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# Mobile Banking Apps and the Informal Economy: Evidence from Survey Data in Indonesia and Bangladesh

By

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# Mobile Banking Apps and the Informal Economy: Evidence from Survey Data in Indonesia and Bangladesh[1]

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## Abstract

Reducing preference for cash and supporting the adoption of digital financial services can help achieve financial inclusion while also diminishing economic informality. However, previous evidence suggests that increased access to formal banking services has not resulted in an immediate reduction in usage of informal services. This paper estimates the effects of mobile phone banking apps on the demand for cash using unique survey data from Bangladesh and Indonesia. Our models indicate that having access to a banking or payment app reduces a variable capturing preference for cash by between 4% and 10%. The results are insensitive to a range of specification checks (including the inclusion/omission of various controls) which suggests that confounding from unobservables is unlikely to be a substantive source of bias. Since cash is the preferred payment mechanism for the poor in developing countries, the results suggest that access to digital banking apps may reduce informality within the finance sector, leading to broader development implications.

**JEL Classification**: O12, O17

**Key Words**: Financial Inclusion, Informal Economy, Digital Finance, Economic Development

## 1. Introduction

Poverty is often characterised by a high prevalence of informal economic activity, with 93 percent of the world's informal employment found in emerging and developing countries (ILO, 2018). The term "informal economy" is often interchangeable with a multitude of terminologies, including the irregular economy, the subterranean economy, the underground economy, the black economy, or the shadow economy (Losby et. al., 2002). In simple terms, the informal economy can be defined as the portion of commercial activity that is either unregulated or insufficiently regulated by the state (García-Bolívar, 2006). While informal economic activities (such as the operation of an unregistered business) are not necessarily criminal in nature, they do occur outside of legal frameworks designed to protect citizens. For example, workers in the informal economy are generally far more vulnerable than those in the formal economy due to higher exposure to risks and low coverage of social protections. Such conditions lead to high exposure to health hazards or greater levels or inequality – especially for women, who earn significantly less than men in the informal sector (ILO, 2023).

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To reduce poverty, a key focus has been to undertake financial inclusion initiatives that extend formal financial services to underserved individuals (CGAP, n.d.). This has included using new technologies, such as mobile banking, to reduce the geographic barriers faced by the rural population. However, to what extent does having access to formal financial services lead to a reduction in dependence upon informal substitutes? This remains an open question in the literature on developmental finance, with several papers citing multiple reasons as to why improved access may not translate into greater uptake. These include a lack of need, religious or cultural factors (Beck, Demirgüç-Kunt, & Honohan, 2009), or low trust in formal financial institutions (Dittus & Klein, 2011). Those who wish to access formal financial services may also face barriers such as affordability, inappropriate product design, and inability to meet eligibility to provide identity documents (Bester et al., 2008 and Hannig and Jansen, 2010).

In this paper, we estimate the scope for mobile phone e-wallets to move economic activity from the untraceable use of cash towards formalized payment mechanisms. We find that the adoption of e-wallets leads to a significant decrease in preferences for the use of cash for transactions. The result holds in two countries (Bangladesh and Indonesia) and is highly robust to variations in controls and statistical methods. As such, we argue that efforts to expand digital financial inclusion among the poor would have a positive influence on reducing informal economic activity, and thus provide additional economic developmental benefits.

Our work is descriptive in that we are unable to definitively identify the causal structure of the data. Thus, while we observe that individuals who have e-wallets are less likely to prefer cash as a medium of exchange, it is unclear whether this represents a causal effect or a reverse-causal effect (or some other determining factor that is omitted from our models). However, we address these endogeneity concerns in two ways. Firstly, we note that cash has been the default mechanism for centuries, and it has only been the rise of technological alternatives that allow for individuals to opt out of making cash payments. Thus, at the aggregate level, we know that the option to not use cash is directly caused by the availability of electronic payment options, and not the reverse. Secondly, we perform a series of diagnostic tests related to stability subject to the inclusion/exclusion of controls. We find that our results are robust to the degree of control over observables, which suggests that omitted factors are unlikely to be a meaningful source of statistical bias.

The findings build upon previous research which has examined the correlation between financial inclusion, including digital financial inclusion, and the informal economy. In their study on the effect of financial inclusion on the use of informal financial intermediaries in Africa, Alhassan et al. (2019) found that bringing people into the formal financial system reduced preferences for cash. Kearney (2018) also found that over a 10-year period (2007-2016) the size of the informal economy as a share of global GDP has decreased and argued that this trend is in part due to the rise of digital payments. Awasthi and Engelschalk (2018) provide further evidence showing a strong negative correlation between digital or formal payment transactions and the size of the informal economy. Furthermore, De Koker and Jentzsch (2013) found through their study across eight African countries that being engaged in informal employment and having a preference for cash reduces a person's willingness to adopt mobile financial services. Each of these studies points to a correlation between the preference for cash and informal economic activity.

The paper is structured as follows. Section 2 provides some background on financial inclusion and formality, while Section 3 previews the data. Section 4 gives our regression models and reports our key estimates. Other issues related to stability and identification are also covered here. Section 5 presents parallel results with an alternative method, replacing our regression model with a propensity score matching estimator. Section 6 contextualises the findings and discusses some broader implications for economic development. Section 7 concludes.

