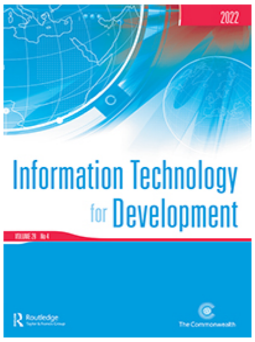

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Exploring the gender gap in mobile money awareness and use: evidence from eight low and middle income countries

Travis W. Reynolds[a], Pierre E. Biscaye[b], C. Leigh Anderson[c], Caitlin O'Brien-Carelli[c] and Joanna Keel[d]

[a]Department of Community Development and Applied Economics, University of Vermont, Burlington; [b]Department of Agricultural and Resource Economics, University of California – Berkeley, Berkeley; [c]Daniel J. Evans School of Public Policy and Governance, University of Washington, Seattle; [d]Environmental Studies Program, Colby College, Waterville

ABSTRACT
We used three waves of Financial Inclusion Insights surveys (2013–2016) to examine gender gaps in mobile money (MM) awareness and use across eight low- and middle-income countries. After accounting for socio-demographic factors (age, marriage, literacy, education, employment, income, and financial numeracy) and other enabling factors (mobile phone, formal identification, and bank account), we found no independent association between gender and MM use in established MM markets in Kenya, Tanzania, and Uganda. In contrast, in emerging MM markets (Bangladesh, India, Indonesia, Nigeria, and Pakistan), significant gender differences in MM use remained. Phone and bank account access had stronger associations with MM use for men than for women in these MM markets, and gender gaps in MM use increased over time. Findings suggest realizing the financial inclusion potential of MM may require a more nuanced understanding of difficult-to-measure and slow-to-change factors – such as legal and social norms – constraining women's MM use.

KEYWORDS
mobile money; digital financial services; women; gender gap

1. Introduction

There have long been dramatic financial disparities between women and men in low- and middle-income countries (LMICs) (Barooah et al., 2018; Buvinić & O'Donnell, 2019; GSMA, 2015b; GSMA, 2020b; GSMA, 2021a; World Bank, 2014), and women remain disproportionately represented among the financially excluded (Demirgüç-Kunt et al., 2018; Minischetti, 2017; Wanjala, 2014). The combination of new digital financial service offerings, advances in mobile technologies, and growing mobile subscriptions in many LMICs has created an opportunity to provide financial services previously inaccessible to unbanked populations, including women (Adaba & Ayoung, 2017; Adegbite & Machethe, 2020; Donovan, 2012; Gahigi, 2017; Qureshi, 2013; Qureshi & Najjar, 2017).[1] In particular, mobile money (MM) – transferring money, paying for goods and services, and conducting other financial transactions via mobile phone without needing to link a bank account[2] – has spread rapidly across sub-Saharan Africa and South Asia (Mugambi et al., 2014; Rahman et al., 2017; Victor, 2014).[3] But studies suggest women are less likely to be aware of or use MM in these

CONTACT Travis W. Reynolds twreynol@uvm.edu Department of Community Development and Applied Economics, University of Vermont, Burlington, VT

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rapidly expanding markets (Barooah et al., 2018; GSMA, 2020b; Mbiti & Weil, 2015). Given widespread recognition that increasing financial inclusion via mobile devices – and among poor women in particular (Koomson et al., 2021; Suri & Jack, 2016) – can also contribute to broader economic development goals (Aker & Mbiti, 2010; Chatterjee, 2020; Ilavarasan, 2017) there are clear benefits to better understanding barriers to growing inclusive MM markets across LMICs.

A wealth of previous scholarship has sought to measure the extent of the 'gender gap' in digital financial services in LMICs (Barooah et al., 2018; Demirgüç-Kunt et al., 2018; GSMA, 2020b; Minischetti, 2017). But while such studies often discuss how socio-demographic and contextual factors may influence gender gaps, most do not formally test the relative importance of different factors in explaining women's lower rates of MM use.[4] This paper examines MM awareness and use by women and men drawing on three waves of data from the Financial Inclusion Insights (FII) survey collected in 2013–2016 across eight LMICs. These include four countries in sub-Saharan Africa and four in South and Southeast Asia. Our initial analysis suggests three country groupings based on aggregate levels of MM awareness and use: High Awareness / High Use countries (Kenya, Tanzania, and Uganda), High Awareness / Low Use countries (Bangladesh, Pakistan), and Low Awareness / Low Use countries (India, Indonesia, and Nigeria). We note that these country-level differences in MM use do not appear to simply reflect general gender inequities across countries by established metrics: for example while Kenya is the country with the largest percentage of women aware of and using MM, it ranks 95th on the most recent Global Gender Gap Index (an index constructed with indicators of gender inequities in four domains: Economic Participation and Opportunity, Educational Attainment, Health and Survival, and Political Empowerment (World Economic Forum, 2021)). In contrast several countries with lower rates of MM use and larger gender gaps rank much higher on the Global Gender Gap Index, including Uganda (66th) and Bangladesh (65th).

If gender gaps in MM use are simply a reflection of known inequities across women and men in access to information, education, income or other enabling factors such as mobile phones or bank accounts, then financial inclusion efforts might be effectively directed toward alleviating these gendered constraints. On the other hand, if factors such as legal or social norms have led women to have less exposure to, perceive less value in, or differentially trust MM than men, then more research may be needed to understand such systemic and formative but difficult-to-measure barriers (Spencer et al., 2018).

Drawing on a conceptual framework informed by the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) and on the literature on MM, we consider a broad set of socio-demographic factors and other enabling factors hypothesized or documented to be associated with MM use. In addition to information on individual gender and rural/urban context, the FII data include comparable measures of respondent age, marital status, literacy, financial numeracy, highest level of education, formal employment status, and income level, as well as mobile phone ownership, having an official form of identification, and having a bank account. We categorize the first seven of these measures as socio-demographic characteristics and the last three as other enabling factors.

Our research questions are: (1) *To what extent are women less likely to be aware of and use MM after controlling for socio-demographic characteristics, other enabling factors, and rural/urban location across the sampled LMICs?;* and (2) *What socio-demographic characteristics, other enabling factors, and rural/urban location variables are associated with women's awareness and use of MM services in LMICs with different levels of MM market development?* We use multivariate regressions across country groupings to estimate the degree to which MM awareness and use are associated with gender after controlling for relevant covariates. For analyses of correlates of MM use we use a maximum likelihood regression model with sample selection (*heckprobit*) to account for the dependence of MM use on MM awareness (in the FII survey only respondents who were aware of MM were asked if they had ever used MM services). The publicly available FII data and study design allow us to highlight differences across LMICs in correlates of MM awareness and use across women and men, holding other factors constant. To our knowledge we are the first study to analyze differences in MM awareness and use among women and men across countries in both Africa and Asia, and the first to explicitly test how the effects of socio-demographic characteristics and other enabling factors on MM outcomes may vary by gender and country. We thus respond to calls in the literature for more empirical research on digital financial services adoption among under-studied groups in diverse LMIC settings (Potnis et al., 2020).

To our first research question, consistent with previous studies we find that women are significantly less likely to be aware of and use MM in almost all sampled LMICs. We observe larger gender gaps for MM use than awareness, indicating additional barriers to women at that later stage of the technology adoption process. After controlling for measured socio-demographics and other enabling factors in multivariate regressions, however, gender alone has little association with MM awareness and use in High Awareness / High Use countries, but remains a significant factor in countries with less-developed MM markets.[5] These results suggest that in established MM markets, eliminating well-known gender inequities in areas such as education, employment, and phone ownership could also eliminate gender gaps in MM use. In emerging MM markets, on the other hand, there appear to be other unmeasured factors contributing to gender gaps in MM beyond the socio-demographics and other enabling factors measured in this study.

To our second research question, we find that similar socio-demographics and other enabling factors are associated with women's and men's MM awareness and use across LMICs, with some differences across country groupings. Among the factors considered, phone ownership consistently appears to be one of the strongest correlates of women's MM awareness and use across all countries. In High Awareness / Low Use countries, however, we observe large differences across women and men in the effects of enabling factors – holding other factors constant, women who are aware of MM and have both a mobile phone *and* a bank account have roughly a 25% lower predicted probability of ever using MM compared with men in the same circumstances. And in Low Awareness / Low Use countries, younger men with both a phone and bank account are nearly three times more likely to have used MM than women in similar circumstances. These results are suggestive of unmeasured barriers, such as legal or slow-to-change social norms, contributing to gender gaps in MM outcomes in these countries even when gendered differences in socio-demographics and other enabling factors are accounted for. Indeed, when we compare our results to 2020 GSMA estimates of mobile money awareness and adoption, we find persistent or widening gender gaps in the same set of countries (GSMA, 2021b).

The remainder of this paper is organized as follows. Section 2 reviews the theoretical bases for modeling technology trial and use, including past efforts to incorporate gender into models of MM use. Section 3 presents the methods and data and summarizes the empirical approach. Findings are presented and discussed in Section 4, and Sections 5 and 6 note implications of the findings, limitations of the study, and potential future research directions.

2. Literature and conceptual framework

A growing body of research on MM and other digital financial services in LMICs has highlighted a range of consumer characteristics and contextual factors that shape propensity to use these technologies (Adaba & Ayoung, 2017; Bongomin et al., 2018; Mukong & Nanziri, 2021; Munyegera & Matsumoto, 2016; Murendo et al., 2018; Pal et al., 2020; Potnis et al., 2020). In a review of technology adoption models applied in the digital financial services literature (including MM but also other mobile financial services), Shaikh and Karjaluoto (2015) conclude the UTAUT model – which frames technology adoption as driven by (i) expectancy of the product's performance, (ii) expectancy of effort required, (iii) social influences, and (iv) 'facilitating conditions' including technological and institutional support enabling access and use – is among the most commonly applied frameworks for the study of digital financial services adoption. Unlike many prior models, the UTAUT directly incorporates demographics (e.g. gender, age, education) which have been shown to substantially improve the explanatory power of technology adoption models in a variety of contexts (Muriithi et al., 2016; Slade et al., 2015; Venkatesh et al., 2003).

A subset of this literature considers the drivers of gender gaps in financial services (Ghosh & Vinod, 2017; Morsy, 2020; Zins & Weill, 2016). In general, studies analyzing gender gaps in financial services run regressions of an outcome of interest on gender and other covariates, including socio-demographic characteristics and contextual factors. Some studies further consider the effects of interactions between gender and covariates of interest or conduct decomposition exercises to identify the contribution of particular factors to any observed gender gaps (Blau & Kahn, 2017).

