-40.72	6,375.18	0.99
Small (0 to 5 employees)	-0.13	0.73	0.86
Other services (811, 812)	18.72	2,897.67	0.99
Food services and drinking places (722)	18.94	2,897.67	0.99
Urban	-0.31	1.11	0.78
British Columbia	0.28	7,082.55	1.00
Ontario	19.12	5,678.59	1.00
Prairies	0.07	7,203.50	1.00
Quebec	19.38	5,678.59	1.00

Note: Logistic regression coefficients are presented as log-odds. Here, the dependent variable is a binary indicator of whether a merchant is a conflict merchant with respect to credit card transactions. 'No Conflict' refers to merchants who do not exhibit any of the three types of conflict and includes merchants for which perceived acceptance was reported as 'don't know' for all transactions, i.e., $v_{+m} = v_{+m}^{p=DK}$. 'Between usage and perception' refers to merchants for which credit card was used at least once, and credit card is perceived to be not accepted at least once: $\{m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} = 0, v_{+m}^{p=N} \geq 1\}$. 'Within perceived acceptance only' refers to merchants for which credit card usage does not occur. Credit card is perceived to be accepted at least once, but is also perceived to be not accepted at least once: {

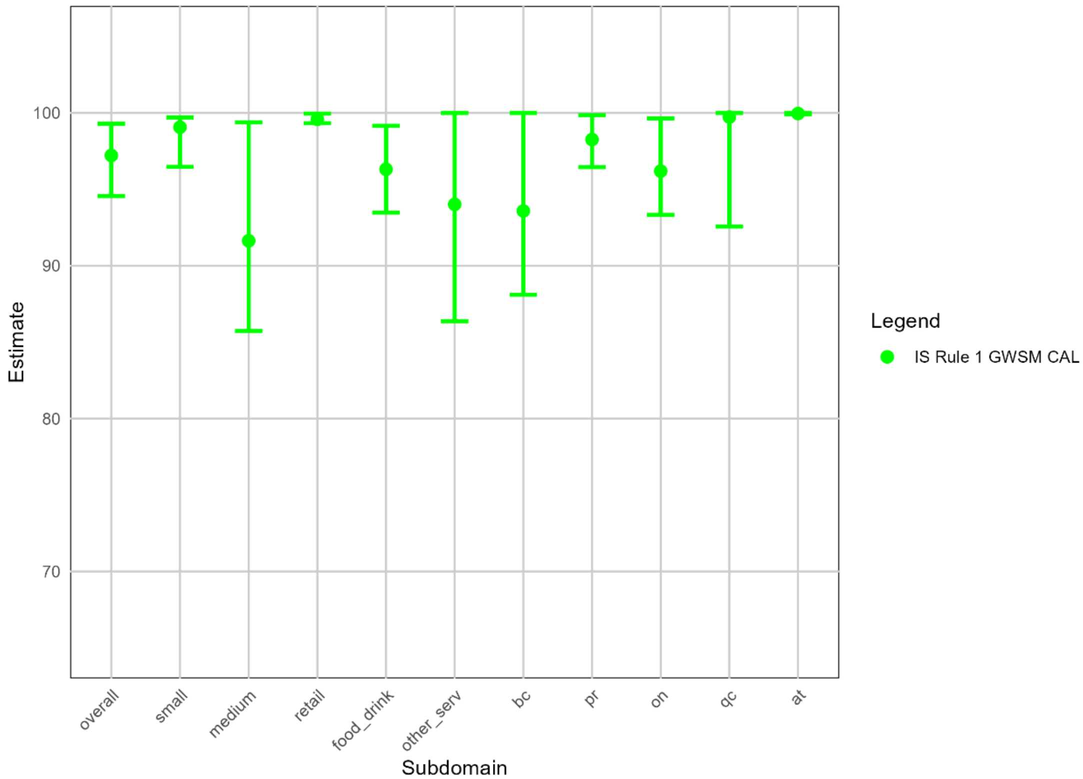
$m \in \hat{S}_M^3 | v_{+m}^{u=Y} = 0, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$. 'Both between usage and perceived acceptance, and within perceived acceptance' refers to merchants for conflicts that exist both between usage and perceived acceptance, as well as within perceived acceptance: $\{ m \in \hat{S}_M^3 | v_{+m}^{u=Y} \geq 1, v_{+m}^{p=Y} \geq 1, v_{+m}^{p=N} \geq 1\}$.

