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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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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, the indirect sampling approach is applied 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 on methods of payments used and accepted. Among merchants receiving multiple transactions during the period of the diary, it is shown 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. Therefore, the consumers are leveraged to be both sampling and reporting units in the indirect sampling application to eliminate merchant response burden. Furthermore, the necessity of weight adjustment to account for the non-recorded-merchant bias due to the relatively shorter duration of the diary (i.e., 3 days) is shown. Finally, the indirect sampling estimates obtained were compared to the ones from a direct sampling survey, and it was found that the results are aligning well.

Key Words: Consumer payment survey and diary; Generalized weight share method; Indirect sampling; Merchant payment acceptance; Sparse network asymptotics.

1. Introduction

To understand cash usage and acceptance, the Bank of Canada has used the direct sampling approach for both consumer and merchant surveys. For example, to estimate the 2021-2022 Canadian merchant payment acceptance, Welte and Wu (2023) sample merchant units directly from a merchant sampling frame and ask a sampled merchant to report her payment acceptance. Here under the direct sampling approach, both the sampling and reporting units are merchants.

However, directly sampling and asking merchant has both a high cost and low response rate. With respect to cost, we need to construct the merchant sampling frame, which is resource intensive. Additionally, data is collected through Computer Assisted Telephone Interview (CATI), which is expensive. Conducting the MAS also suffers from low response rates (Welte and Wu, 2023), which is indicative of potential bias and requires non-response follow-ups which further increases costs. So, directly surveying merchants is both expensive and challenging. 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 they conduct transactions at. This reduces the cost and bias associated with sampling merchants directly. This is because when conducting consumer surveys there is an available sampling frame. Additionally, the data is collected through the Internet Self Response mode (the U.S. Census 2024), is relatively less expensive than CATI, and the consumer surveys generally have higher response rates (Henry, Shimoda and Rusu, 2023). In this paper, we leverage the 2022 Bank of Canada Method-of-Payment (MOP) diary. The consumer records of in-person transactions during a three-day period are used to map out the linked merchants, which we consider indirectly sampled.

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Regarding the indirect sampling methodology, we make two innovations differing from the existing literature: one is concerning the survey design, and the other concerning the statistical adjustment. First, our new design feature chooses consumer as both the sampling and reporting unit to eliminate merchant response burden, in contrast to the typical indirect sampling approach where the consumer is the sampled unit, but the linked merchant is the reporting unit. Although this typical indirect sampling approach avoids the cost of constructing the merchant frame, the linked merchant would still have to respond via expensive CATI and the low response rate could likely occur when asking merchant to report. 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.

Second, we show the necessity of weight adjustment to account for non-recorded-merchant bias due to the relatively shorter duration of the diary (i.e., 3 days). In practice, some consumers may only visit a specific merchant on a biweekly or monthly basis. In this case, this merchant may not be recorded in the three-day diary. In other words, the non-recorded-merchant bias occurs because the sampled consumer from the indirect sampling can only record linked merchants during the three days, which could lead to potential missing merchants if she could have recorded more transactions over a longer period. This could be analogously thought as if consumer sub-samples merchants, or as if missing merchants in the current three-day diary are non-respondents in a hypothetical longer duration diary. As a result, we need to adjust weights typically used in the indirect sampling method, as these generalized weight share method weights (GWSM) requires no missing merchants to obtain the unbiased estimate. Because in our application of the indirect sampling we do not observe the missing merchants, our adjustment approach is to calibrate weights from the GWSM to external merchant characteristics from the administered 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), or to correct for the selection bias in non-probabilistic sample as in Wu (2022).

By integrating the above two innovations into the classical 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 are aligning well. The remainder of this manuscript proceeds as follows. Section 2 presents the overview of the indirect sampling method, Section 3 offers details of our indirect sampling estimator, Section 4 provides our indirect sampling estimates with comparisons to the ones from the 2022-22 MAS direct sampling approach, and Section 5 concludes.

2. Overview of Indirect Sampling and Our Empirical Setup

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 the direct sampling using some sampling design with the inclusion probability $\pi_m > 0$ for every $m \in U_M$, or the weight w_m , the inverse of π_m . To get a design-unbiased estimator for μ , the Horvitz-Thompson-estimator (HT-estimator) can be applied as

$$\tilde{\mu} \equiv \frac{\sum_{m \in S_M} w_m y_m}{\sum_{m \in S_M} w_m}. \quad (1)$$

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 on whether they accept cash and other payment methods at the point of sale.

