Low Response Rate from Merchants? Sample and Ask Consumers!

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Overview

We apply indirect sampling outlined by Deville and Lavallée (2006) and Lavallée (2007) to estimate merchant payment acceptance through a consumer payment diary.

- **Key Contribution 1**: Consumers are both the sampling and reporting units
- **Key Contribution 2**: account for three-day diary structure through statistical adjustment

Motivation

	Merchant Surveys	Consumer Surveys
Survey frame	Custom-built	Readily available
Survey methodology	Computer Assisted Telephone Interview	Online
Response Rate	2.5% (2015), 2.8% (2018) and 4.8% (2021/22)	7.4 % (2017)

	Direct Sampling	Indirect Sampling
Sampling Unit	Merchants	Consumers
Response Unit		
S_M	Drawn from sample frame	Mapped from consumer-merchant transactional data
y_m	Reported by merchants	Reported by consumers
w_m	Known (design-based sampling)	Estimated using Generalized Weight Share Method (GWSM)

Indirect Sampling Estimator

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

- $\hat{S}_M^3 \equiv \cup_{c\in S_C} \Omega_c^3$
  - where Ω_c^3 the set of merchants visited by consumer c over three-days
- $\hat{w}_m^{cal} = \hat{w}_m F(\hat{\boldsymbol{\lambda}}^{\mathrm{T}}\boldsymbol{x}_m)$
  - where $\hat{w}_m$ is the GWSM weight, $\boldsymbol{x}_m$ is the vector of auxiliary variables (business size, industry, locality, region) and $F(\hat{\boldsymbol{\lambda}}^{\mathrm{T}}\boldsymbol{x}_m)$ is the calibration objective function
- $\hat{y}_m = f(usage, perceived\ acceptance) = f(u_m, p_m)$

