

Executive Summary: *Identifying Hand-to-Mouth Households: Evidence from India*

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Objective

The paper quantifies and characterizes *poor hand-to-mouth (P-HtM)* and *wealthy hand-to-mouth (W-HtM)* households in India—those who consume most of their income and face liquidity constraints despite varying levels of wealth. It adapts the *Kaplan, Violante, and Weidner (2014)* framework to a developing-economy setting where households hold substantial illiquid assets (e.g., land, gold) but have limited liquid wealth and credit access.

Data and Methodology

The authors construct harmonized household balance sheets by combining:

- **AIDIS (2019):** Detailed cross-sectional data on assets, liabilities, and wealth.
- **CPHS (2018–2019):** High-frequency panel with income, consumption, and demographics.

Since AIDIS lacks income data, the study imputes income using CPHS through five techniques:

1. Consumption-bin averages
2. Ordinary Least Squares (OLS) regression
3. Decision tree
4. Random forest
5. Neural network
6. XGBoost (default and fine-tuned versions)

Households are classified as:

- **Poor Hand-to-mouth (P-HtM):** Low income, negligible liquid and illiquid wealth.
- **Wealthy Hand-to-mouth (W-HtM):** Substantial illiquid wealth but little liquidity.
- **Non Hand-to-mouth (N-HtM):** Adequate liquidity to smooth consumption.

Robustness checks vary credit limits, pay frequency, and asset definitions to ensure consistency.

Key Findings

- **Prevalence:**
 - P-HtM: **2–5%** of households
 - W-HtM: **15–27%**
 - Total HtM: **17–32%** of population
 - Based solely on net worth (Zeldes, 1989), only **3–12%** qualify—showing that liquidity constraints are far broader than wealth constraints.
- **Average Propensity to Consume (APC):** Roughly similar across HtM and non-HtM groups, indicating that even wealthier households face liquidity frictions.
- **Robustness:** Estimates remain stable under alternative liquidity definitions and credit-limit assumptions.
- **Machine Learning Performance:** Random forest and XGBoost models provide the most accurate income imputations (RMSE \approx 0.32).

Implications

The findings reveal that *a large share of Indian households are liquidity-constrained despite high aggregate savings*. This has major implications for:

- **Macroeconomic modeling:** Monetary and fiscal multipliers may be stronger when many households cannot smooth consumption.
- **Policy design:** Liquidity-enhancing tools (credit access, short-term transfers, financial inclusion) may be more effective than wealth-building programs in stabilizing demand.
- **Data policy:** Calls for more frequent, integrated household balance-sheet surveys to track liquidity dynamics.

Conclusion

India's macroeconomic response to policy shocks depends crucially on the behavior of a vast segment of households that are *asset-rich but cash-poor*. By combining two national surveys and applying machine learning, this paper provides the first comprehensive, data-driven mapping of liquidity constraints in India—offering a foundation for HANK-style macroeconomic calibration and future cross-country comparisons.

Figure: Predicted Monthly Household Income Distribution in AIDIS using XGBoost, fine tuned