## 2. Background

Financial inclusion, or the expansion of access and usage of financial products and services among the underserved or unbanked, sits at the forefront of the digitalisation agenda, with clear links to the informal economy. Empirical evidence has shown that financial development is correlated with informality, with underdeveloped financial systems being identified as a potential cause (Ohnsorge and Yu, 2022). Financial systems which have successfully integrated digitalisation can create a range of benefits for those operating in the informal economy. Some common examples include enabling mobile banking and digital payments, facilitating security apparatus such identity verification, or improving the information environment (GPFI, 2018).

Mobile financial services have been central to this pattern of enhanced digitalization (Aker and Mbiti, 2010). As the population of mobile financial service users grows, this has stimulated the emergence of new financial products that have likely increased the appeal of formal financial services. A good example is the emergence of online microfinance loans for the poor (Dorado, 2014). The growth of digital infrastructure, the declining cost of mobile phone ownership, and the emergence of pre-paid service plans have all likely increased the appeal of mobile financial services. As a greater share of the population own mobile phones network effects are generated (James, 2015), especially for mobile remittance services and mobile money (Aron, 2018).

Efforts to enhance the adoption of digital financial transactions through the use of innovative features such as electronic wallets installed on mobile phones represent part of this process. In particular, they may play a key role in reducing informality by driving increased adoption of formal financial instruments (Ky, Rugemintwari and Sauviat, 2021) or creating a more transparent financial ecosystem which can be monitored by authorities and make it more difficult to hide informal activities from authorities (Kearney, 2018). The growing prevalence of digital finance, and in particular digital payments, therefore has great potential for reducing preference for cash and eroding informal economic activity.

Successful transition from the informal to formal economy is no easy task. The plethora of environmental, political, institutional, and social aspects involved create multi-dimensional issues which require long-term planning and persistence to address. Interventions include information campaigns, simplifying registration processes, reducing payroll taxes or enforcement of formalisation (Jessen and Kluve, 2021). Enhancing access to, and adoption of, digital financial products and services stands out as one strategy which has the potential to act as a catalyst to promote greater formalisation of informal economic activity. This is especially the case for developing countries where the preference for cash transactions is more prevalent, particularly among the poor who often lack access to a bank account or other technology infrastructure necessary to facilitate cashless transactions (Buchholz, 2021).

## 3. Data

Data was collected from 2000 survey respondents within two developing countries – 1000 in Bangladesh and 1000 in Indonesia. These two countries were selected due to their respective stages of digital transformation. Indonesia represents a relatively advanced digital economy, largely driven by a substantial young and digitally savvy proportion of the population (Negara and Meilasari-Sugiana, 2022); whereas Bangladesh represents an emerging digital economy (Bhuiyan et al., 2023). Both countries are currently undergoing significant digital transformation leading to a rapid increase in the availability of mobile banking services (Akhter and Khalily, 2020; Angelina and Rahadi, 2020).

Collection took place over a four-week period during March and April 2023. In Bangladesh, data were collected from 81 villages with the Louhajang Upazila of the Munshiganj District. In Indonesia, data were collected from 87 villages in West Java. These locations were targeted due to their high proportion of low-income households. The survey instrument comprised a total of 57 questions designed to gather insights on demographics, household makeup, livelihoods, financial behaviours, and usage of digital technology including attitudes towards, and usage of, e-wallets.

The data are only approximately representative of the total adult populations of these countries. A series of selection criteria questions were used to identify eligible participants. This included meeting a minimum age requirement (18 years old), a maximum average household income (local equivalent of USD 300 per month), having regular access to a smartphone and a stable internet connection, and a requirement that the respondent be the primary money manager of the household. All eligible participants were provided with an explanation of the study and asked to agree to participating before collecting their responses.

Enumerators collecting the data followed a systematic random sampling method for the selection of respondents in both countries. From a starting point, an eligible household was identified from one structure. After completion of that survey, the enumerator skipped the next two structures and screened the third structure to identify an eligible household. If that household was found eligible, the enumerator surveyed that household and if not, then the enumerator moved on to the immediate next structure to identify the eligible household for survey. In this method, the enumerators skipped every two structures to identify and survey an eligible household.

Descriptive statistics of our estimation sample are provided in Table 1. The average age of respondents in Indonesia was about 40, whereas the average age of respondents in Bangladesh was slightly lower (about 35). About 80% of respondents in both countries were married, with about 50% of respondents in Bangladesh being male and 40% being male in Indonesia. Household size was typically larger among respondents in Bangladesh, with an average of 4.4 persons per household when compared to about 3 people per household in Indonesia.