The framework that informs our empirical work is therefore in line with both the UTAUT model of technology adoption and with prior studies analyzing gender gaps in financial services. We consider MM use (measured as having ever used any MM service) as a function of socio-demographic characteristics associated with awareness of MM (measured as familiarity with any MM provider) and perceived net benefits from MM services, as well as other enabling factors and contextual factors that might influence awareness and propensity to use MM (Figure 1). We theorize that any differences associated with gender after controlling for other measured factors is a residual of unmeasured social norms 'operationalized through beliefs, attitudes and practices,' that affect women's agency, exposure, and access differently than men's (UNDP, 2020a).

The specific socio-demographics, other enabling factors, and contextual variables included in the study and summarized in Figure 1 reflect the available data and are drawn from the literature on MM deployment in LMICs, which has revealed several correlates of MM use, as well as from the broader literature on digital financial services (which at times blends MM with other DFS offerings).

2.1 Gender and MM awareness and use

Several studies have reported women are less likely to be familiar with or use MM in various LMICs (GSMA, 2021b; Minischetti, 2017; Mndolwa & Alhassan, 2020; Potnis et al., 2020; Spencer et al., 2018; Waitara et al., 2016). Early reports attributed gender gaps to a combination of women lacking

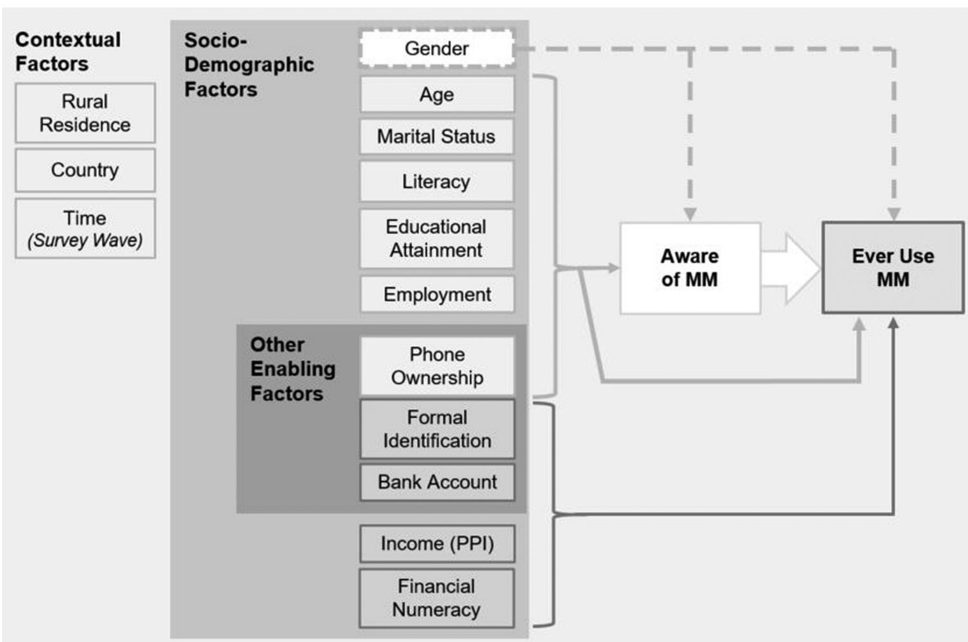

Figure 1 . Conceptual framework of awareness and use of mobile money (MM) as a function of *socio-demographics* associated with knowledge and perceived net benefits of MM, *other enabling factors* associated with relative ease of access to and potential net benefits from MM, and *contextual* factors further associated with policy context, MM service availability, and potential net benefits.

knowledge of and trust in MM, as well as lack of literacy, lower rates of mobile phone ownership, and other social/cultural barriers including MM services not necessarily meeting women's financial needs (Scharwatt & Minischetti, 2014). Some studies broadly cite 'gender norms' and 'cultural barriers' as factors that can both shape women's perceptions of the potential value of MM in LMICs and also constrain women's knowledge of and access to new digital technologies (Muriithi et al., 2016; Potnis, 2016). Others more specifically emphasize women's relatively constrained access to education (Osei-Assibey, 2015) and other enabling factors including mobile phones and formal financial institutions (Potnis et al., 2020; Spencer et al., 2018). Spencer et al. (2018) conclude women's lower rates of digital financial services use (including MM) in LMICs reflect a combination of social norms, economic inequalities, and policy, resulting in women's lesser exposure to technology and commercial service providers, relatively limited financial literacy, lower income levels, and greater general vulnerability leading to higher risk aversion *vis à vis* new technologies.

2.2 Other socio-demographic factors associated with MM awareness and use

In addition to gender, the FII data include comparable measures of seven socio-demographic factors relevant to MM and digital financial services access and use: age, marital status, literacy, highest level of education, employment status, income level, and financial numeracy. This set of characteristics is similar to those considered in studies of gender gaps in financial inclusion more broadly (e.g. Ghosh & Vinod, 2017; Mndolwa & Alhassan, 2020; Zins & Weill, 2016).

Age is one of the most common variables in models of MM adoption and use including early work on M-PESA (Mbiti & Weil, 2015) and related work on mobile banking (Safeena et al., 2012; Shaikh & Karjaluoto, 2015). Age is often negatively associated with MM and other digital financial services use (across women and men), which may reflect younger consumers' greater familiarity and comfort with new digital technologies (Potnis et al., 2020). Being married may either increase or decrease the likelihood of MM use depending on intra-household resource allocation dynamics and gender norms relating to women's access to mobile services (Mothobi & Grzybowski, 2017; Potnis, 2015; 2016).

Beyond age and marital status, gender gaps in MM use may simply be derivative of general gender inequities in a country. Women in LMICs often have lower literacy rates and educational attainment than men (World Bank, 2018a), such that they may have less opportunity to learn about or use digital financial services (Scharwatt & Minischetti, 2014). We thus consider educational variables expected to relate to MM awareness and ability to use financial services including literacy and formal education (Ajayi & Ross, 2018; GSMA, 2018a; Kiconco et al., 2019).

Differences in employment may also contribute to gender gaps in MM awareness and use. Onyia and Tagg (2011) argue that women may have reduced demand for digital financial services as they are less likely to have regular income from employment. Higher household work burdens and childcare duties may also leave women with less time to work outside the home (Spencer et al., 2018), which may translate into reduced access to MM agents to learn about MM, to set up an account, or to perform transactions. Related to employment differences, lower incomes for women potentially affect MM use (even among women aware of MM) via both reduced access to and lower perceived benefits from MM services (Scharwatt & Minischetti, 2014).

Similarly, financial numeracy might relate to MM use (if not necessarily to MM awareness): numeracy has recently been highlighted by Matthews (2019) as a potential barrier to financial inclusion in LMICs, particularly among women. Potnis et al. (2020) further observe that numeracy-related skills beyond basic number recognition – including understanding the technical terms used by financial services companies ('financial literacy') – may particularly constrain women's and older customers' ability to use new MM services. We thus focus not merely on simple numeracy, but more specifically on financial numeracy, defined as the numeracy skills required to carry out financial transactions with understanding, in real time, without help from a third person (Matthews, 2019).

2.3 Other enabling factors associated with MM awareness and use

The FII data also include measures of three 'other enabling factors' that might be associated with MM use among LMIC consumers: mobile phone ownership, formal identification, and bank account ownership. While some of these other enabling factors may be particularly relevant to mobile money use, studies of gender gaps in financial inclusion more broadly also include similar covariates in their analyses (e.g. Ghosh & Vinod, 2017; Minischetti, 2017).

Globally women are 14% less likely to have access to a mobile phone than men (GSMA, 2015b), and in LMICs women are 20% less likely to own a smartphone (GSMA, 2020b). These gaps may reduce women's access to information about MM (awareness) as well as MM use. Gender disparities in mobile phone ownership may be the product of the costs of mobile phones or credit, which may be less affordable for women (Munoz Boudet et al., 2018), or of inequitable social norms which restrict women's access to mobile phones, digital financial services, or both (GSMA, 2020b; Potnis et al., 2020; Scharwatt & Minischetti, 2014).

Access to formal identification is often another prerequisite for participation in a 'typical business model' of MM (whether e-Money Wallet or OTC with MM agents) (Ghosh, 2017; Potnis et al., 2020). But in many countries, women are less likely than men to have official identification documents that might be needed to access digital financial services (GSMA, 2013; Scharwatt & Minischetti, 2014). Similarly, although MM by definition does not require access to a bank account (Ernst & Young, 2016), MM use might be more likely among consumers with existing ties to a financial institution, especially in countries where MM services are provided by or in partnership with licensed banks (Reynolds et al., 2018). Although in theory for some consumers having existing access to financial services through banks might lead MM to be perceived as having limited value (Mothobi & Grzybowski, 2017), in many cases the ability to engage in mobile banking services linked to a bank account is highlighted as a benefit of new digital financial services platforms and thus might provide additional incentive for use of MM (GSMA, 2015a). The observed tendency for MM adoption to occur more rapidly among already-banked consumers has even led some authors to question whether the benefits of emerging MM markets may be concentrated among those who are already engaged in the formal financial system, rather than among financially excluded groups (including women) (Wyche et al., 2016).

2.4 Contextual factors associated with MM awareness and use

We further consider contextual variables that may impact MM awareness and use (Lashitew et al., 2019; Potnis et al., 2020; Wenner et al., 2017), specifically rural versus urban location, country context, and the passage of time. Some studies suggest rural consumers may be more likely to use MM than their urban counterparts, as those in rural areas are also less likely to have access to physical banking infrastructure (Allen et al., 2014), potentially increasing the perceived value of MM services (Kikulwe et al., 2014). Ultimately, however, as summarized by Potnis et al. (2020), living in a more isolated context ('spatial separation') has more commonly been negatively associated with MM use in LMICs. And in a recent survey of MM providers more than half reported goals of targeting specialized products towards rural customers, in part reflecting recognition of barriers to MM access in rural areas (GSMA, 2019). Combined with expectations that social norms restricting women's access to and use of technologies might be more restrictive in more traditional rural communities (Wyche et al., 2016), we thus expect rural location will be negatively associated with MM awareness and use among women and men, and perhaps even more so for women.