Estimation based on indirect sampling: Start from taking a sampling frame of 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 $v_{cm} > 0$, and we define $v_{cm} \geq 0$ as the number of transactions between consumer unit c and merchant unit m , and let $v_{+m} \equiv \sum_{c \in U_C} v_{cm}$, the total number transactions received by merchant m . Our 2022 MOP payment diary satisfies this underlying data structure, where the consumers with the variables $\{(\pi_c, z_{cm}), c \in S_C\}$ 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 . In addition, the sampled consumer c records the detailed transaction at the linked merchant m captured in the variables z_{cm} , which consist of the name of merchant, the actual method-of-payment use and perceived acceptances. Based on merchant names, we can construct the linked 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 (more details in Section 3.2), instead of asking merchants themselves. Then our baseline indirect sampling estimator is

$$\hat{\mu} \equiv \frac{\sum_{c \in S_C} w_c \left(\sum_{m \in \Omega_c} \frac{v_{cm}}{v_{+m}} \hat{y}_m \right)}{\sum_{c \in S_C} \sum_{m \in \Omega_c} w_c \frac{v_{cm}}{v_{+m}}} = \frac{\sum_{m \in \hat{S}_M} \hat{w}_m \hat{y}_m}{\sum_{m \in \hat{S}_M} \hat{w}_m}, \quad (2)$$

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 $m \notin \hat{S}_M$ (Kiesel, 2016). For $\hat{\mu}$ to be unbiased, the following three assumptions must hold:

- **Assumption 1** (Good coverage of 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 some consumer, where 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 reported by the merchant m itself.
- **Assumption 3** (Few non-recorded merchants during the three-day diary): For every sampled consumer $c \in S_C$, we have $\Omega_c \equiv \{m \in U_M: v_{cm} > 0\} \in \hat{S}_M$ where $\hat{S}_M \equiv \bigcup_{c \in S_C} \Omega_c$.

Following Deville and Lavallée (2006), the unbiasedness of the $\hat{\mu}$ requires Assumption 3: i.e. the set Ω_c consists of all merchants in U_M are being visited by the sampled consumer $c \in S_C$. However, due to the relatively shorter duration of the diary (i.e., 3 days), consumer c might not record merchants outside these 3 days. Let Ω_c^3 denotes the set of merchants being visited by consumer c during the three-day period and define $\hat{S}_M^3 \equiv \bigcup_{c \in S_C} \Omega_c^3$ as set of all merchants visited by the consumer sample S_C . Since in practice 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 estimate based on the three-day diary is then

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

In order to address this, we propose accounting for the shorter diary duration under the framework of nonresponse calibration (Haziza and Lesage 2016), obtaining

$$\hat{\mu}^{3,cal} = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal} \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal}}, \quad (4)$$

3. Construction of indirect sample estimates

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 payment 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 $\hat{S}_M^3 \equiv \bigcup_{c \in S_C} \Omega_c^3$. 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 to first identify, and then consolidate these variations and duplicates, resulting in $\hat{S}_M^3$, the indirect sample of unique merchants. This results in an indirect sample size of 595 merchants, recorded by a sample size of 826 consumers, who over the course of three days makes a total of 1445 transactions.

3.2 Merchant acceptance $\hat{y}_m$

The consumer diary asks respondents to report the method of payment used on a transaction that is made in-person, as well as their perceived acceptance of method of payment not being used. The survey logic proceeds as follows: for example, a consumer recording a transaction is first asked about cash usage, to which they can respond ‘yes’, or ‘no’. If they respond no, they are then asked about their perceived acceptance of this cash, to which they can respond ‘yes’, ‘no’, or ‘don’t know’. 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.

We provide empirical evidence that these consumer-reported usage and perceived acceptance values are high quality, thus providing evidence for Assumption 2. We do this by showing that the incidence and intensity of conflict in $\hat{S}_M^3$ is low. Conflict merchants can occur in three ways: between usage and perceived acceptance, within perceived acceptance, or both between usage and perceived acceptance and within perceived acceptance. We observe that the proportion of conflict merchants is low for cash, debit card and credit card, which indicates that the consumer responses are of good quality: only 1.35% 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. Furthermore, we find that when conflict does occur, it occurs at a low intensity. These two findings provide evidence for Assumption 2, and so we use these consumer-reported usage and perceived acceptance values to derive $\hat{y}_m$ through a ‘majority rules’ mapping rule, in which the value of $\hat{y}_m$ is determined by the most frequently occurring value across usage and perceived acceptance².

3.3 Merchant weights $\hat{w}_m$

To calculate each merchant weight, $\hat{w}_m \equiv \sum_{c \in S_C} w_c \frac{v_{cm}}{v_{+m}}$, 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 $\hat{w}_m$ can be interpreted as the average of the weights of the consumers that conduct transactions at it. Consumers who conduct more transactions at merchant m contribute 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 Section, in practice for each consumer $c \in S_C$ we do not observe Ω_c but only Ω_c^3 , thus we use

$$\hat{\mu}^3 = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m} \text{ where } \hat{S}_M^3 \equiv \bigcup_{c \in S_C} \Omega_c^3. \text{ So, Assumption 3 is likely to be violated due to potential non-recorded}$$

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, leading to bias.