**Table 1. Descriptive Statistics – Indonesia and Bangladesh**

| | Indonesia | | | | | Bangladesh | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | St Dev | Min | Max | N | Mean | St Dev | Min | Max |
| Prefer Cash | 1,000 | 0.787 | 0.410 | 0 | 1 | 1,000 | 0.878 | 0.327 | 0 | 1 |
| Have e-wallet | 1,000 | 0.473 | 0.500 | 0 | 1 | 1,000 | 0.762 | 0.426 | 0 | 1 |
| Log income | 1,000 | 14.89 | 0.286 | 13.76 | 15.32 | 1,000 | 9.772 | 0.390 | 8.699 | 10.31 |
| Female | 1,000 | 0.500 | 0.500 | 0 | 1 | 1,000 | 0.400 | 0.490 | 0 | 1 |
| Age | 1,000 | 39.86 | 10.01 | 18 | 80 | 1,000 | 35.21 | 10.71 | 18 | 60 |
| Age Squared | 1,000 | 1689 | 846.4 | 324 | 6400 | 1,000 | 1354 | 819.7 | 324 | 3600 |
| Married | 1,000 | 0.873 | 0.333 | 0 | 1 | 1,000 | 0.826 | 0.379 | 0 | 1 |
| Widowed | 1,000 | 0.051 | 0.220 | 0 | 1 | 1,000 | 0.017 | 0.129 | 0 | 1 |
| No of Adults | 1,000 | 2.123 | 0.618 | 1 | 5 | 1,000 | 3.181 | 1.234 | 1 | 9 |
| No of Children | 1,000 | 0.930 | 0.859 | 0 | 5 | 1,000 | 1.324 | 0.989 | 0 | 5 |
| Completed School | 1,000 | 0.292 | 0.455 | 0 | 1 | 1,000 | 0.151 | 0.358 | 0 | 1 |
| Uni Degree | 1,000 | 0.010 | 0.100 | 0 | 1 | 1,000 | 0.501 | 0.500 | 0 | 1 |
| Post-G Degree | 1,000 | 0.001 | 0.032 | 0 | 1 | 1,000 | 0.164 | 0.370 | 0 | 1 |
| Blue Collar | 1,000 | 0.556 | 0.497 | 0 | 1 | 992 | 0.026 | 0.160 | 0 | 1 |
| White Collar | 1,000 | 0.062 | 0.241 | 0 | 1 | 992 | 0.125 | 0.331 | 0 | 1 |
| Self Employed | 1,000 | 0.151 | 0.358 | 0 | 1 | 992 | 0.143 | 0.350 | 0 | 1 |

Note: The table presents descriptive statistics for our full samples. Figures for the Indonesian subsample appear in the left panel while figures for the Bangladesh subsample appear on the right. Observation counts, sample means, standard deviations, and minimum/maximum values appear across the columns.

When asked about e-wallet ownership[6], respondents in Bangladesh were given multiple examples of common digital finance applications to consider such as bKash, Nagad or Rocket. In response, 76% of respondents in Bangladesh reported owning an e-wallet. In the case of Indonesia, respondents were given common local examples such as goPay, OVO, DANA and Shopeepay. 47% of respondents in Indonesia reported having an e-wallet. In both countries, respondents showed a strong preference for using cash over digital transactions, with 79% in Indonesia and 87% in Bangladesh expressing such a preference.

## 4. Models and Estimates

To determine whether having an e-wallet is predictive of a diminished preference for cash, we fit linear regression models of the form below to the subsamples from both countries. The specification is of the form

$$y_i = \alpha + v_p + \gamma E_i + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i$$

where $y_i$ is a dichotomous indicator of a preference for cash (such that the specification above is a Linear Probability Model)[7], $E_i$ a dummy variable indicating the individual uses an e-wallet, and $x_{i1}, \dots, x_{ik}$ a set of demographic and socioeconomic control variables. Variable $v_p$ denotes a fixed-effect at the village level. Thus parameter $\gamma$ captures the reduction in preference for cash associated with $E$ holding a variety of personal, economic, familial and geographic

[6] The specific question respondents were asked was "Do you have an e-wallet?" This question was followed by a description of relevant examples of e-wallet apps prevalent in each country.

[7] We prefer this to models for binary data such as probit or logit models due to ease of interpretation. We note that the findings are near identical if a binary choice model is used.

characteristics constant. Note that since the LHS variable is binary, $\gamma$ can be interpreted as the change in the overall fraction of people who prefer cash. The model is fitted by OLS with robust covariance, with the key estimates presented in the top row.

Six versions of the model are estimated – three for Indonesia and an equivalent three for Bangladesh. The first (leftmost columns) exclude all controls such that the coefficient $\phi$ simply reflects the average difference in rates of preference for cash between people who do and do not use e-wallets, accounting for structural differences across regions. As the use of these wallets may be systematically correlated with various socioeconomic characteristics that may also be linked to cash preference, the second and third columns add in increasingly rich additional sets of controls.