Formal and informal institutions governing MM and the level of development of the MM sector within different country contexts may also substantially influence consumer perceptions of and behaviors towards MM services (Baganzi & Lau, 2017; Chauhan, 2015; GSMA, 2017; Heyer & Mas, 2011; Lepoutre & Oguntoye, 2018; Suárez, 2016). Recent research on the large disparity in MM adoption between Kenya and Nigeria, for example, has highlighted differences in institutional support and industry behavior in the two countries. Lepoutre and Oguntoye (2018) conclude that the Kenyan government's proprietary stake in Safaricom as well as its active oversight of the digital financial services sector were key factors supporting Kenya's burgeoning MM transaction system, while in Nigeria they find public support for the sector has been more limited (or in some cases subject to corruption), deterring MM expansion. Such findings are consistent with broader research on Information and Communications Technology (ICT) in Africa, which suggests that variation in policy context across countries and changes over time in country-specific ICT policies may be key factors in ICT adoption and use (Kayisire & Wei, 2016). We thus include survey country – as well as dummy variables for the year in which survey data were collected (survey wave) – as additional control variables in all models reported.

3. Methods

3.1 Data

To examine differences in MM awareness and use among women and men across LMICs at varying levels of MM market development we draw on nationally-representative household survey data from the Financial Inclusion Insights (FII) program, which provides detailed publicly accessible datasets collected by Intermedia (2019)[6] and funded by the Bill and Melinda Gates Foundation. We combine data from three waves of surveys collected between 2013 and 2016[7] in four countries in sub-Saharan Africa (Kenya, Nigeria, Tanzania, Uganda) and four in South / Southeast Asia (Bangladesh, India, Indonesia, and Pakistan) (Figure 2).

The FII survey is a cross-sectional, multi-stage, cluster-randomized household survey based on regional proportional distributions of samples, stratified by urban and rural populations as determined by the most recently available national census data in each of the eight survey countries (Intermedia, 2019). All respondents were aged 15 and over, and samples were selected independently for each survey wave in each country, with no attempt to survey respondents from previous waves.[8]

We measure MM awareness using two dichotomous variables: general awareness of the concept of MM ('*Have you heard of something called mobile money?*') and any recognition of the names of specific service providers ('*Have you ever heard about the following MM services?*' asked along with the names of regional MM providers[9]). We consider respondents who could name at least one

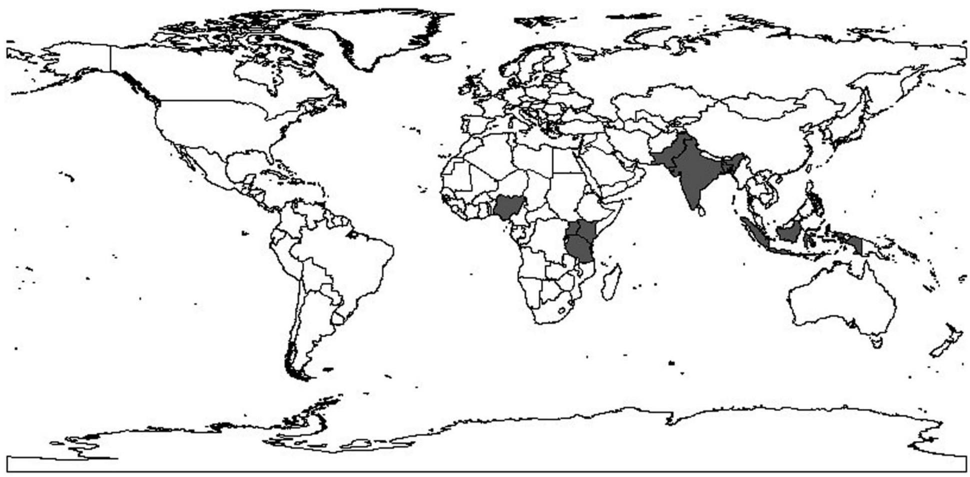

Figure 2 . Study countries in the sample of eight Financial Inclusion Insights (FII) surveys (Intermedia, 2019): Kenya, Nigeria, Tanzania, Uganda, Bangladesh, India, Indonesia, and Pakistan.

MM provider or who recognized the name of at least one specific provider in the FII surveys to be aware of MM.[10] We measure use of MM using the question '*Have you ever used MM for any financial activity?*' Respondents were only asked this question if they were able to identify at least one MM provider, either spontaneously or when prompted. As a result, this variable represents the number of people who used MM at least once among respondents who were aware of any MM provider.[11] Respondents not aware of any MM provider who were not asked this question are coded as not having used MM.

For each wave, the FII survey data also include ten variables relevant to our conceptual framework for MM awareness and use, in addition to gender and rural/urban location. Socio-demographic characteristics captured in the data include age, marital status (either monogamous or polygamously married respondents are coded as married), literacy (measured as the ability to read and understand the FII survey consent form in the local language), highest educational attainment (measured as dummies for no formal education, primary school education, and secondary school or further education), formal employment status, income level (for cross-country comparability, we measure whether the respondent reports an income greater than the Progress out of Poverty Index (PPI) cutoff point of $2.50 per day in purchasing power parity terms), and financial numeracy (measured as the ability to perform basic addition, subtraction, and percentage calculations relating to personal finance questions on the FII survey). The other enabling factors for MM use included in the data are mobile phone ownership, having an official form of identification, and having a bank account.

The FII dataset provides a large sample for all eight survey countries, with similar sample sizes across years, women comprising ~50% of the sample in all countries, and ample variation on other socio-demographics and other enabling factors (Table 1).[12] Survey weights are provided by Intermedia (2019) to make sample estimates nationally representative; these weights are applied to all results.

Three distinct country groupings emerge from the summary data, those with high MM awareness and use (Kenya, Tanzania, Uganda), high MM awareness but limited use (Bangladesh, Pakistan), and low MM awareness or use (Nigeria, India, Indonesia).[13] In subsequent analyses we thus disaggregate findings using these three country groups, roughly corresponding to levels of MM market development as reflected by aggregate MM awareness and use levels, as summarized in Figure 3.

3.2 Empirical approach

We use multivariate probit regression models with pooled survey data for all three survey waves (from 2013-2016) to examine associations between gender and MM awareness or use across countries and over time, controlling for socio-demographic characteristics, other enabling factors, and location. We consider MM awareness and use behaviors in sequence, assuming that consumers must first become aware of MM (awareness) before trying it (use).

For the initial probit model for MM awareness, we define the dependent variable *MM_Aware* as a dummy with a value of 1 if respondents answered 'Yes' to being aware of MM or were able to name any MM provider and 0 if not. This leads to a 'selection equation' (Heckman, 1979) of the form:

$$MM\_Aware^* = \beta_0 + \beta_1 female + \beta_2 age + \beta_3 married + \beta_4 literacy + \beta_5 education\_level + \beta_6 employed + \beta_7 own\_phone + \beta_8 rural + \beta_9 country + \beta_{10} wave + u_1$$

$$with\ MM\_Aware = \begin{cases} 1 \text{ } if \text{ } MM\_Aware^* > 0 \\ 0 \text{ } if \text{ } MM\_Aware^* \leq 0 \end{cases} \tag{1}$$

where *MM_Aware** is a latent variable defining whether the respondent is aware of MM. The coefficient β_1 represents the estimated association[14] between gender and the likelihood of MM awareness, controlling for the other specified factors. Other coefficients reflect the estimated associations between the dependent variable and socio-demographic characteristics and other

Table 1. MM outcomes, socio-demographic characteristics, and other enabling factors by country (%, pooled waves 1-3).

		Sub-Saharan Africa				South / Southeast Asia			
		Kenya$^{+,+}$	Tanzania$^{+,+}$	Uganda$^{+,+}$	Nigeria$^{-,-}$	Bangladesh$^{+,-}$	Pakistan$^{+,-}$	India$^{-,-}$	Indonesia$^{-,-}$
MM Outcomes									
Aware of MM		96.53	91.14	90.67	11.35	90.85	71.04	9.65	8.98
Ever use MM		75.45	51.25	44.47	0.59	26.05	8.23	0.35	0.45
Gender									
Female		51.06	51.44	53.11	49.96	49.00	47.63	48.92	50.75
Socio-demographic Characteristics									
Mean age (years)		33.49	35.21	34.01	33.20	34.49	34.22	36.69	38.13
Age Level	15–24	36.05	25.99	34.45	34.64	30.34	28.14	27.88	23.12
	25–34	25.96	29.50	23.26	26.52	26.18	29.22	22.76	22.96
	35–44	15.81	19.75	16.53	16.85	18.93	16.87	18.88	20.83
	45–54	10.32	12.00	11.12	10.78	11.32	15.35	13.33	15.76
	55+	11.86	12.08	14.64	10.75	13.23	10.41	17.15	17.21
Married		56.01	59.61	50.08	47.12	75.21	69.70	69.55	62.50
Literacy		80.42	85.51	61.23	80.37	61.72	65.03	64.39	90.60
Education Level	No formal ed.	9.09	9.67	13.32	8.46	25.45	31.21	29.04	3.67
	Primary ed.	44.07	64.19	48.70	13.16	26.94	22.79	12.85	37.76
	Secondary ed.	36.31	23.07	32.33	56.02	39.19	35.58	50.19	51.75
	Higher ed.	10.53	3.07	5.65	22.36	8.42	10.42	7.91	6.82
Employed		62.52	76.57	74.66	61.12	43.11	43.68	50.69	57.59
Income (>PPI $2.50)		49.74	14.85	29.46	10.40	24.48	48.83	22.44	37.83
Financial numeracy		90.93	89.58	80.48	89.11	91.32	89.48	85.75	97.61
Other Enabling Factors									
Owns a phone		74.43	71.97	58.40	87.85	61.12	57.41	53.88	63.35
Has an official ID		93.32	78.66	76.81	85.87	94.42	91.88	97.06	99.66
Has a bank account		27.32	13.44	12.61	39.42	18.51	8.08	56.13	24.45
Other Contextual Factors									
Rural		64.01	69.22	77.88	57.00	67.54	66.62	67.48	47.96
Sample (n)		8,989	8,998	9,001	18,003	18,000	18,000	135,147	18,120

$^{+,+}$High awareness, high use country; $^{+,-}$High awareness, low use; $^{-,-}$Low awareness, low use.

		MM Use (Ever Used MM)	
		High	Low
MM Awareness	High	Kenya, Tanzania, Uganda	Bangladesh, Pakistan
	Low		Nigeria, India, Indonesia

Figure 3 . Distinct groupings of countries in the sample by aggregate levels of MM awareness and use (author calculations based on 2013–2016 Financial Inclusion Insights surveys).

enabling factors hypothesized to relate to MM awareness. Most variables are binary except for age, which is continuous. In addition, we control for rural/urban location, survey country and survey wave in models using pooled survey data. Finally u_1 is the error term. All estimated associations are presented in the form of mean marginal effects; for example, a mean marginal effect of 0.01 on the gender variable would suggest that women in the sample, on average, were 1 percentage point more likely to be aware of MM than men, controlling for other factors.