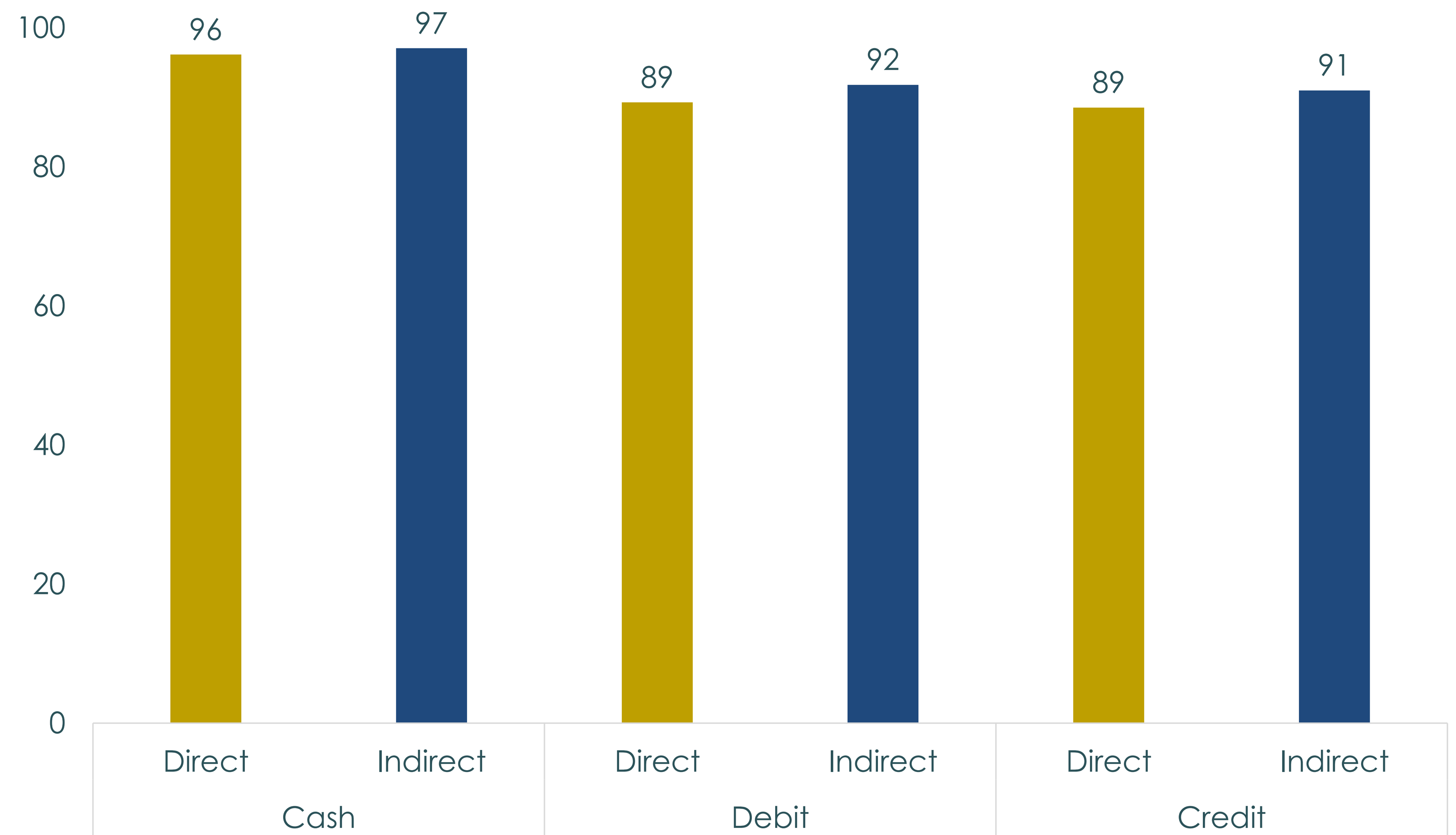
Assumptions

- Good coverage of merchant population
- High quality of consumer responses
- Few non-recorded merchants

References

- Deville, J., & Lavallée, P. (2006). Indirect sampling: The foundations of the generalized weight share method. Survey Methodology, 32(2), 165.
- Lavallée, P. (2007). Indirect sampling. New York: Springer.
- Haziza, D., & Lesage, É. (2016). A discussion of weighting procedures for unit nonresponse. Journal of Official Statistics, 32(1), 129-145.

Indirect and direct estimates are comparable



Direct sampling (2022 MAS):
Indirect sampling Rule 3 (2022 Consumer MOP):

Merchants report MOP acceptance
Consumers report **Merchant's** MOP acceptance

Step 1: Constructing merchant sample $\hat{S}_M$

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

String-matching is performed on all reported merchant names to identify the set of unique merchants, $\hat{S}_M$. Evidence of coverage of merchant population: coverage of consumer sample $\boldsymbol{S_C}$ (Table 1) and coverage of merchant sample $\hat{S}_M^3$ (Table 2)