**Table 2. Regression Outputs – E-Wallet Use and Preference for Cash**

| | Indonesia | | | Bangladesh | | |
|---|---|---|---|---|---|---|
| **E-Wallet** | **-0.097*** ** | **-0.103*** ** | **-0.098*** ** | **-0.040** ** | **-0.041** ** | **-0.043** ** |
| | (0.029) | (0.029) | (0.029 | (0.020) | (0.020) | (0.021) |
| Female | | 0.016 | 0.007 | | 0.003 | -0.005 |
| | | (0.053) | (0.053) | | (0.025) | (0.025) |
| Log Income | | 0.007 | 0.010 | | -0.011 | -0.001 |
| | | (0.018) | (0.019) | | (0.019) | (0.021) |
| Age | | -0.004 | -0.005 | | -0.003 | -0.002 |
| | | (0.006) | (0.006) | | (0.007) | (0.007) |
| Age Squared | | 0.000 | 0.000 | | 0.000 | 0.000 |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Married | | 0.107 | 0.116* | | 0.003 | 0.008 |
| | | (0.066) | (0.066) | | (0.036) | (0.037) |
| Widowed | | 0.049 | 0.055 | | 0.062 | 0.062 |
| | | (0.072) | (0.072) | | (0.078) | (0.080) |
| 1 Adult | | -0.07 | -0.067 | | 0.032 | 0.025 |
| | | (0.063) | (0.065) | | (0.280) | (0.284) |
| 2 Adults | | -0.071 | -0.066 | | 0.053 | 0.050 |
| | | (0.075) | (0.077) | | (0.279) | (0.283 |
| 3 Adults | | -0.159 | -0.151 | | 0.042 | 0.040 |
| | | (0.097) | (0.098) | | (0.280) | (0.284) |
| 4 Adults | | -0.409** | -0.379** | | 0.039 | 0.036 |
| | | (0.168) | (0.167) | | (0.283) | (0.286) |
| 1 Child | | -0.013 | -0.017 | | 0.008 | 0.010 |
| | | (0.028) | (0.028) | | (0.026) | (0.026) |
| 2 Children | | -0.023 | -0.018 | | 0.041 | 0.040 |
| | | (0.035) | (0.035) | | (0.027) | (0.027) |
| 3 Children | | 0.134 | 0.147 | | 0.067* | 0.067* |
| | | (0.101) | (0.097) | | (0.038) | (0.038) |
| 4 Children | | 0.189* | 0.168 | | 0.075 | 0.082 |
| | | (0.103) | (0.105) | | (0.082) | (0.083) |
| 5 Children | | 0.444*** | 0.455*** | | 0.228 | 0.234 |
| | | (0.160) | (0.160) | | (0.144) | (0.149) |
| School Educ | | | -0.042 | | | -0.029 |
| | | | (0.026) | | | (0.032) |
| Bachelor's Deg | | | 0.030 | | | -0.001 |
| | | | (0.031) | | | (0.025) |
| Post-Graduate | | | -0.053* | | | 0.005 |
| | | | (0.028) | | | (0.030) |
| Blue Collar | | | 0.102*** | | | 0.029 |
| | | | (0.033) | | | (0.079) |
| White Collar | | | 0.052 | | | 0.021 |
| | | | (0.041) | | | (0.034) |
| Self Employed | | | 0.018 | | | 0.032 |
| | | | (0.038) | | | (0.028) |
| Constant | 0.822 | 0.856 | 0.924 | 0.640*** | 0.615 | 0.714* |
| | (0.752) | (0.764) | (0.764) | (0.133) | (0.399) | (0.404) |
| Village FE | Y | Y | Y | Y | Y | Y |
| R-Squared | 0.538 | 0.549 | 0.557 | 0.393 | 0.401 | 0.402 |
| N | 1000 | 1000 | 1000 | 1000 | 1000 | 992 |

Note: The table gives coefficient estimates from linear probability models estimated by OLS using preference for cash as the dependent variable. The base individual is a male in a household with more that four adults with no children, less than high-school education and unspecified work type. Parameter estimates are given in regular type with robust standard errors below in parentheses. Symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

The estimates from Table 2 show that possession of an e-wallet significantly predicts a decreased preference for cash across all models and in both countries. In the simplest models, we see that e-wallets are associated with a reduction in the fraction of cash preference by -

0.097 units (almost ten percentage points) in Indonesia, and -0.04 (around four percentage points) in Bangladesh. The higher percentage points observed in Indonesia may be indicative of the local context. The use of digital payment systems may be more prevalent and culturally acceptable, perhaps driven by the relatively young and technologically savvy population. If a parsimonious set of controls is introduced gender, income, age, marital status, and family structure) the estimates are virtually unchanged at -0.103 and -0.041. If additional controls around education and employment are included, the key estimates are -0.098 and -0.043 respectively. The stability of these estimates across controls is an important feature of these models. Since the results are highly robust once observable factors are accounted for, this suggests that confounding through unobservable factors (i.e., omitted variable bias) is unlikely to be a serious problem (Oster, 2019).

## 5. Robustness Check Using Propensity Score Matching Estimators

The results presented above make some fairly restrictive specification assumptions that may bias our statistical estimates (e.g., linearity of the underlying relationships). In this section we present two robustness checks. Firstly, we model the treatment assignment mechanism (i.e., the function that allocates e-wallets to individuals) to see if there are large systematic differences between people who use this technology and those who do not. If we find that there are relatively few significant correlates of application use in our data, this suggests the variable may be fairly close to randomly allocated, which reduces the scope for unobserved confounding. After estimating this mechanism (using a probit model) we then interpret the fitted values as propensity scores, and match treated individuals with counterparts who do not have the banking app to observe across-group differences.

Table 3 gives our probit models that provide the propensity scores. We use a model where we capture family size and composition (numbers of adults and children) using linear scales rather than dummies, as the latter had some subgroups with very few observations, which complicated convergence in the models. However, we note that the effect sizes obtained from regression models are almost totally unaffected by this assumption. The model is of the form $P(EW = 1|X) = \phi(X\beta)$ where $EW$ is a dummy variable indicating the individual uses an e-wallet, $X$ a vector of controls, and $\phi(.)$ a cumulative normal distribution.