The final probit model for MM use, conditional on MM awareness, then takes the form:

$$MM\_Use^* = \beta_0 + \beta_1 female + \beta_2 age + \beta_3 married + \beta_4 literacy + \beta_5 education\_level + \beta_6 employed + \beta_7 income + \beta_8 numeracy + \beta_9 own\_phone + \beta_{10} own\_official\_id + \beta_{11} own\_bank\_account + \beta_{12} rural + \beta_{13} country + \beta_{14} wave + u_2$$

$$with\ MM\_Use = \begin{cases} 1 \ if \ MM\_Use^* > 0 \\ 0 \ if \ MM\_Use^* \leq 0 \end{cases} \tag{2}$$

where *MM_Use* is a binary variable taking the value of 1 if respondents answered 'Yes' to ever using MM and 0 otherwise. In addition to the socio-demographics and other enabling factors from Equation 1, coefficients $\beta_7 - \beta_{11}$ in Equation 2 represent the estimated associations of additional factors hypothesized to relate to MM use, and u_2 is the error term. However in this final model the outcome *MM_Use* is only observed if *MM_Aware** > 0 (the selection equation), where $u_1 \sim N(0,1)$, $u_2 \sim N(0,1)$ and $corr(u_1,u_2) = \rho$. The extent of sample selection – i.e. the degree to which estimating the equation for *MM_Use* using only respondents who were aware of MM, without correcting for selection, would yield biased estimates – is given by the significance level of ρ.[15] All estimated associations are again presented in the form of mean marginal effects; in this model, a mean marginal effect of 0.01 on the gender variable would suggest that women in the sample, on average, were 1 percentage point more likely to use MM than men, controlling for other factors and also accounting for possible non-random selection of those who are aware of MM and hence potential MM users (Heckman, 1979).

We estimate the full models using the *heckprobit* procedure in Stata v16, a maximum-likelihood probit model with sample selection that produces coefficients in the MM use equation that have been adjusted to take into account respondents' MM awareness. Several factors including financial numeracy, having income beyond a poverty threshold, having an official government identification, and holding a bank account are hypothesized to be associated with MM use (Equation 2), but not necessarily with awareness (Equation 1), thus meeting the *heckprobit* identification restrictions.

We run all models for the three country groups (High Awareness / High Use, High Awareness / Low Use, Low Awareness / Low Use), and then estimate models separately for women and men within country groups, using pairwise comparisons to test for significant differences in effects of socio-demographics and other enabling factors on MM awareness and use among women and men.

As a final step we further consider the possibility of interaction effects among selected socio-demographics and other enabling factors, as having access to both a phone and a bank account, for example, might have a more powerful combined effect on MM use than either enabling factor alone. We examine such interactions graphically in the form of predictive margins (Williams, 2012). Based on the results of the empirical analysis, we focus on the predictive margins of selected significant predictors of MM use (literacy, phone and bank account ownership), disaggregated by gender, age, and country group (High Awareness / High Use, High Awareness / Low Use, and Low Awareness / Low Use). Together these analyses allow us to explore relationships between gender, other socio-demographic characteristics, other enabling factors, location and MM use in a diverse sample of LMICs.

4. Findings & discussion

Findings are structured following our two research questions. Sections 4.1-4.4 consider whether gender differences in MM use remain significant across different LMICs after controlling for socio-demographics, other enabling factors, and rural/urban location. Sections 4.5 and 4.6 report how these different variables relate to women's and men's MM awareness and use in LMICs with different levels of MM market development.

4.1 Cross-country patterns in MM awareness and use by gender

Across the eight LMICs studied 33.5% of men and 27.0% of women were aware of MM, and 10.9% of men versus 8.0% of women had ever used an MM service at the time of the FII surveys (2013-2016). However we observe large differences across countries in the sample: Figure 4 summarizes patterns in MM awareness and use across countries and across women and men.

Overall MM awareness and use rates were higher in sub-Saharan Africa than in South and Southeast Asia, with more than 92% awareness among men and more than 88% among women in Kenya, Tanzania, and Uganda. MM use in these countries ranged from a low of 40.0% (among women in Uganda) to a high of 77.3% among men in Kenya. In Nigeria however MM awareness was much

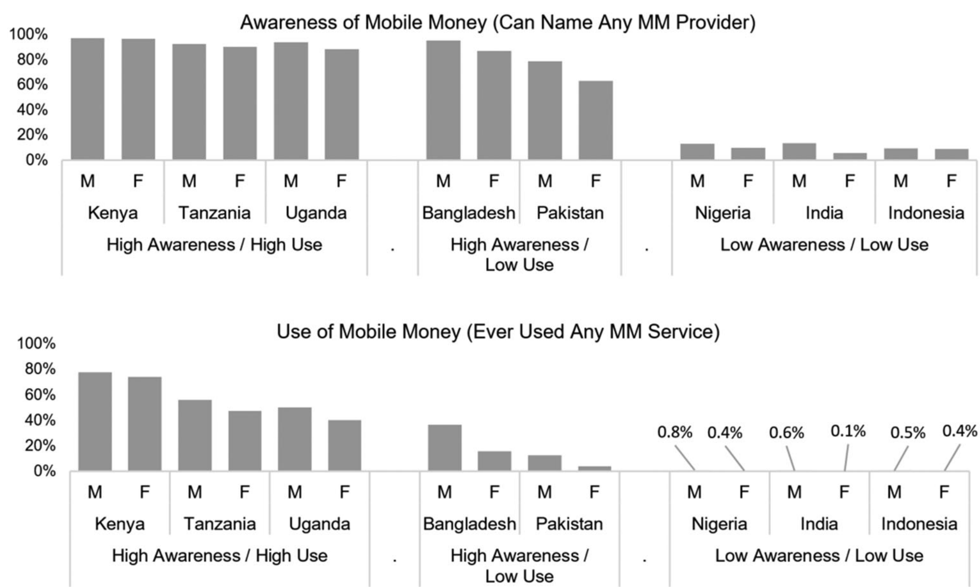

Figure 4 . MM awareness and use by country group and gender, 2013–2016 pooled samples (M = male; F = female).

lower (12.9% among men and 9.8% among women) and MM use rates less than 1%. Awareness rates in South and Southeast Asia were highest in Bangladesh (94.8% among men, 86.8% among women) and Pakistan (78.4% among men, 63.0% among women). In India and Indonesia awareness of MM was also limited, with less than 14% of men and 6% of women able to name any MM provider; at the time of data collection (2013-2016) rates of MM use were less than one percent (across both men and women) in both countries.

The persistent pattern of women being less likely to be aware of or use MM across LMICs is consistent with the large literature on gender gaps in digital financial services adoption (e.g. GSMA, 2020b). However, differences across countries were much more pronounced than differences across women and men within countries, underscoring the importance of country-specific factors shaping MM use across LMICs. Such factors may include gender norms, other socio-demographics and other enabling factors, as well as variation in telecommunications infrastructure, formal financial institutions, and national policy (Lepoutre & Oguntoye, 2018).

4.2 Gender and MM awareness and use controlling for socio-demographic characteristics and other enabling factors, by level of MM market development

Consistent with previous studies (Potnis et al., 2020; Waitara et al., 2016), we find women were less likely to be aware of or use MM even after controlling for other factors in pooled multivariate analyses (not shown) predicting MM awareness and use across all eight countries and three survey waves.[16] Overall women had a 3.4 percentage point lower likelihood of awareness of MM relative to men in the sampled LMICs ($p < 0.001$), other factors held equal, about half the size of the gender gap in MM awareness with no controls. Women were also on average less likely to use MM, with roughly a 1 percentage point lower likelihood of MM use among women across the LMICs in the sample ($p < 0.001$), even after controlling for socio-demographics, other enabling factors, and location. Given the relatively low baseline rates of awareness and use in the pooled LMIC sample, these mean marginal effects of gender are meaningfully large. In terms of predicted probabilities, after controlling for other factors women had a 12.4% lower probability of being aware of MM than men across LMICs, and a 7.9% lower probability of using MM services.

Owing to substantial variation across the sample, we focus on results for disaggregated models grouping countries based on similar levels of MM market development, as measured by overall rates of MM awareness and use. Table 2 presents results of multivariate models predicting MM awareness and use across countries in each grouping. All reported coefficients are mean marginal effects. The first model considers all survey respondents in estimating a probit regression for MM awareness. Then, given the structure of our framework – which assumes awareness of MM must precede use – the second column provides results of a heckprob selection model considering MM use conditional on awareness. We find clear support for the need to consider non-random selection in estimating a model of MM use conditional on MM awareness in these LMIC contexts: the significant athrho statistic suggests the model is improved by accounting for sample selection.

The results in Table 2 show noteworthy variation in the estimated association between gender and MM behaviors across country groups, and in the effects of other factors as well. Despite small bivariate gender gaps in MM adoption in all three countries, in the three High Awareness / High Use countries (Kenya, Tanzania, Uganda), in the multivariate models it appears women may have been *more* likely to use MM than men after controlling for other factors. In these East African countries women were no less likely than men to be aware of MM, and women on average were 1.9 percentage points more likely to have ever used MM after controlling for other socio-demographics, other enabling factors, and awareness. In terms of predicted probabilities (not shown) women in High Awareness / High Use countries had a 3.2% greater probability of using MM than men, all else equal. Women's essentially equal propensity to use MM in these countries, given the opportunity and agency, supports a hypothesis that gender gaps were driven by gendered inequalities in factors such as access to education, income, and other enabling factors. In particular,

Table 2. Cross-wave selection models of MM awareness and use by country group (High / High, High / Low, and Low / Low level of awareness and use). Estimates are mean marginal effects of the probit selection model (Aware) and mean marginal effects of second-stage equations in the heckprob selection model (Use | Aware).