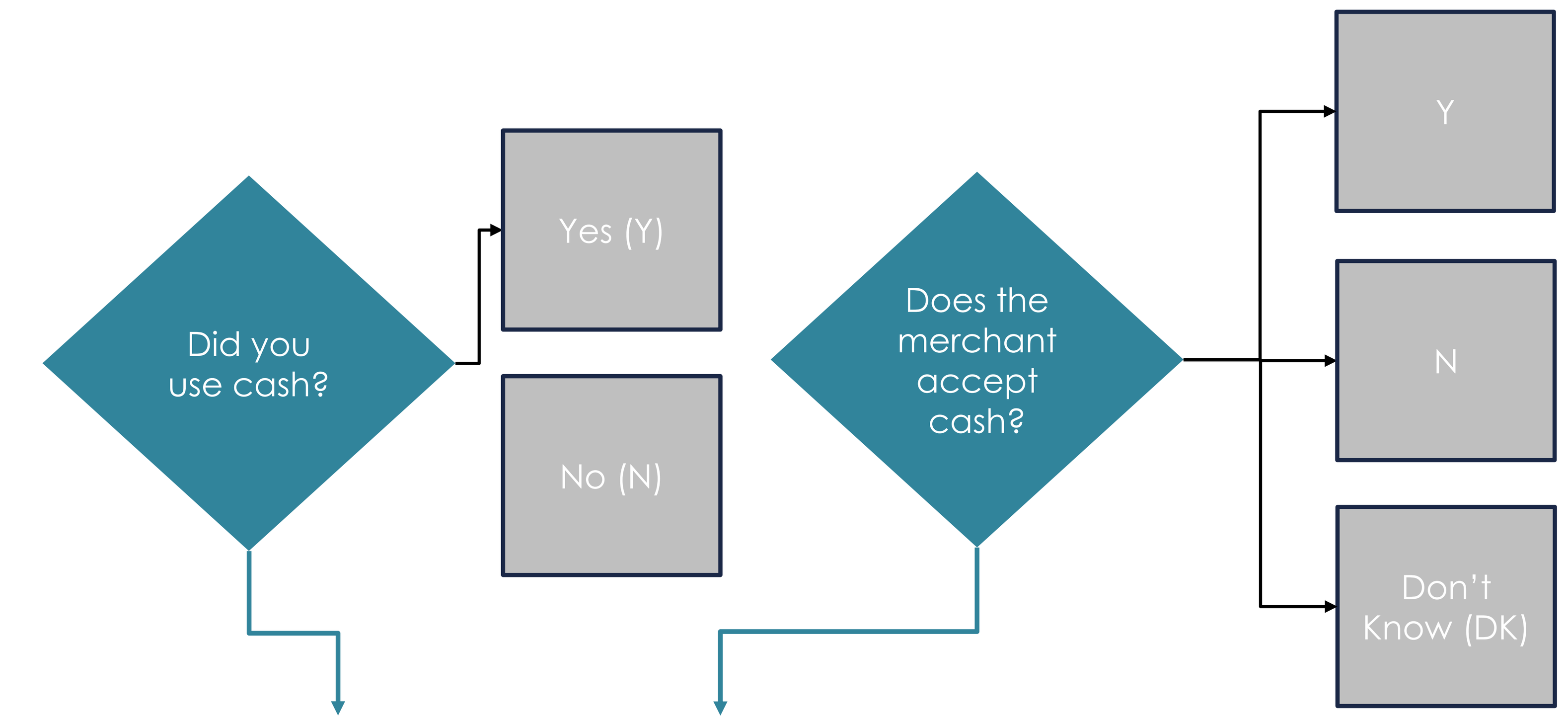
Table 1: Sample Composition of $\boldsymbol{S_C}$

Age	**18-34**	28.10
	35-54	32.00
	55+	39.90
Gender	**Male**	49.41
	Female	50.59
Income	**<$40K**	19.04
	$40K-$80K	28.38
	>$100K	52.58

Table 2: Sample Composition of $\hat{S}_M^3$

Size	**Small (0-5 employees)**	49.83
	Medium (6-49 employees)	50.17
Industry	**Retail trade (NAICS 44/45)**	52.33
	Food services and drinking places (NAICS 722)	40.83
	Other services (NAICS 81)	6.83
Locality	**Rural**	16.17
	Urban	83.83
Region	**British Columbia**	18.83
	Prairies	17.17
	Ontario	38.17
	Quebec	15.00
	Atlantic	10.83

