

# Leveraging Detailed Payment History Data for Better Credit Scoring Methods to Improve Women's Access to Credit

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## Motivation

- ▶ Although women default less than men (Karlan and Zinman, 2009; D'Espalier et.al., 2011) gender gaps in access to credit have persisted (Demirguç-Künt and Klapper, 2013, Agier and Szafarz, 2013, Alesina et.al. 2013)

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  - ▶ Gender is excluded (Mester,1997) or included without sufficient flexibility (Johnston and Morduch, 2008)

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  - ▶ Randomize access to a credit card among women rejected by standard models but approved by the new model (randomly assign credit scoring models)

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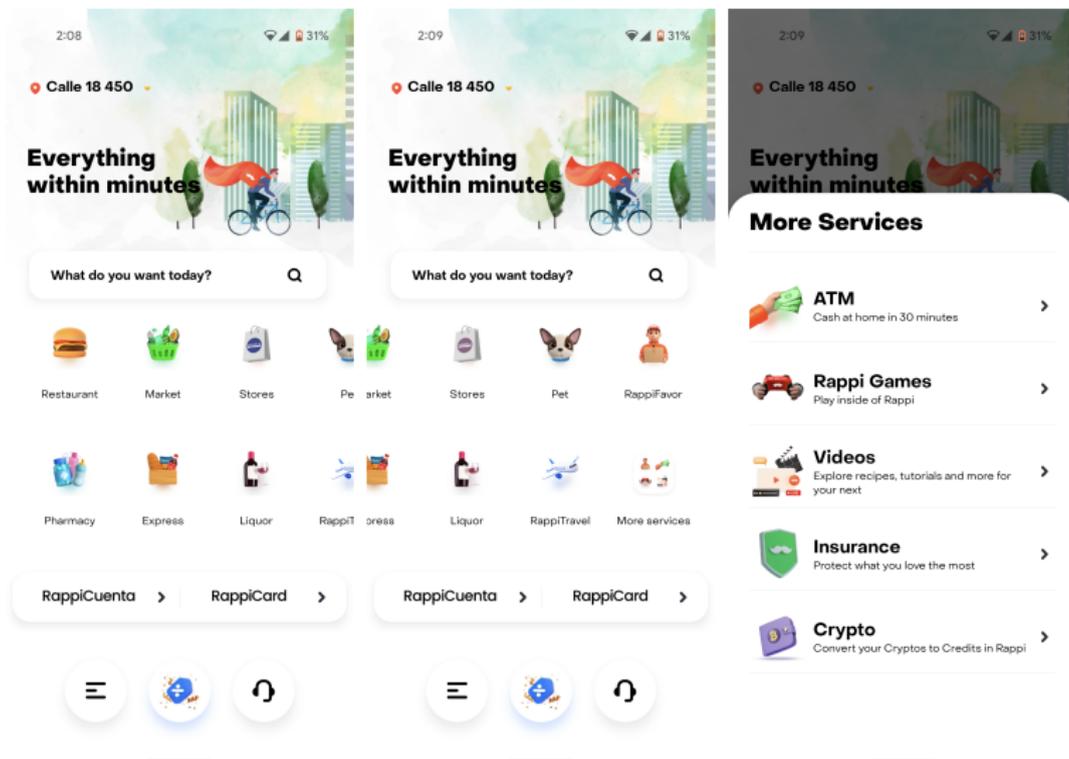
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# Rappi data: A new type of digital footprint



Data includes: groceries, pharmacies and medical lab services, cash, air-travel, special deliveries, crypto-payments (coming-up), and other retail shops

# Why gender-differentiated algorithms? Intuition



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### Heart attack diagnosis missed in women more often than in men

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## Why gender-differentiated algorithms?

- ▶ Conditional on observable, differences in default rates could arise if women behave intrinsically differently than men: more reluctant to compete (Nieerle and Vesterlung 2011), more risk averse and less self-confident (Charness and Gneezy 2012 Eckel and Grossman 2008), and less responsive to pay-for-performance incentives (Bandiera et.al. 2021)

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- ▶ Preliminary analysis with RappiCard Mexico shows promising results

## Main outcomes of interest

- ▶ Delinquency, default, credit card use and profitability of women approved under the pooled or gender-differentiated model
- ▶ Ownership of assets and self-reported control over assets within the household
- ▶ Labor supply and access to other sources of credit
- ▶ Risk coping and consumption smoothing
- ▶ Intra-household bargaining power
- ▶ Subjective well-being, self-reported measures of stress and mental-health

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- ▶ Next steps: ML model + Pilot + RCT