		High Awareness / High Use (Kenya, Tanzania, Uganda)		High Awareness / Low Use (Bangladesh, Pakistan)		Low Awareness / Low Use (Nigeria, India, Indonesia)	
		Aware (Can Name Provider)	Use | Aware (Ever Use MM)	Aware (Can Name Provider)	Use | Aware (Ever Use MM)	Aware (Can Name Provider)	Use | Aware (Ever Use MM)
Socio-demographic Characteristics	Female	−0.004	0.019**	−0.075***	−0.086***	−0.032***	−0.017**
		(0.004)	(0.007)	(0.006)	(0.007)	(0.002)	(0.006)
	Age	−0.000***	0.001***	−0.003***	−0.001***	−0.002***	−0.001*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Married	−0.002	0.005	0.010*	−0.006	−0.027***	−0.002
		(0.004)	(0.006)	(0.004)	(0.006)	(0.002)	(0.006)
	Literacy	0.040***	0.060***	0.055***	0.013	0.043***	−0.015
		(0.005)	(0.009)	(0.006)	(0.007)	(0.002)	(0.008)
	No formal education	—	—	—	—	—	—
	Primary education	0.067***	0.073***	0.035***	0.024**	0.009***	−0.046*
		(0.008)	(0.012)	(0.006)	(0.007)	(0.002)	(0.016)
	Secondary education +	0.090***	0.141***	0.098***	0.046***	0.085***	−0.047**
		(0.008)	(0.014)	(0.007)	(0.008)	(0.002)	(0.014)
	Employed	0.022***	0.063***	−0.014**	0.032***	−0.008***	0.012
		(0.004)	(0.008)	(0.006)	(0.007)	(0.002)	(0.006)
	Income > $2.50/day		0.072***		0.006		0.027**
			(0.008)		(0.005)		(0.008)
	Financial numeracy		0.025*		0.012		−0.069***
			(0.010)		(0.010)		(0.020)
Other Enabling Factors	Owns phone	0.080***	0.390***	0.114***	0.110***	0.078***	0.005
		(0.004)	(0.009)	(0.005)	(0.005)	(0.001)	(0.008)
	Has any official ID		0.052***		0.023*		−0.003
			(0.009)		(0.011)		(0.020)
	Has bank account		0.088***		0.078***		0.043***
			(0.009)		(0.007)		(0.009)
	Rural	−0.023***	−0.099***	−0.039***	−0.022***	−0.076***	0.010*
		(0.004)	(0.007)	(0.004)	(0.005)	(0.002)	(0.005)
Country/Wave Fixed Effects							
Kenya$^{+,+}$, Tanzania$^{+,+}$, Uganda$^{+,+}$		Yes	Yes				
Bangladesh$^{+,-}$, Pakistan$^{+,-}$				Yes	Yes		
Nigeria$^{-,-}$, India$^{-,-}$, Indonesia$^{-,-}$						Yes	Yes
Wave Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Athrho (selection models)			0.236*		0.817***		3.033***
			(0.117)		(0.204)		(0.611)
Observations		25,886	24,024	34,532	27,815	169,651	14,199

Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. $^{+,+}$High awareness, high use; $^{+,-}$High awareness, low use; $^{-,-}$Low awareness, low use.
A significant athrho indicates the selection model provides improved explanatory power over a model not controlling for selection.

secondary education and phone ownership were by far the strongest predictors of MM use (associated with a 14.1 and a 39.0 percentage point increase in the likelihood of MM use conditional on awareness). All educational variables and all other enabling factors (phone ownership, official identification, and bank account access) were also strongly associated with MM use in this country group, suggesting these are key areas where reducing female-male disparities can lead to increased women's MM use.

In contrast, in High Awareness / Low Use countries (Bangladesh, Pakistan) women were 7.5 percentage points less likely to be aware of MM and 8.6 less likely to have ever used any MM service, even after controlling for other factors. In terms of predicted probabilities, women in High Awareness / Low Use countries had an 8.8% lower probability of awareness of MM and a 37.4% lower probability of use (conditional upon awareness) than men, all other factors held equal. In these countries gender had the largest association with use among all socio-demographics considered. Educational attainment was also significant, and was positively associated with both MM awareness and use. But other enabling factors were the strongest correlates of MM use overall: phone ownership was associated with an 11.0 percentage point increase in the likelihood of MM use, and having a bank account was also strongly positively associated with use. These findings suggest access to other enabling factors, which differs by gender, as well as gender norms (Mahmud, 2012), may play a stronger role than socio-demographics such as age, marital status, literacy, or financial numeracy in shaping MM gender gaps in High Awareness / Low Use countries.

Women in Low Awareness / Low Use countries (Nigeria, India, Indonesia) were also less likely to be aware of or use MM even after controlling for other factors. Marginal effects are small due to low use rates among both women and men in these countries but controlling for other factors women had a 28.9% lower predicted probability of being aware of MM than men and a 33.6% lower predicted probability of use conditional on awareness. Combined, these gender gaps in MM awareness and use mean that women on average were roughly 57.1% less likely than men to use MM in Low Awareness / Low Use countries, ceteris paribus.[17] This is consistent with findings summarized by Potnis et al. (2020) that women remain much less likely to use MM in South Asia's emerging digital financial services markets. We find no evidence of educational attainment increasing the likelihood of MM use in these three countries, and we also note marital status was negatively associated with MM awareness in these countries – perhaps reflecting cross-country differences in gender norms around spousal responsibilities for household finances (Mothobi & Grzybowski, 2017). The most significant overall predictor of MM use in these countries was access to a bank account – also matching recent findings by Potnis et al. (2020).

Among other variables in these models, consistent with previous studies of digital financial services adoption across a variety of LMIC contexts, age was negatively associated with MM awareness and use, while literacy and education had positive effects except for use in Low Awareness / Low Use countries. Marital status had no effect on MM use and contrasting effects on MM awareness in the two groupings of Low Use countries, perhaps reflecting differences in intra-household dynamics across the countries in these groupings. Contrary to expectations (e.g. Onyia & Tagg, 2011) employment was negatively associated with MM awareness in the Low Use country groupings, but not in the High Use countries. Though we cannot be certain, this may reflect efforts to target MM to the previously unbanked in newly emerging MM markets. Being above the poverty line had the expected positive association with MM use, though the significance varied across the country groupings. Financial numeracy was positively associated with MM use in High Awareness / High Use countries and negatively associated with MM use in Low Awareness / Low Use countries, perhaps suggesting use of alternative financial services by financially numerate populations in those nascent MM markets. Consistent with past research all other enabling factors were positively associated with MM use, though the associations were not all significant in Low Awareness / Low Use countries. Rural location was negatively associated with MM awareness and use, except for use in Low Awareness / Low Use countries. Coefficients for wave fixed effects are not shown but indicate that MM awareness was increasing over time, while the trend in MM use over time among the 'aware' population was also positive but fluctuated.

4.4 Gender and MM awareness and use by individual country

Owing to the significant remaining heterogeneity in MM outcomes across countries even within the High Awareness / High Use, High Awareness / Low Use, and Low Awareness / Low Use country groups, we further disaggregate model results for MM awareness and use by individual country. A full discussion of differences in effects of socio-demographics, other enabling factors, and location across the eight countries in the sample is beyond the scope of this paper, hence Table 3 summarizes findings by country for gender alone. As previously shown in Figure 4, women were significantly less likely to be aware of or use MM in almost all LMICs when considering 'raw' gender gaps (not controlling for other factors). After controlling for measured socio-demographics and other enabling factors this negative association was reduced or eliminated in some countries but remained in others.

In High Awareness / High Use countries there was no difference in MM awareness by gender in any country after controlling for other socio-demographics and other enabling factors. For MM use, in selection models accounting for other covariates and for selection based on MM awareness, women in Kenya or Uganda were more likely to have ever used MM than men (by up to 2.4 percentage points), and in Tanzania women and men were equally likely to have ever used MM. In other words, in all three countries with high overall levels of MM awareness and use, women were as likely or more likely to use MM as men after accounting for other factors. This finding is consistent with past optimism about the potential for MM to benefit previously financially excluded women (Suri & Jack, 2016). This result is perhaps not surprising since high overall MM use levels in these countries indicate that large proportions of women must also have used MM services. But such findings may also suggest that some of the unobserved factors (e.g. social norms) constraining women's MM use in other countries may pose relatively less of a barrier in East Africa's established MM markets.

Meanwhile in High Awareness / Low Use countries although large gender gaps in MM awareness and use became smaller when accounting for other factors, women were still significantly less likely to be aware of or use MM. And in the Low Awareness / Low Use country of India women also had a lower likelihood of MM awareness (−3.9 percentage points) or use (−2.4 percentage points conditional on awareness) after controlling for other covariates. Together these findings are consistent with the hypothesis that other unmeasured gender-related factors such as social norms remain barriers to both MM awareness and use in emerging MM markets in South Asia (Buvinić & O'Donnell, 2019; Chatterjee, 2020; Siegmann, 2009).

Finally, in Nigeria – the only Low Awareness / Low Use country in sub-Saharan Africa in our sample – controlling for socio-demographics and other enabling factors women also had a lower likelihood of MM awareness (−3.2 percentage points), potentially reflecting further barriers to women in more nascent MM markets in Africa (Abhulimen, 2016). There was no association between gender and MM use in the sample selection model for Nigeria, however, suggesting no statistically significant effect of gender on MM use among the 'aware' subpopulation.

For brevity the remainder of this paper reports findings for country groups (High Awareness / High Use, High Awareness / Low Use, and Low Awareness / Low Use), focusing on patterns across countries at earlier versus later stages of MM market development (Ngugi et al., 2010). However full model results for MM awareness and use by each sample country – including estimated effects of all socio-demographics, other enabling factors, and location variables across specific LMICs – are provided in Supplemental Material A.

4.5 Correlates of MM use conditional on awareness, by gender

Table 4 shows mean marginal effects for models of MM use disaggregated by country group and by gender. These results provide preliminary insights into the different correlates of MM use among

Table 3. Gender gaps in MM awareness and use by country compared with mean marginal effects of gender in multivariate regression models (probit model of MM awareness, and heckprob selection model of MM use | awareness). Multivariate models control for socio-demographic characteristics, other enabling factors, location and year (2013-2016).