## Table 3. Probit Models for Treatment Assignment

| | Indonesia | | | | Bangladesh | | | |
|---|---|---|---|---|---|---|---|---|
| | *β* | *SE(β)* | *Z* | *P(Z)* | *β* | *SE(β)* | *Z* | *P(Z)* |
| Log income | 0.694*** | 0.158 | 4.39 | 0.000 | 0.143 | 0.121 | 1.18 | 0.239 |
| Female | -0.027 | 0.084 | -0.32 | 0.749 | -0.181 | 0.111 | -1.64 | 0.101 |
| Age | -0.082*** | 0.028 | -2.96 | 0.003 | 0.074** | 0.030 | 2.49 | 0.013 |
| Age Squared | 0.001** | 0.000 | 1.99 | 0.046 | -0.001** | 0.000 | -2.41 | 0.016 |
| Married | -0.138 | 0.198 | -0.70 | 0.485 | -0.173 | 0.170 | -1.02 | 0.308 |
| Widowed | 0.011 | 0.253 | 0.04 | 0.965 | 0.145 | 0.418 | 0.35 | 0.729 |
| No of Adults | 0.016 | 0.084 | 0.19 | 0.852 | 0.061 | 0.040 | 1.52 | 0.128 |
| No of Children | -0.146*** | 0.053 | -2.75 | 0.006 | -0.043 | 0.049 | -0.88 | 0.377 |
| Completed School | -0.378*** | 0.098 | -3.87 | 0.000 | -0.301* | 0.155 | -1.94 | 0.052 |
| Uni Degree | 0.495 | 0.482 | 1.03 | 0.305 | -0.132 | 0.127 | -1.04 | 0.300 |
| Post-G Degree | | | | | 0.090 | 0.160 | 0.56 | 0.572 |
| Blue Collar | -0.478*** | 0.107 | -4.45 | 0.000 | -0.204 | 0.287 | -0.71 | 0.476 |
| White Collar | -0.543*** | 0.196 | -2.77 | 0.006 | -0.211 | 0.144 | -1.47 | 0.142 |
| Self Employed | 0.043 | 0.139 | 0.31 | 0.758 | 0.180 | 0.147 | 1.22 | 0.221 |
| Constant | -7.598*** | 2.305 | -3.3 | 0.001 | -1.849 | 1.241 | -1.49 | 0.136 |

Note: The table gives parameter estimates from probit models linking having an e-wallet with our economic and demographic control variables. The left columns give the estimates, with standard errors, z-statistics and p-values reported across the columns. Results for Indonesia appear in the left panel with Bangladesh on the right. *, **, and *** denote statistical significance at 10%, 5% and 1% respectively. There was insufficient variation for the post-graduate education variable to estimate the model in Indonesia, hence the covariate was omitted in this model.

The results show that income, age, education, and white/blue collar employment are all significant predictors of using an e-wallet in Indonesia. Thus, it is plausible that there may be some other unobserved factors driving this variable. However, in Bangladesh, only age is significant in these regressions, and the effect sizes are smaller than for Indonesia. Therefore, we are a little more confident in the results for Bangladesh, which suggests that the true effect sizes may be towards the smaller end (4% in Bangladesh) rather than the larger estimate of 10% (in Indonesia).

Estimates from the matching process are presented below in Table 4. Here we specify a series of callipers (tolerance bands for matching propensity scores) which link individuals in the non-app group with comparable individuals who do use the e-wallet application. This process allows us to construct synthetic treatment and control groups with similar characteristics that can be used to simulate an experiment with random app allocation. The difference in preference for cash across these groups is then analogous to our estimate of $\gamma$ from the regression model.

## Table 4. PSM Estimates of the Effects of E-Wallet Use on Cash Preference

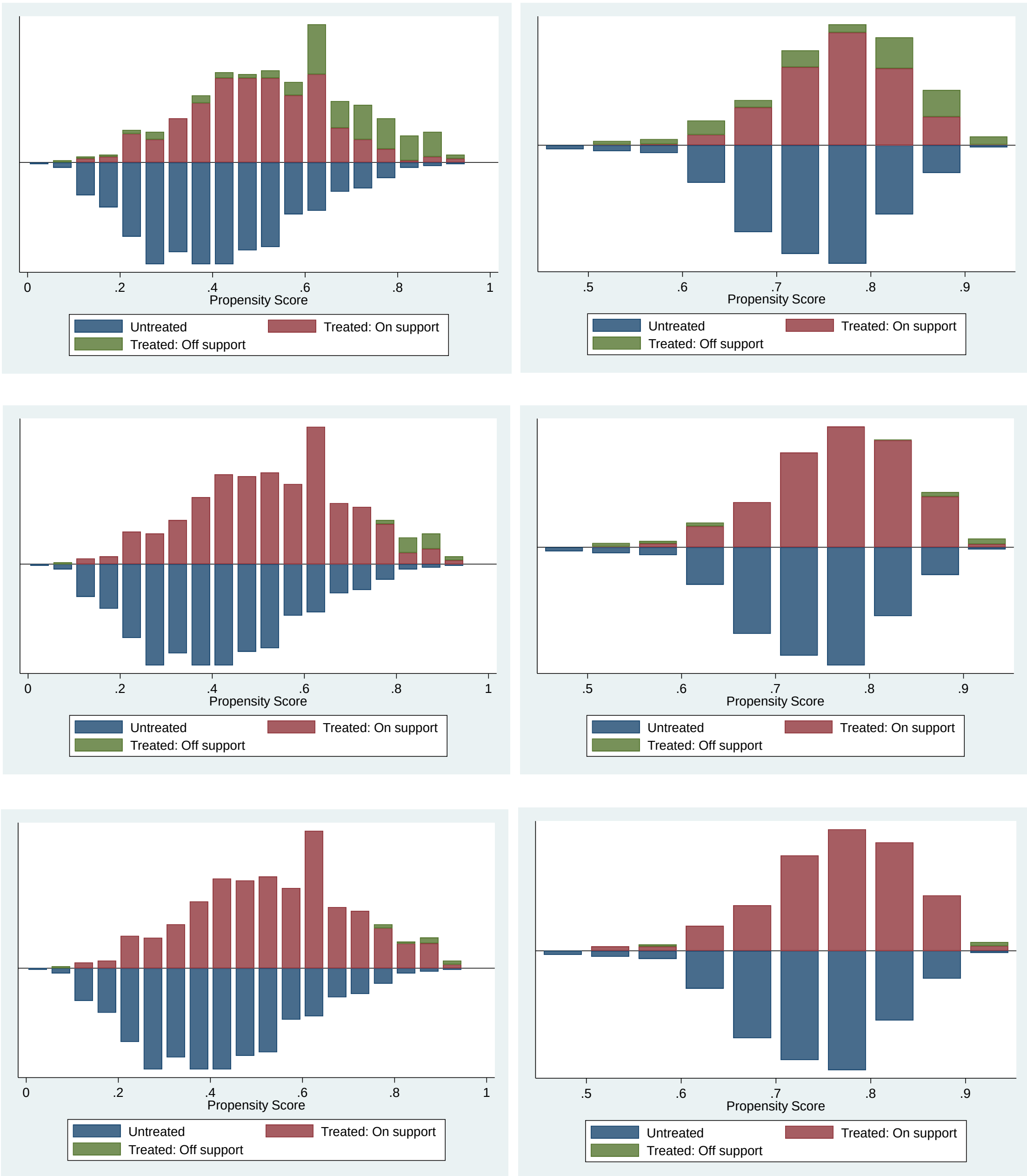
| | Indonesia | | | | Bangladesh | | | |
|---|---|---|---|---|---|---|---|---|
| Calliper | Treatment - γ | SE(γ) | P-Value | Common Sup | Treatment - γ | SE(γ) | P-Value | Common Sup |
| 0.001 | -0.114*** | 0.036 | 0.000 | 868/999 | -0.089*** | 0.025 | 0.000 | 797/992 |
| 0.005 | -0.115*** | 0.035 | 0.000 | 978/999 | -0.088*** | 0.024 | 0.000 | 959/992 |
| 0.010 | -0.118*** | 0.035 | 0.000 | 990/999 | -0.088*** | 0.024 | 0.000 | 983/992 |