Step 2: Constructing merchant MOP acceptance $\hat{y}_m$



$$f(usage, perceived\ acceptance) = f(u_m, p_m) = \hat{y}_m$$

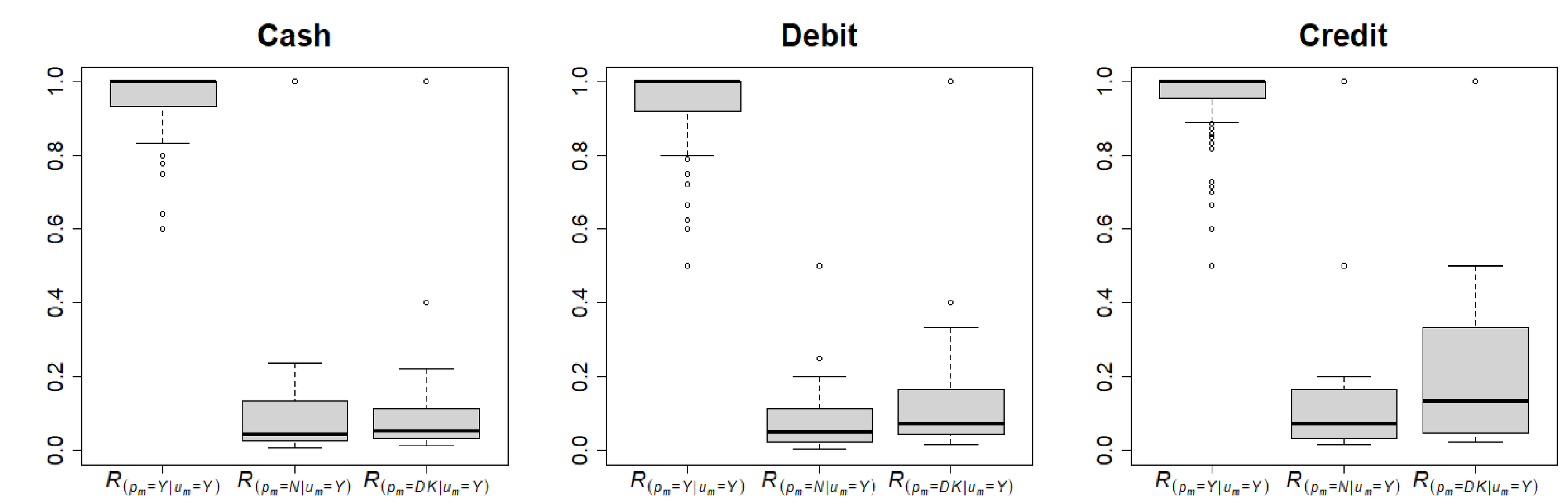
Rule 1: $\hat{y}_m$ determined by the most frequently occurring value across u_m and p_m.
Rule 2: $\hat{y}_m$ determined as the weighted average of all values across u_m and p_m
Rule 3: $\hat{y}_m$ is mapped to Y if usage occurs at least once, otherwise $\hat{y}_m = f_1(u_m, p_m)$

Incidence and Intensity of conflicts are low

Table 3: Incidence of conflict in $\hat{S}_M^3$

	Cash		Debit		Credit	
	1 visit	**> 1 visit**	**1 visit**	**> 1 visit**	**1 visit**	**> 1 visit**
No Conflict	80.73	16.64	80.73	16.26	80.73	17.01
Conflict						
Between		0.09				0.28
Within		0.28		0.56		0.09
Both		2.26		2.44		1.88

Chart 1: Intensity of Conflict



$R_{p_m=Y|u_m=Y} = \frac{\sum_{v=1}^{v+m} 1_{p_{m,v}=Y}}{\sum_{v=1}^{v+m} 1_{u_{m,v}=N}} = \frac{v_{+m}^{p=Y}}{v_{+m}-v_{+m}^{u=Y}}$, $R_{p_m=N|u_m=Y} = \frac{\sum_{v=1}^{v+m} 1_{p_{m,v}=N}}{\sum_{v=1}^{v+m} 1_{u_{m,v}=N}} = \frac{v_{+m}^{p=N}}{v_{+m}-v_{+m}^{u=Y}}$, $R_{p_m=DK|u_m=Y} = \frac{\sum_{v=1}^{v+m} 1_{p_{m,v}=DK}}{\sum_{v=1}^{v+m} 1_{u_{m,v}=N}} = \frac{v_{+m}^{p=DK}}{v_{+m}-v_{+m}^{u=Y}}$. This chart only includes merchants where $v_{+m} > 1$ and $v_{+m}^{u=Y} > 1$.

Step 3: Constructing merchant weights $\hat{w}_m^{cal}$

Table 4: Number of merchants visited

Days Complete	# Consumers	Min # Merchants	Max # Merchants	Avg # Merchants
1	53	1	4	1.47
2	163	1	8	2.09
3	872	1	11	2.79

Longer diary → fewer missing merchants. We treat missing merchants as unit-nonrespondents. Since in practice we are unable to observe these merchants $\hat{S}_M \backslash \hat{S}_M^3$ (our diary only lasts for the maximum three days), we employ nonresponse calibration outlined in Haziza and Lesage (2016), obtaining $\hat{w}_m^{cal}$