	High Awareness /High Use (Kenya, Tanzania, Uganda)			High Awareness /Low Use (Bangladesh, Pakistan)		Low Awareness /Low Use (Nigeria, India, Indonesia)		
	Kenya	Tanzania	Uganda	Bangladesh	Pakistan	Nigeria	India	Indonesia
Gender gap by country (F-M) †								
Aware of MM (Can Name Provider)	−0.009	−0.024***	−0.054***	−0.080***	−0.154***	−0.031***	−0.079***	−0.006
Use MM (Ever Tried MM)	−0.037**	−0.086***	−0.099***	−0.208***	−0.085***	−0.004**	−0.005***	−0.001
Effect of gender in multivariate models (effect of female = 1):								
Aware of MM (Can Name Provider)	0.003	−0.008	−0.008	−0.063***	−0.075***	−0.032***	−0.039***	0.006
	(0.005)	(0.007)	(0.007)	(0.006)	(0.011)	(0.005)	(0.002)	(0.005)
Use MM | Aware (Selection Model)	0.023**	−0.011	0.024*	−0.126***	−0.040***	−0.011	−0.024***	0.000††
	(0.010)	(0.011)	(0.012)	(0.011)	(0.008)	(0.008)	(0.005)	(0.001)
Sample (n)	8,754	8,852	8,260	17,954	16,578	15,969	135,027	17,432

Standard errors in parentheses, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

†Gender gap calculated at the country level as proportion of awareness or use among women (F) minus proportion of awareness or use among men (M).

††Indonesia multivariate results for use reflect small sample size: n = 66 respondents using MM, the vast majority of these respondents were numerate and had official IDs hence these variables were removed from the Indonesia models for MM use.

Table 4. Cross-wave selection models of MM awareness and use by country group (High / High, High / Low, and Low / Low level of awareness and use) and gender. Estimates are mean marginal effects of the probit selection model (Awareness) and mean marginal effects of second-stage equations in heckprob models (Use | Awareness).

	High Awareness / High Use: Men (Kenya, Tanzania, Uganda)		High Awareness / High Use: Women (Kenya, Tanzania, Uganda)		High Awareness / Low Use: Men (Bangladesh, Pakistan)		High Awareness / Low Use: Women (Bangladesh, Pakistan)		Low Awareness / Low Use: Men (Nigeria, India, Indonesia)		Low Awareness / Low Use: Women (Nigeria, India, Indonesia)	
	Aware (probit)	Use | Aware	Aware (probit)	Use | Aware	Aware (probit)	Use | Aware	Aware (probit)	Use | Aware	Aware (probit)	Use | Aware	Aware (probit)	Use | Aware
Age	−0.000	0.000	−0.001**	0.001**	−0.002***	−0.002***	−0.003***	−0.001***	−0.002***	−0.001***	−0.001***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	−0.015**	0.014	0.003	−0.006	−0.016**	−0.004	0.029***	0.007	−0.028***	−0.000	−0.020***	−0.011
	(0.005)	(0.011)	(0.005)	(0.008)	(0.007)	(0.011)	(0.007)	(0.007)	(0.003)	(0.004)	(0.002)	(0.007)
Literacy	0.043***	0.057***	0.029***	0.062***	0.046***	0.013	0.063***	0.013	0.069***	−0.001	0.030***	−0.019
	(0.006)	(0.013)	(0.007)	(0.010)	(0.007)	(0.011)	(0.008)	(0.008)	(0.005)	(0.008)	(0.003)	(0.014)
No formal education	—	—	—	—	—	—	—	—				
Primary education	0.039***	0.066***	0.060***	0.070***	0.017**	0.044***	0.045***	0.009	0.026**	0.015	0.014**	−0.053*
	(0.007)	(0.019)	(0.007)	(0.013)	(0.007)	(0.012)	(0.008)	(0.009)	(0.009)	(0.023)	(0.005)	(0.024)
Secondary education +	0.058***	0.145***	0.095***	0.131***	0.071***	0.099***	0.125***	−0.002	0.144***	0.023	0.080***	−0.064**
	(0.008)	(0.021)	(0.010)	(0.016)	(0.008)	(0.013)	(0.010)	(0.010)	(0.008)	(0.020)	(0.004)	(0.023)
Employed	0.029***	0.112***	0.018**	0.030***	0.000	0.041***	−0.030**	0.049***	−0.021***	0.004	0.001	0.014*
	(0.006)	(0.014)	(0.005)	(0.009)	(0.007)	(0.010)	(0.010)	(0.009)	(0.003)	(0.004)	(0.002)	(0.007)
Income > $2.50/day		0.077***		0.064***		0.014		−0.009		0.012***		0.020**
		(0.012)		(0.010)		(0.008)		(0.006)		(0.003)		(0.007)
Financial numeracy		0.011		0.035**		0.039*		0.002		−0.003		−0.073***
		(0.016)		(0.011)		(0.019)		(0.010)		(0.013)		(0.019)
Owns phone	0.062***	0.306***	0.080***	0.327***	0.095***	0.158***	0.122***	0.083***	0.124***	0.037**	0.061***	−0.003
	(0.005)	(0.011)	(0.006)	(0.007)	(0.006)	(0.010)	(0.007)	(0.006)	(0.004)	(0.011)	(0.002)	(0.008)
Has any official ID		0.046**		0.054***		0.034		0.013		0.009		−0.025
		(0.015)		(0.011)		(0.022)		(0.013)		(0.015)		(0.023)
Has bank account		0.097***		0.076***		0.073***		0.059***		0.020***		0.035***
		(0.012)		(0.013)		(0.009)		(0.008)		(0.005)		(0.010)
Rural	−0.015**	−0.090***	−0.032***	−0.102***	−0.029***	−0.035***	−0.049***	−0.005	−0.096***	−0.001	−0.052***	−0.003
	(0.006)	(0.012)	(0.007)	(0.009)	(0.006)	(0.008)	(0.007)	(0.006)	(0.003)	(0.003)	(0.002)	(0.006)
Country Group Fixed Effects												
High-High	Yes	Yes	Yes	Yes								
High-Low					Yes	Yes	Yes	Yes				
Low-Low									Yes	Yes	Yes	Yes
Wave Fixed Effects												
Wave 2	−0.041***	−0.023**	−0.030***	−0.013	0.081***	−0.005	0.113***	0.001	0.066***	−0.007	0.031***	−0.017*
Wave 3	−0.022***	0.067***	−0.016***	0.065***	0.056***	0.066***	0.100***	0.042***	0.050***	0.013**	0.021***	0.005
Athrho		0.042		0.386*		1.115		0.336		0.935		−4.439***
(Selection Models)		(0.149)		(0.175)		(5.256)		(0.250)		(0.593)		(0.437)
Observations	11,089	10,446	14,777	13,578	17,480	14,979	17,052	12,836	73,501	8,796	96,150	5,601

Standard errors in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. A significant athrho indicates the selection model provides improved explanatory power over a model not controlling for selection. Light shading denotes statistically significant ($p < 0.05$) differences in estimated mean marginal effects across women's and men's probit models for MM awareness; dark shading denotes significant differences across women's and men's heckprob models for MM use conditional on awareness.

women and men across the three country groups. An in-depth discussion of the contextual factors that might explain differences across groups is beyond the scope of this paper; we focus instead on documenting any differences which might be a focus of further research.

In High Awareness / High Use countries (Kenya, Tanzania, Uganda) many correlates of MM awareness and use were similar across women and men, though the magnitudes often differed significantly. Higher age and financial numeracy were associated with MM use among women, but not men (though the associations were not significantly different), while literacy and education were associated with MM awareness and use among both women and men. Other enabling factors such as a mobile phone or bank account were also associated with MM use across women and men, and rural location was consistently associated with a lower likelihood of awareness (especially among women) and use.

In High Awareness / Low Use countries (Bangladesh, Pakistan), age was negatively associated with MM awareness and use for women and men. But education was only linked with MM awareness and use for men, while for women the effects of education were limited to effects on awareness alone – again suggesting that gender norms may constrain women's access to MM services even if awareness is expanded (Siegmann, 2009). MM use among women in these countries was primarily associated with enabling factors (phone ownership, employment, and having a bank account). Both women and men were less likely to be aware of MM in rural areas, but for women MM use conditional on awareness was equally likely in rural or urban contexts.

In Low Awareness / Low Use countries (Nigeria, India, Indonesia) MM awareness and use among men was again associated with education and enabling factors. But MM use by women was only positively linked with employment, income and bank account ownership. The finding that access to a bank account was a key predictor of MM use across women and men in all LMICs studied here – as has been reported by some previous country-specific research – raises questions about the potential of MM to support financial inclusion among the previously unbanked (Della-Peruta, 2018; GSMA, 2015a; Van Hove & Dubus, 2019). Women's MM use in Low Awareness / Low Use countries was also negatively associated with education and financial numeracy – these unexpected results may reflect lower perceived value of MM among more educated women (perhaps with access to alternative financial services), or it may reflect efforts by service providers and policymakers to reach less-educated women in early stages of MM market expansion (Mothobi & Grzybowski, 2017).

We also consider whether changes in the likelihood of MM use by women and men over time (i.e. across the three survey waves, 2013-2016) suggest gender gaps are likely to converge over time in the absence of intervention. The coefficients for the survey waves suggest no difference in MM use over time by gender in the High Awareness / High Use countries (where there is no residual gender gap). In High Awareness / Low Use countries we see rates of MM awareness increasing more quickly over time among women versus men, controlling for other factors, while in Low Awareness / Low Use countries MM awareness increases more quickly among men. In both High Awareness / Low Use countries and Low Awareness / Low Use countries the wave coefficients indicate MM use was increasing faster among men than among women from 2013-2016, all else equal. Increasing MM use over time in these countries therefore may have increased gender gaps, based on these multi-year trends.

4.6 Interactions among predictors

As a final step in the analysis, Figure 5 summarizes predictive margins for MM use, conditional on awareness, with a focus on interactions among selected socio-demographics, other enabling factors, and location (rural vs. urban) drawn from the preceding models. All predictive margins are shown by gender and over age, disaggregated by country group. To mitigate possible confounding effects from the passage of time, all predictive margins are for the most recent FII survey data for each country (2015-2016), excluding the previous two survey waves.

The first column of Figure 5 shows that in High Awareness / High Use countries (Kenya, Tanzania, Uganda), holding other factors constant, older respondents had a higher probability of using MM, while neither gender nor literacy alone was significantly associated with MM use among any age group. But older women with high literacy were more likely than younger women or younger men with low literacy to use MM – suggesting education-related interventions might be more important for financial inclusion among older women in these countries (Matthews, 2019). There were no significant differences in predicted probabilities of MM use by gender or age with access to enabling factors – rather, both women and men of varying ages saw similar increases in the probability of MM use with access to a mobile phone, bank account, or both. Similarly, urban respondents in these countries were more likely to use MM, with no significant contrasts by gender or age.