Note: The table presents estimates of the treatment effect based upon mean differences in outcomes for matched groups using propensity scores. Calliper widths of 0.001, 0.005, and 0.01 are used to perform the matching. Mean differences are given in the treatment (γ) column with standard errors and p-values to the right. The fraction of observations with common support for each matching algorithm is also provided. *, ** and *** denote significance at 10%, 5% and 1% respectively.

The estimates in Table 4 are slightly larger and more significant compared with the corresponding estimates from Table 2. Here the effect sizes range from almost 12% (Indonesia, calliper width 0.01) to around 9% (Bangladesh, all three calliper widths).

The quality of the matching procedures can be evaluated by examining the distributions of propensity scores across the treated and untreated groups. Figure 1 shows histograms for each, where the distributions of scores for treated observations lie above the horizontal axis (red), while the histograms for the corresponding untreated group lie below (blue). Observations that are treated but unable to be matched to an untreated observation are depicted in green. The fact that there is a wide overlap of probability mass for the blue and red histograms indicates that in all cases, the matching algorithm was able to identify individuals with comparable propensity scores in both groups in the vast majority of cases. The only violations were (i) when the very small calliper of 0.001 in the first estimates (row 1 of Figure 1) where the narrow bandwidth meant that some data remained unused, and (ii) for some very high propensities in the treatment groups.

**Figure 1. PS Distributional Plots: Indonesia (left) and Bangladesh (right)**




Note: The figure presents distributional plots (histograms) of propensity scores for treated (i.e., have an e-wallet) and untreated (no e-wallet) subsamples as estimated by the probit model. The treated observations are depicted in red while the untreated observations are shown in blue. Observations that do not have common support are shown in green. The first row is based on a caliper width of 0.001; the second row on a width of 0.005; while the third is based on 0.01. Plots for Indonesia are on the left with Bangladesh on the right.

Finally, we consider some aggregate diagnostics related to matching quality based upon covariate balance in the treated and untreated subgroups. The goal is to have covariate distributions to be as similar as possible between treatment and control subgroups to eliminate as much confounding as possible. Here, Rubin's B is a measure of aggregated differences in means between the synthetic treatment and control groups, while Rubin's R is the analogous ratio of variances. It is normally recommended that B is less than 25 while R should lie between a lower bound of 0.5 and an upper bound of 2 (Rubin, 2001). In Table 5, the only instance where any diagnostic statistic lies outside of the recommended range is the first matching estimate for Indonesia, where the aggregated standardized ratio of means is 27.1 and therefore slightly above the recommended threshold for mean differences.

**Table 5. Matching Diagnostics**

| | Indonesia | | Bangladesh | |
|---|---|---|---|---|
| Calliper | Rubin B | Rubin R | Rubin B | Rubin R |
| 0.001 | 27.1* | 0.83 | 20.2 | 0.86 |
| 0.005 | 20.2 | 0.96 | 17.8 | 1.35 |
| 0.010 | 20.3 | 0.99 | 18.8 | 1.22 |

Note: The table gives estimates of Rubin's B and R metrics that measure covariate distributional differences between covariates of treatment and control groups. The Rubin B metric measures aggregate mean differences while Rubin R measures differences in variance. Estimates are provided for caliper widths of 0.001, 0.05, and 0.01.

## 6. Discussion

Our results indicate that access to e-wallets among poor populations in developing countries predicts a reduced preference for cash. Estimates established through baseline regression of our survey data indicate that having an e-wallet reduced the preference for cash by 10% in Indonesia, and 4% in Bangladesh. This result holds in the presence of multiple controls. While we are not able to determine how much of the result is causal, we do know that in aggregate, people preferring other options to cash can only be caused by those other options being available – which in this case, digital financial services presents itself is the most obvious alternative. Our diagnostics are slightly stronger for Bangladesh, suggesting it may be best to lean towards the lower effect size (4%). But PSM gives bigger effect sizes (9-11% for both). Together these estimates point to an effect size in the vicinity of 5-10%.