Figure B.1: COVID-19 stringency index by region



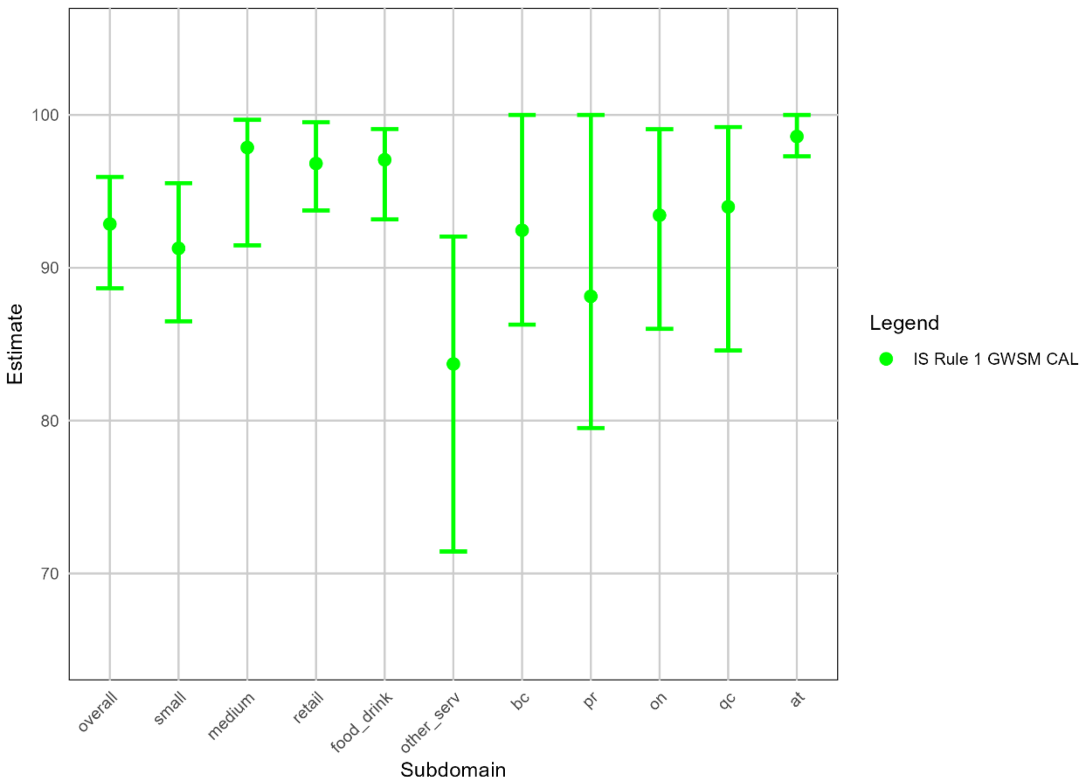
Note: Stringency index values are obtained from the Bank of Canada's calculations. Values range from 0 to 100, where higher values correspond to stricter measures.

Figure B.2: Confidence intervals of $\hat{\mu}^{3,\text{cal}}$ for cash acceptance