In High Awareness / Low Use countries (Bangladesh, Pakistan), however, patterns differ markedly (second column of Figure 5). Older respondents had a lower predicted probability of use, and women had a lower probability of using MM across all age groups. Higher literacy was positively associated with MM use, but only among younger women and younger men. The importance of enabling factors in these countries is dramatically clear – younger men with both a mobile phone and a bank account had by far the highest probability of using MM. Figure 5 also highlights large gender differences in the effects of enabling factors in these contexts – holding other factors constant, women who were aware of MM and had both a mobile phone and a bank account had roughly a 25% lower predicted probability of using MM compared with men in the same circumstances. Men with either a phone and no bank account, or a bank account and no phone, had the same probability of using MM as women who had both.

Finally, in Low Awareness / Low Use countries (India, Indonesia, Nigeria) rates of MM use were very low among older respondents, with no significant differences across women and men in the higher age categories. Among the lower age groups, however, we see a pattern that is similar to the High Awareness / Low Use countries – with younger, literate men and younger, urban men more likely to use MM than women with similar characteristics. We again find that access to both a mobile phone and a bank account was by far associated with the greatest likelihood of using MM, further suggesting MM use in these emerging MM markets may be concentrated among those who are already engaged in the formal financial system, rather than among the financially excluded (Wyche et al., 2016). We also observe again a much stronger association between enabling factors and MM use among men as opposed to women. Holding other factors constant, younger men with both a phone and bank account had a predicted probability of using MM that was nearly three times greater than women in similar circumstances in Low Awareness / Low Use countries.

5. Implications

5.1 Implications for theory

In 2021, the mobile money industry processed more than $1 trillion in transactions globally (GSMA, 2022). We respond to calls for expanded research on MM that include a broader range of individual characteristics, household attributes, contextual factors, and policies that together influence digital financial services market development (Potnis et al., 2020). We contribute to the literature on MM by exploring how several socio-demographics, other enabling factors, and contextual factors interact with gender in shaping patterns of MM awareness and use, including considering how to treat MM use as being dependent on initial awareness. The FII data allow us to analyze how the importance of a large set of hypothesized correlates of MM outcomes differs by gender and across contexts and time, building on prior literature that analyzed these correlates either singly or in a particular context.

Study findings underscore the importance of continuing to consider gender in studies of MM use across social-cultural contexts. We find in models controlling for relevant co-variates, gender still emerges as a significant predictor of MM awareness and use across LMICs with low levels of overall MM market development. Given that differences in MM use by gender are eliminated in our analyses in established MM markets in East Africa, we attribute residual gender gaps in emerging

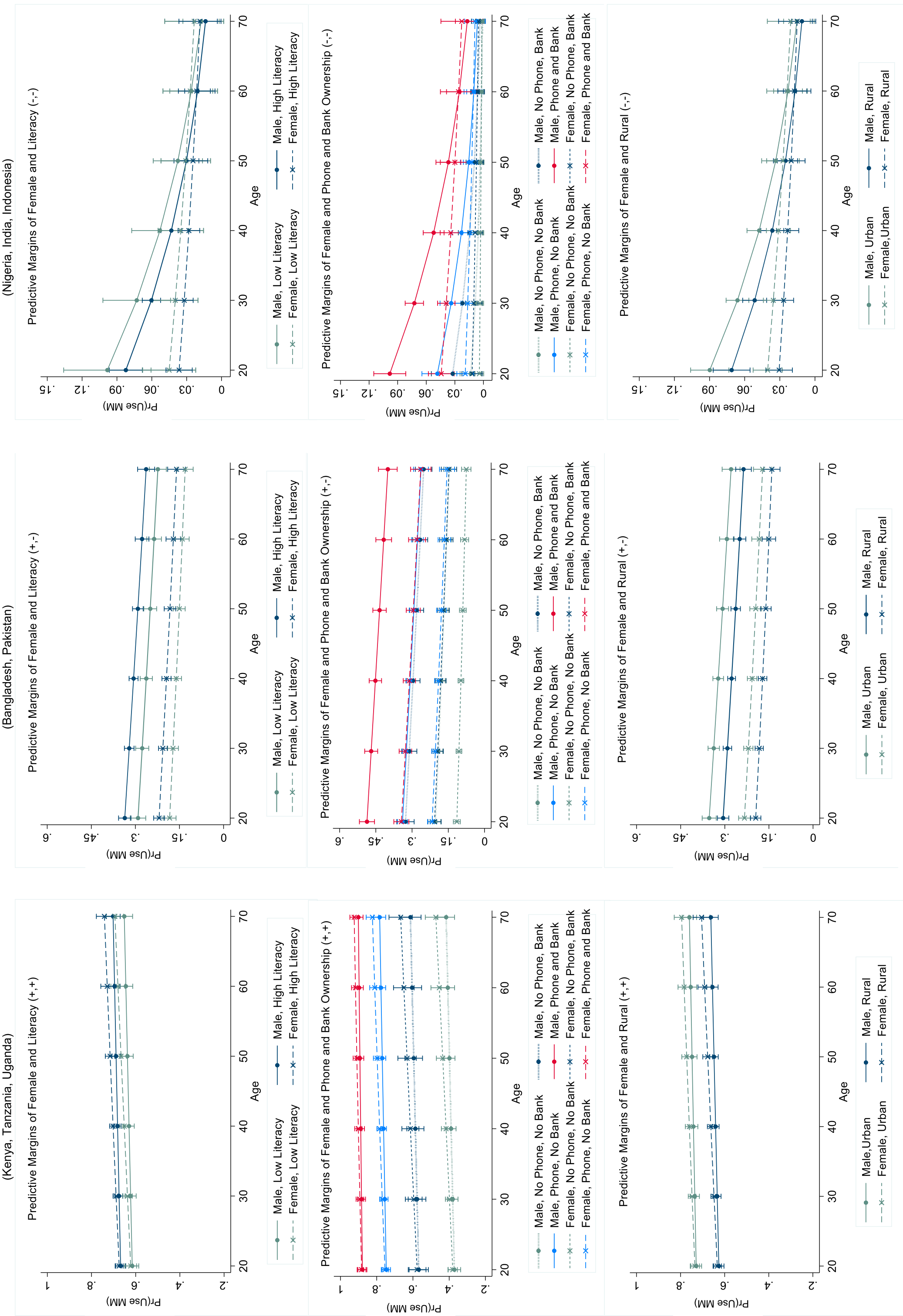

Figure 5. Probability of use across countries grouped by aggregate levels of MM awareness and use. Heckprobit selection model results restricted to the most recent FII survey wave for each country (2015-2016): Graphs show predictive margins (probability of MM use | MM awareness) of selected demographics, enabling factors, and rural/urban location by gender and age.

MM markets in Nigeria and South and Southeast Asia to factors not measured in the FII data and therefore not included in our study. Mukong and Nanziri (2021) note women's and men's social networks may play important roles in the adoption of MM, but social network data are inconsistently captured in FII surveys. Other important factors may include cultural norms and systemic gender biases that we do not account for other than crudely through location variables (country and rural/urban setting). We note with interest that gender gaps in MM across countries do not appear to simply reflect a country's relative gender inequities by other indices such as the Global Gender Gap Index or the UNDP Gender Inequality Index (constructed on health, empowerment and labor market dimensions (UNDP, 2020b)). Future studies can draw on our cross-country findings as justification for expanded inquiry into gender-related constraints to MM use.

This study also empirically controls for nonrandom selection of potential MM users. While many studies have treated MM awareness as a control variable in multivariate models of MM use (e.g. Potnis et al., 2020), we show that while socio-demographics including gender as well as age, literacy, education, and income are consistently significant in models predicting awareness of MM, in heckprobit sample selection models such factors are often not significant predictors of MM use conditional on awareness. Rather, our findings suggest that among 'aware' subpopulations, other enabling factors such as mobile phones and bank account ownership were more strongly and consistently associated with MM use. This is especially the case among women in Low Use countries – consistent with some past studies in LMICs suggesting women and men may face distinct barriers at different stages of the technology adoption process (e.g. awareness and use) (Mothobi & Grzybowski, 2017; Waitara et al., 2016). Future research can benefit from considering the different stages of the MM adoption process – and differences in outcomes among women and men and other subpopulations engaged in these processes in emerging LMIC markets – in a more systematic and rigorous fashion.

5.2 Practical implications

Consistent with past studies of digital financial services adoption in a variety of LMICs, we found women were less likely to be aware of MM in many emerging MM markets (Barooah et al., 2018; GSMA, 2020b; GSMA, 2021a; Mbiti & Weil, 2015). We also found literacy and education were generally positively associated with women's MM awareness. But factors like mobile phones, income and bank accounts were more consistently associated with women's use of MM – while living in a rural area was almost always associated with lower levels of awareness or use among both women and men. Better understanding the combination of gender norms, socio-demographics, and other enabling factors that facilitate or constrain MM use among different sub-populations and across regions over time is essential to inform programs and policies seeking to increase financial inclusion. At the time of writing, at least 26 MM operators across Africa, Asia and Latin America have made formal commitments to reduce gender gaps in their MM customer base (GSMA, 2021a), through a combination of machine learning tools seeking to better understand women's and men's MM usage patterns (GSMA, 2018b), alongside applied research using gender-disaggregated survey data to better understand barriers to MM adoption.

While our findings suggest addressing gendered inequities in areas such as education, phone ownership, and having a bank account may reduce gender gaps, policies aiming to close gender gaps in MM adoption in LMICs will need to consider what other (possibly country-specific) factors are correlated with both gender and MM outcomes but not measured in our data. As one example of such an approach, data from the Women's Workplace Equality Index (Council on Foreign Relations, 2020) reveals large differences in employment laws across countries that might help partially explain residual gender gaps in MM use in Low Use countries. Bangladesh and Pakistan rank the lowest (with Indonesia) on the average score for women's workplace equality, a measure that includes formal legal obstacles to women's economic opportunity and participation. All of the Low Use countries in our sample rank below the High Use countries in the 'Getting a Job

Category', comprised of 16 indicators measuring, for example, equal rights to paid and parental leave, hours, remuneration, and non-discrimination.[18] Hence some of the residual effect on MM use picked up by the gender variable in Low Use countries may reflect not only 'gender norms', but also specific social and legal barriers to women's participation in labor markets, social networks (Mukong & Nanziri, 2021), and the broader economy.

Importantly, our findings also suggest the presence of widening gender gaps over time in Low Use countries, and also wider gender gaps among younger versus older respondents. Wyche et al. (2016) highlight the potential for mobile technologies to amplify preexisting social inequalities facing women in Kenya, and Potnis et al. (2020) underscore the risk that new MM markets might reinforce gaps between 'haves' and 'have-nots' in India. This study broadens the generalizability of such past findings across a larger sample of LMICs, and suggests that particularly in newly emerging MM markets in Nigeria and South and Southeast Asia increasing awareness of MM alone will not be sufficient to reduce gender gaps in MM use. Rather, gendered inequities in access to enabling factors, as well as restrictive gender norms more broadly, will need to be addressed.