While our results are not overwhelmingly high, they do point to a small, desirable spillover in terms of its relevance to advancing financial inclusion and reducing poverty in developing countries. On this point, studies have already concluded that increasing financial inclusion in developing countries plays a significant role in poverty reduction at the household level (Wong et al., 2023; Polloni-Silva et al., 2021). Furthermore, research has also demonstrated the specific positive value of digital financial services as a tool for poverty reduction as part of the financial inclusion equation (Peng and Mao, 2023; Luo and Li, 2022). Our results build upon such studies by showing that as the poor become included in the formal financial system through the use of e-wallets, their reduced preference for cash and increased formality of economic activity could bring additional positive development outcomes impacting the broader society. Some standout examples of this are the prospect of increased access to formal credit markets, increased government spending through higher tax revenues, and the reduction of criminal activity.[8] We briefly outline some of these mechanisms below.

***Access to formal credit markets***

A major disadvantage of informality is that it often limits options for accessing services from regulated institutions. A primary example of this is access to credit. Being able to access affordable capital can enable small-scale entrepreneurs to increase the scale of their business and generate higher income, or enable a household to manage a sudden economic shock such as a death in the family or a natural disaster. For the poor, access to credit can support consumption smoothing and enable households to invest in their future (Seefeldt, 2015).

Informal credit markets, such as family, friends or moneylenders, may often be easier or quicker for the poor to access, but also bring significant risks which can increase their vulnerability to poverty. Some of the most common risks associated with informal credit include limited transparency and documentation increasing the possibility of disputes; lack of consumer protection leaving borrowers more exposed to exploitation or excessive interest rates; inability to establish a credit history, further limiting their ability to access credit on favourable terms; and potential loss of social capital where payment defaults can strain relationships and damage the borrower's reputation with their family or community (Protium Finance Limited, 2023). If digital financial inclusion can successfully bring more people into the formal economy, the poor may gain access to a higher quality and quantity of credit options which could play a role in broader economic growth and development.

***Increased government spending through higher tax revenues***

Since the global financial crisis experienced from 2007-2009, donor countries have been putting more pressure on developing countries to improve their own revenue raising efforts and reduce dependency on foreign aid (Fjeldstad, 2014). However, as Besley and Person (2014) point out, developing countries struggle to raise revenue through taxation due to limited capacity of government to collect tax, dependency on aid, and limited government activity to modernise weak tax systems and incentivise the formalisation of informal economic activity. As noted earlier, informal economic activity often results in lower productivity and reduced tax revenues for governments. A key aspect of digital financial services is that they enable a more transparent financial system, at least in the long-term (Gao, 2023). The adoption of digital financial services also makes it easier for informal firms to formalise their businesses (Klapper et al., 2019) while also making it easier for governments to identify and communicate with taxpayers, monitor and enforce compliance, and also reduce compliance costs (Santoro et al., 2022). Furthermore, there is also an opportunity for governments to tax digital financial services directly (Pushkareva, 2021).

The development outcomes of additional or more efficient taxation enabled through digitisation and decreased informality are potentially significant for developing countries. Perhaps the most critical outcome could be the potential for greater investment into key areas such as health,

[8] Interestingly, we also note that the effect sizes reported above do not appear for possession of a bank account, which is arguably another measure of financial access. In Appendix A we show results for the regression in Section 3 replacing the E-Wallet dummy with a dummy variable denoting ownership of an account. The results show that individuals in Indonesia who have a bank account are actually 6% more likely to express a preference for cash, whereas in Bangladesh there was no relationship between these variables.

education, social protections, and key infrastructure. As Long and Miller (2017) point out, increased domestic resource mobilisation can lead to greater progress towards achieving the Sustainable Development Goals, while also providing broader benefits to society beyond raising finance such as increasing accountability or the effectiveness of institutions.

Of course, the potential for taxation to enable positive development outcomes is highly dependent on the ability, and willingness, of governments to utilise tax revenue appropriately and effectively. In many developing countries, investment into areas which could lead to greater public goods and services is often sacrificed due to misaligned priorities (i.e. defence or ostentatious purposes such as public buildings or other lavish spending) (Kaldor, 1965).

***Reduced criminality***

Promoting digital payment services, reducing consumer preference for cash, and creating more opportunities for inclusion in the formal economy could also play a role in reducing certain forms of criminality. As noted earlier in this paper, not all informal economic activity is illegal. However, with its lack of regulations and oversight, the informal economy does often enable illegal activities to occur including the exploitation of employees or organised crime (Edelbacher et al., 2015). The circulation of cash in the economy, especially high denomination notes, helps to fuel nefarious activity such as corruption, terrorism, tax evasion and illegal immigration (Regoff, 2016; Regoff, 2017). The increased levels of consumer protection typically associated with the firms operating in the formal economy, as well as increased transparency and monitoring enabled through digital financial services, could have an impact in reducing criminal activity.