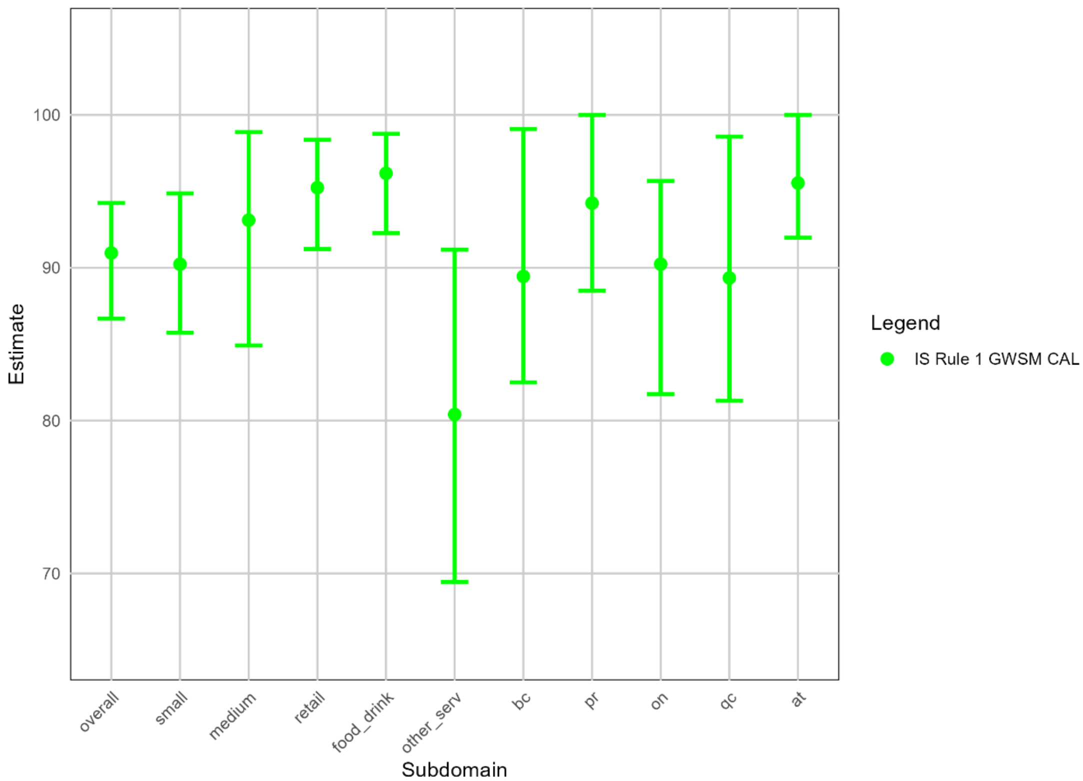
Note: Confidence intervals for indirect estimates $\hat{\mu}^{3,\text{cal}}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling for single-phase survey (Chen and Tsang, forthcoming) where we first resampled the consumer pseudo-population constructed from the consumer sample S_C, and then we re-computed the b^{th} resampling version of $\hat{\mu}^{3,cal\,(b)}$ along with the resampled data $\hat{S}_M^{3\,(b)}$, $\widehat{w}_m^{cal\,(b)}$ and $\hat{y}_m^{(b)}$(generated under mapping Rule 1).

Figure B.3: Confidence intervals of $\hat{\mu}^{3,\text{cal}}$ for debit card acceptance



Note: Confidence intervals for indirect estimates $\hat{\mu}^{3,\text{cal}}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling for single-phase survey (Chen and Tsang, forthcoming) where we first resampled the consumer pseudo-population constructed from the consumer sample S_C, and then we re-computed the b^{th} resampling version of $\hat{\mu}^{3,cal\,(b)}$ along with the resampled data $\hat{S}_M^{3\,(b)}$, $\widehat{w}_m^{cal\,(b)}$ and $\hat{y}_m^{(b)}$(generated under mapping Rule 1).

Figure B.4: Confidence intervals of $\hat{\mu}^{3,\text{cal}}$ for credit card acceptance



Note: Confidence intervals for indirect estimates $\hat{\mu}^{3,\text{cal}}$ were calculated by using the empirical CDF of estimates generated through pseudo-population resampling for single-phase survey (Chen and Tsang, forthcoming) where we first resampled the consumer pseudo-population constructed from the consumer sample S_C, and then we re-computed the b^{th} resampling version of $\hat{\mu}^{3,cal\,(b)}$ along with the resampled data $\hat{S}_M^{3\,(b)}$, $\widehat{w}_m^{cal\,(b)}$ and $\hat{y}_m^{(b)}$(generated under mapping Rule 1).