6. Conclusions, limitations, and future research

Study findings suggest that the gender gaps in MM awareness and MM use documented in other studies remained in certain LMICs even after accounting for a variety of other factors hypothesized to affect MM outcomes. Residual gender gaps in countries with lower rates of MM use point to unmeasured factors such as differences in social norms limiting women's economic inclusion. We further find that the factors associated with MM awareness and use by gender differ across countries with different levels of overall MM use. These results together suggest that realizing the potential of MM to promote financial inclusion will require pursuing different strategies across countries and across stages of market development.

Our analysis was limited by available microdata. The FII surveys omit some potential variables of interest (such as caste in India, for example, or non-binary gender options), and there were also small samples of MM users in some countries at the time of data collection (especially Nigeria and Indonesia). More generally, our analysis is potentially limited by the use of data from 2013-2016, especially given the rapid growth in both awareness and use of MM in the study countries (GSMA, 2021a; World Bank, 2018b). But we note that even in the most recent available datasets providing gender-disaggregated estimates of MM awareness and account ownership (summarized in Supplemental Material B), substantial gender gaps remain, supporting a hypothesis of slow-to-change norms and policies impeding women's use of MM and underscoring the need for further study.

As emphasized by Adaba and Ayoung (2017), MM services and delivery mechanisms are changing over time and may alleviate some of the barriers associated with socio-demographics and other enabling factors reflected in this study (though possibly introducing new barriers). GSMA's *Global Adaptation Survey*, for example, notes a correlation between the number of women MM agents and the number of women clients in MM provider networks using agent-based business models. This suggests inclusion of women in the MM industry as service *providers* may further support women's financial inclusion in MM platforms (GSMA, 2019), especially for women in rural areas or with limited mobility. Future research should further consider how MM platform design and business models (e.g. e-Money Wallet versus agent-based), as well as overarching policy environments, may affect women's use (Qureshi, 2013).

A full discussion of the myriad differences in policy environments, socio-demographics, other enabling factors and gender norms across the eight sample LMICs is ultimately beyond the scope of a single paper. Nevertheless, this study offers a valuable baseline for comparison as additional and more up-to-date national-level data on MM awareness and use – as well as other covariates from these countries and other LMICs – become available. Ultimately, the results of this study underscore the importance of continuing to collect gender-disaggregated data on MM enrollments, and developing context-specific strategies to support women's MM use.

Notes

1. Of the approximately 1.7 billion adults across the world who lack access to secure, reliable or convenient financial services through formal banking infrastructure, a majority now has access to a mobile phone, which can facilitate access to digital financial services (GSMA, 2015a; GSMA, 2020a; Rea & Nelms, 2017). Across LMICs the median mobile phone penetration rate now far exceeds the coverage of traditional financial infrastructure such as banks (Mirani, 2014).
2. MM can be distinguished from other digital financial services in that links to formal financial institutions such as banks are not required, meaning consumers are able to use MM services without having been previously banked (Jack & Suri, 2014; Pénicaud & Katakam, 2014; Suri, 2017). Jenkins (2008) categorizes MM activities as including mobile transfers (e.g., person-to-person (P2P) transmissions of money via mobile phone), mobile payments (transfers of money via mobile phones to exchange goods or services), and 'other mobile financial services' enabled when a MM account is linked to a bank account. The data used in this study define MM similarly broadly, hence all of these activities are included in the definition of MM used in this paper.
3. By 2021 there were 1.35 billion registered MM accounts worldwide (90.1% in Sub-Saharan Africa, South Asia, or East Asia and Pacific regions) and 346 million active accounts (91.6% in Sub-Saharan Africa, South Asia, or East Asia and Pacific), and the value of global MM transactions topped $1 trillion (GSMA, 2022).
4. Other studies do test for drivers of the gender gap in financial inclusion more generally (Ghosh & Vinod, 2017; Morsy, 2020; Zins & Weill, 2016) but do not focus on digital financial services or mobile money.
5. Both awareness and use are very low overall in Indonesia, and there is no gender gap in either measure.
6. Data obtained upon request from http://finclusion.org/data_fiinder/ with the permission of Intermedia.
7. 2016 was the final year of consistent FII data collection across the eight study countries, though some additional FII surveys were undertaken in select countries in 2017, 2018, and 2020. The Global Findex also includes data for the same survey countries for 2014 and 2017. We are not aware of any more recent publicly-available household surveys with consistent gender-disaggregated data on mobile money use across these countries. More recent cross-county summary estimates of gender differences in mobile money outcomes come from proprietary GSMA research (2020b, 2021a). We discuss potential limitations with using data from 2013–2016 in the rapidly-evolving mobile money space in Section 6.
8. Sample sizes vary by country, with larger samples in countries with larger populations to support the goal of a nationally-representative cross-section. Respondents are not tracked from wave to wave; rather, a new cross-section of respondents is surveyed in each wave. Data for Kenya, Nigeria, Tanzania, Uganda, Bangladesh, India, and Pakistan were collected in 2013, 2014, and 2015; data for Indonesia were collected in 2014, 2015, and 2016.
9. Providers listed in the survey include: *Kenya*: Safaricom M-Pesa, Airtel Money, YU Cash, Orange Money, Tangaza, Mobicash, Equitel; *Nigeria*: Airtel Money, eaZymoney, Ecobank Mobile money, Etisalat Easywallet, Firstmonie, Glo mobile money, GT mobile money, MTN Mobile Money, Paga, Pocket moni, Stanbic mobile money, U-mobile, Vcash; *Tanzania*: Vodacom M-PESA, Tigo Pesa, Airtel Money, Zantel Ezy-pesa, SMART-B Pesa; *Uganda*: MTN Mobile Money, Airtel Money, M-Sente, Ezee Money, Vodafone M-PESA, Africell money, Safaricom M-PESA; *Bangladesh*: bKash, DBBL Mobile Banking, M Cash, M Pay, U Cash, Mobi Cash, Sure Cash; *India*: Aircel Money, Airtel Money, Alpha Money, Beam Money, EkoCounter, Idea Mycash, Loop wallet (M-Pay) , Money on Mobile, Mrupee, Oxicash, State Bank Mobicash, Suvidhaa money, Vodafone M-Pesa, Union Bank Money; *Indonesia*: BBM Money, Dompetku, E-Cash, MoCash, Rekening Ponsel, Skye, T-Cash, XL Tunai, Sakuku, True Money; *Pakistan*: Telenor Easy, Paisa Money, UBL Omni, Ufone /Upayment, MCB Mobile, Zong Timepey, HBL Express, Mobile Paisa, Mobilink Mobicash.
10. This definition of MM awareness based on both spontaneous recall (the respondent could name an MM provider) and follow-up prompts (the respondent recognized the name of an MM provider) is consistent with Intermedia's reporting of MM awareness by country. In supplemental analyses (not shown) we test the robustness of our findings to a more restrictive definition of MM awareness based on spontaneous recall only. Although gender gaps in MM awareness are often larger when based on spontaneous recall, our main multivariate findings are robust to the choice of MM awareness measure. These results are available from the authors on request.
11. This definition of MM use as not implying continued use is consistent with other literature on MM (GSMA, 2019a; Potnis et al., 2020). The FII surveys also ask respondents who ever used MM whether they used it in the last 90 days. Patterns and correlates of continued MM use in the FII are analyzed in Reynolds et al. (2017).
12. All statistical code developed by the authors for this study can be downloaded via the public repository GitHub, including annotated code for cleaning, standardization of measures, merging, and analysis of the 24 country-years of FII survey data used.
13. These findings are largely consistent with Evans and Pirchio (2015), who characterize the MM market in Kenya, Tanzania, Uganda, and Bangladesh as seeing 'ignition with explosive growth', Pakistan as 'ignition with weak growth', and Nigeria, India, and Indonesia as 'failed to ignite.'

14. We do not interpret the estimated effects as causal. Rather, they reflect statistical associations that may reflect the effects of unobserved variables affecting both the specified socio-demographic characteristic/enabling factor and the MM outcome.
15. *N*(0,1) represents the standard normal distribution. The estimation approach of the probit model with sample selection was described in Van de Ven and Van Praag (1981), bulding on efforts to overcome 'sample selection bias' as summarized by Heckman (1979).
16. Results for the pooled cross-country analyses available upon request.
17. The combined effects of gender on MM awareness and MM use are estimated as the unconditional probability of MM use if female = 1 in the second-stage regression model, i.e., Pr(Use = 1) not conditional on MM awareness.
18. Such differences are reflected in gender employment gaps in our data, with Bangladesh and Pakistan having the highest difference between female and male employment rates, followed by India and Indonesia. The gender employment gap is much smaller in Nigeria than in these four Asian countries, but remains larger than in Kenya, Tanzania, and Uganda, the three countries with high rates of MM use.

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Notes on contributors

Travis W. Reynolds is an Associate Professor in the Department of Community Development and Applied Economics at the University of Vermont. His main research interests relate to rural and agricultural development, with an emphasis on factors contributing to poverty alleviation, sustainability, and resilience in low-income smallholder farming communities in sub-Saharan Africa.

Pierre E. Biscaye is a PhD Candidate at the University of California Berkeley studying Agricultural and Resource Economics. He studies microeconomics in the context of gender, environment, agriculture, and energy issues in low-income countries, primarily using natural experiments and publicly available data to conduct empirical research.

C. Leigh Anderson is the Marc Lindenberg Professor of Humanitarian Action, International Development and Global Citizenship at the University of Washington's Daniel J. Evans School of Public Affairs. Her primary research interest is in how individuals and households living in poverty make financial, environmental, health, and other livelihood decisions, especially when outcomes are highly risky or spread over time.

Caitlin O'Brien-Carelli is a graduate of the MPH in Global Health and MPA in International Development programs at the University of Washington interested in program implementation and evaluation in low-resource settings with an emphasis on quantitative methods. She is currently a Senior Strategic Information and Evaluation Officer at the Elizabeth Glaser Pediatric AIDS Foundation.

Joanna Keel holds a degree in Environmental Policy and English from Colby College. A Davis United World College Scholar from the Kingdom of Eswatini (formerly known as Swaziland), her interests broadly include development policy and sustainability. She is currently a Research Assistant at the Health Effects Institute.

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