To address this, we can treat these merchants in $\hat{S}_M \setminus \hat{S}_M^3$ as unit non-respondents driven by non-recorded merchants in the three-day diary, and thus employ the tools from the unit nonresponse framework. Since in practice we are unable to observe these merchants $\hat{S}_M \setminus \hat{S}_M^3$ (our diary only lasts for the maximum three days), we employ nonresponse calibration outlined in Haziza and Lesage (2016).

The general procedure of Haziza and Lesage (2016) is to adjust the $\hat{w}_m$ with some adjustment factor $F(\lambda^T, \mathbf{x}_m)$, so that the new weight $\hat{w}_m^{cal}$ accounting for the nonresponse merchants from $\hat{S}_M \setminus \hat{S}_M^3$ will be

$$\hat{w}_m^{cal} = \hat{w}_m F(\hat{\lambda}^T \mathbf{x}_m),$$

where the function F is specified according to some calibration objective function.³ In order to estimate $\hat{\lambda}^T$, we use the below calibration equation

² We also derive $\hat{y}_m$ through two additional rules: (2) weighted average, in $\hat{y}_m$ is the weighted average of all values across u_m and p_m and (3) Acceptance is always right; in which $\hat{y}_m$ is mapped to ‘yes’ if usage occurs at least once, otherwise it is determined by ‘majority rules’.

³ Note that such calibration approach to calibrate is equivalent to the PIW estimator; see Wu (2022).

$$\sum_{m \in \hat{S}_M^3} \hat{w}_m F(\hat{\lambda}^T \mathbf{x}_m) \mathbf{x}_m = \sum_{m \in U_M} \mathbf{x}_m ,$$

where for each merchant $m \in \hat{S}_M^3$, we define a vector of auxiliary variables $\mathbf{x}_m = (x_{1m}, x_{2m}, x_{3m}, x_{4m})$, where the x_{jm} correspond to merchant business size, industry, locality and region and U_M is known and obtained from the Statistics Canada BR. The choice of auxiliary variables follows the methodology in Chen and Shen (2017). By substituting $\hat{w}_m^{cal}$ into the estimate for $\hat{\mu}^3$, we obtain the non-response calibrated indirect estimate:

$$\hat{\mu}^{3,cal} = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal} \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal}}, \quad (4)$$

where the resulting weighted composition $\hat{S}_M^3$ is equal to the composition of the Statistics Canada BR.

4. Comparing indirect sample estimates to direct sample estimates

In this section, we compare the indirect estimates with their direct estimate benchmarks and find that the indirect estimates calculated under our proposed methodology aligns well. 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

$$\tilde{\mu} \equiv \frac{\sum_{m \in S_M} w_m y_m}{\sum_{m \in S_M} w_m}, \quad (1)$$

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 $\hat{w}_m$, as well as indirect sample estimates $\hat{\mu}^{3,cal}$ calculated using calibrated GWSM weights $\hat{w}_m^{cal}$ to account for potential non-recorded merchants:

$$\hat{\mu}^3 = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m y_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m}, \quad (2)$$

$$\hat{\mu}^{3,cal} = \frac{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal} \hat{y}_m}{\sum_{m \in \hat{S}_M^3} \hat{w}_m^{cal}}. \quad (3)$$

Table 4-1 below illustrates that the indirect estimates $\hat{\mu}^3$ align moderately well with their direct sample benchmarks, and that $\hat{\mu}^{3,cal}$ aligns even better.

Table 4-1:
Direct and indirect estimates of cash, debit card and credit card acceptance

	Direct Sampling	Indirect Sampling	
	$\tilde{\mu}$	$\hat{\mu}^3$	$\hat{\mu}^{3,cal}$
Cash	96.88	98.64	97.22
Debit	87.89	97.29	92.86
Credit	88.18	94.51	90.97

5. Discussion and future research

Compared to 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 2021-2022 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 for her actual payment use and perceptions of acceptance at the merchant where she conducts the in-person transaction. 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, notice that such high-quality of the consumer perception is context-specific. In our application, we conjecture the mechanisms behind consumer perceiving merchant acceptance could be that consumers either see merchant signages, or observe other consumers' payment choice in the queue, or recall her previous shopping experience at this merchant. Thus, it would be interesting for the future work to disentangle the exact informational channel on how consumers form their perceptions.

The second innovation of the paper is related to adjusting the GWSM weights to account for potential non-recorded-merchant bias due to the shorter duration of the payment diary. We show that such adjustment is crucial for our indirect sampling application because our current three-day diary might not be able to record merchants outside of the 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 linked merchant sample $\hat{S}_M^3$. Under the data integration framework between the probabilistic and non-probabilistic samples, we can treat the linked merchants in $\hat{S}_M^3$ as the non-probabilistic sample while the direct sampled merchants in the 2021-2022 MAS as the probabilistic sample, and then employ the pseudo maximum likelihood to estimate the above probability following Chen, Li and Wu (2020). We leave such data integration approach for future investigation.

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