***Potential negative considerations***

It should also be noted that an increase in the usage of digital financial services also creates new challenges, including certain risks of which the poor are often more vulnerable. Despite cash being the preferred currency for criminal activity, digital financial services also create new opportunities for criminals to conduct financial fraud including data theft (Zakaria, 2023; Ozili, 2020). The poor in developing countries are more likely to fall victim to such nefarious activity as a result of limited digital skills or capabilities. Furthermore, they are generally more vulnerable due to lack of access to redress mechanisms, weak criminal justice systems, or lack of affordable insurance options to reduce the severity of the risk. Lower levels of literacy and digital capability among the poor also increase the risk of human error. Concerning transparency, many people may resist entering into a digital financial system if they fear increased government oversight may lead to income loss from taxation. These are just a few examples of some of the challenges digital financial inclusion efforts persistently encounter to make it a viable solution for the poor in developing countries.

## 7. Conclusion

Our models have shown that having access to digital payment services in the form of an e-wallet likely reduces consumer preferences for cash. From this finding, we argue that there could be broader development implications associated with promoting digital payments in relation to the informal economy. Namely, adoption of digital financial services and reduced preference for cash could potentially drive greater development of, and participation in, formal economic activity. In the context of developing countries, where a significant portion of the economy generally operates informally, our findings and predictions give weight to the argument that digital financial inclusion will aid poverty reduction and broader economic growth and development. Some examples of broader implications associated with promoting more formality within the economy include enhancing access to formal credit, increased government spending to support development through higher tax revenues or a reduction in certain forms of criminal activity. However, advancements in digital financial inclusion also bring new challenges which policymakers and practitioners will need to address. Challenges such as limited literacy or digital skills costs, or weak institutions make the poor in developing countries particularly vulnerable to risks associated with digital financial services.

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## Appendix A

### Table A1. Regression Outputs – Having a Bank Account and Preference for Cash

| | Indonesia | | | Bangladesh | | |
|---|---|---|---|---|---|---|
| **Bank Account** | **0.062**** | **0.062**** | **0.061**** | **0.018** | **0.015** | **0.019** |
| | (0.027) | (0.028) | (0.028) | (0.019) | (0.020) | (0.020) |
| Female | 0.019 | 0.015 | 0.008 | | 0.006 | -0.002 |
| | (0.052) | (0.053) | (0.053) | | (0.025) | (0.025) |
| Log Income | | 0.004 | 0.007 | | -0.009 | 0.002 |
| | | (0.019) | (0.019) | | (0.019) | (0.021) |
| Age | | -0.001 | -0.002 | | -0.003 | -0.003 |
| | | (0.006) | (0.006) | | (0.007) | (0.007) |
| Age Squared | | 0.000 | 0.000 | | 0.000 | 0.000 |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| Married | | (0.109 | 0.118* | | 0.005 | 0.010 |
| | | (0.067) | (0.068) | | (0.036) | (0.037) |
| Widowed | | 0.047 | 0.054 | | 0.058 | 0.055 |
| | | (0.073) | (0.073) | | (0.078) | (0.081) |
| 1 Adult | | -0.072 | -0.069 | | 0.028 | 0.020 |
| | | (0.064) | (0.066) | | (0.281) | (0.286) |
| 2 Adults | | -0.071 | -0.067 | | 0.047 | 0.042 |
| | | (0.076) | (0.078) | | (0.281) | (0.285) |
| 3 Adults | | -0.171* | -0.164 | | 0.036 | 0.032 |
| | | (0.099) | (0.099) | | (0.282) | (0.286) |
| 4 Adults | | -0.381** | -0.351** | | 0.034 | 0.028 |
| | | (0.172) | (0.173) | | (0.284) | (0.289) |
| 1 Child | | -0.011 | -0.015 | | 0.008 | 0.010 |
| | | (0.028) | (0.028) | | (0.026) | (0.026) |
| 2 Children | | -0.016 | -0.011 | | 0.042 | 0.041 |
| | | (0.035) | (0.035) | | (0.027) | (0.027) |
| 3 Children | | 0.138 | 0.151 | | 0.069* | 0.070* |
| | | (0.099) | (0.095) | | (0.038) | (0.038) |
| 4 Children | | 0.154 | 0.134 | | 0.076 | 0.082 |
| | | (0.105) | (0.105) | | (0.084) | (0.084) |
| 5 Children | | 0.400*** | 0.415*** | | 0.206 | 0.212 |
| | | (0.155) | (0.156) | | (0.141) | (0.145) |
| School Educ | | | -0.036 | | | -0.027 |
| | | | (0.026) | | | (0.032) |
| Bachelor's Deg | | | 0.042 | | | 0.001 |
| | | | (0.035) | | | (0.025) |
| Post-Graduate | | | 0.010 | | | 0.005 |
| | | | (0.023) | | | (0.030) |
| Blue Collar | | | 0.108*** | | | 0.034 |
| | | | (0.032) | | | (0.078) |
| White Collar | | | 0.063 | | | 0.025 |
| | | | (0.042) | | | (0.034) |
| Self Employed | | | 0.017 | | | 0.031 |
| | | | (0.038) | | | (0.028) |
| Constant | 0.548 | 0.626 | 0.673 | 0.572*** | 0.537 | 0.618 |
| | (0.776) | (0.785) | (0.780) | (0.135) | (0.413) | (0.418) |
| Village FE | Y | Y | Y | Y | Y | Y |
| R-Squared | 0.534 | 0.544 | 0.553 | 0.392 | 0.399 | 0.400 |
| N | 1000 | 1000 | 1000 | 1000 | 1000 | 992 |

Note: The table gives coefficient estimates from linear probability models estimated by OLS using preference for cash as the dependent variable. The base individual is a male in a household with more than four adults with no children, less than high-school education and unspecified work type. Parameter estimates are given in regular type with robust standard errors below in parentheses. Symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.