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Summary

This paper investigates whether adopting mobile money services influences non-resource tax revenues in emerging markets and developing countries. Using a sample of 97 countries over the period 1990–2021, our empirical analyses, based on instrumental variables, system-GMM, and endogenous switching regression methods, suggest that digital finance leads to more tax revenue. We also find that bill payments, merchant payments, person-to-person payments, and person-to-government payments have a greater impact on tax revenues than other mobile money services. The potential positive impact mechanisms are the decline of the informal sector, the reduction of corruption, and the facilitation of international remittance inflows.

Keywords: digital finance, mobile financial services, tax revenue, non-resource tax revenue, emerging markets, developing countries.

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Acronyms

AT	Airtime top-ups
ATT	Average treatment effect on the treated
BP	Bill payment
CI	Cash-in
CO	Cash-out
EBM	Electronic billing machine
EMDCs	Emerging markets and developing countries
ESR	Endogenous switching regression
GSMA	GSM Association
IR	International remittances
IV	Instrumental variables method
LICs	Low-income countries
MIMIC	Multiple indicators, multiple causes
MM	Mobile money
MP	Merchant payment
NDE	Natural direct effects
NIE	Natural indirect effects
NRTAX	Non-resource tax revenue
PPP	Purchasing power parity
P2G	Person-to-government
P2P	Person-to-person
SYS-GMM	System generalised method of moments
VAT	Value-added tax
WDI	World Development Indicators (World Bank)

1. Introduction

The context of multiple crises in recent times, including the COVID-19 crisis, the war in Ukraine, and the rising number of severe climate-related events, has once again stressed the importance of emerging markets and developing countries (EMDCs) increasing their fiscal space. This is crucial not only for dealing with short term shocks, but also for effectively implementing structural reforms and making long-term investments to strengthen productive capacities and resilience to future shocks. Identifying new tax revenue drivers is now a key concern for many governments and researchers worldwide.

Digital finance has been a game changer for financial inclusion and poverty alleviation in developing countries by allowing people and firms previously excluded from the formal financial sector to access basic financial services. Since its successful introduction in sub-Saharan Africa, notably in Kenya in 2007, there has been a swift proliferation of mobile money (MM) services, which refer to using a mobile phone to access financial services, usually independent of internet access. From its initial focus on domestic person-to-person (P2P) transfers, the mobile money services industry has diversified its product range considerably. It now offers mobile solutions for bill payments (BP), merchant payments (MP), person-to-government (P2G) transfers and international remittances (IR) (GSMA 2017a).[1] In addition, some operators (often in conjunction with financial institutions) provide micro-credit facilities, savings products, and, more recently, insurance products.

This paper is put forward in that context as it explores the relationship between non-resource tax revenue and digital finance (or mobile money). Our goal is to investigate whether and how the rapid expansion of mobile money services might affect tax revenue in the developing world.

To identify the effect of mobile money on tax revenue, we use a large sample of 97 EMDCs and an instrumental variable method over the period 1990–2021. We provide evidence supporting that the introduction of mobile money positively affects non-resource tax revenues. Looking at the effect of the type of mobile money services, we find that bill payments, merchant payments, person-to-person payments, and person-to-government payments impact tax collection more than other services. Our analyses also suggest that the beneficial effect of mobile money is more pronounced in low-income countries. We also identify three potential transmission mechanisms through which mobile money influences tax revenue: the decline of the informal economy, a decrease in corruption, and the facilitation of international remittance inflows. Moving from cash to mobile payments improves tax administration effectiveness by limiting physical

[1] See Table A1 in Appendix 1 for a full list of mobile money services.

interactions (prone to corruption) and introducing more transparency in fiscal policy management. Furthermore, as shown by Jacolin, Keneck Massil and Noah (2021), digital finance reduces the size of the informal sector, particularly through improved access to finance for micro-firms and the growth of the formal sector. Finally, mobile money services-related international remittance inflows will likely increase households' income and consumption expenses, thereby improving tax revenue. Our findings suggest that these channels mediate nearly 50 per cent of the total effect of mobile money on tax revenue.

This paper relates to at least two strands of literature. The first is research on the determinants of tax revenue. Several factors have been identified in the literature as having a positive or negative impact on tax revenue. Studies reveal that tax revenue is mainly explained by the variation in the macroeconomic environment, institutional framework, and socio-demographic characteristics (Torgler and Schaltegger 2005; Gupta 2007; Crivelli and Gupta 2014; Gnangnon and Brun 2019; Gnangnon 2022). With the development of information and communication technologies (ICTs), many papers have recently offered an interesting insight into the role of digitalisation in tax revenue mobilisation. Using a sample of 164 countries, Gnangnon and Brun (2019) investigate the relationship between the 'internet gap' (measured by the ratio of a country's internet usage intensity to the world average) and tax collection and find that countries can increase tax revenues by reducing the internet gap. More importantly, this effect is particularly notable in low-income countries. Better access to the internet can directly influence tax revenue by improving the efficiency of tax and customs administrations. The impact of internet access on tax revenue mobilisation can also indirectly be channelled through international trade, economic growth, inflation, tax evasion activities, foreign direct investment, and corruption.[2] Gnangnon and Brun (2019) also examine the effect of the internet on resource versus non-resource revenues, highlighting a negative impact of the internet usage intensity on resource revenue (or tax revenue related to natural resources) and a positive effect on non-resource tax revenue. The impact of internet usage intensity is also more significant in low-income countries.[3] Other studies also look at the role of electronic billing machines (EBMs) and highlight their positive impact on tax compliance and value-added tax (VAT) collection (Mascagni, Mengistu and Woldeyes 2021; Mascagni *et al*. 2023.[4] More recently, a few studies have examined how mobile money affects tax revenue in developing countries. Using the entropy balancing method, Apeti and Edoh (2023) find that mobile money increases tax revenues. This positive effect is larger for direct tax

[2] Hjort and Poulsen (2019) show that high-speed internet access has allowed African firms to increase their exports by tapping into new markets.

[3] Also see Moore and Prichard (2020).

[4] See also Okunogbe and Santoro (2023) for an overview of the role of information technology in tax collection in developing countries.

revenue than for indirect tax revenue. They also identify tax base, institutional quality and ease of tax payments as the main channels. Wandaogo, Sawadogo and Lastunen (2022) find an increase in direct tax revenue of up to 1.3 percentage points due to the implementation of person-to-government payments, channelled through control of corruption and the decline of the informal sector.

Finally, there is a rapidly growing literature on the socio-economic impacts of mobile money services, from economic growth and improved household welfare to financial development, reduced corruption, and firm formalisation (Nan, Zhu and Markus 2021). Using a sample of 50 African countries, Avom, Bangaké and Ndoya (2023) find that adopting mobile money positively affects financial inclusion. Jack, Ray and Suri (2013) and Jack and Suri (2014) show, for instance, that mobile money helps Kenyan households share risks and smooth shocks. A similar finding is made by Riley (2018) in Tanzania.[5] Suri and Jack (2016) find that access to mobile money lifted 2 per cent of Kenyan households out of extreme poverty. Islam, Muzi and Rodríguez Meza (2018) highlight a positive effect of firms' mobile money use on firm investment in Kenya, Uganda and Tanzania. This impact is related to reduced transactional costs, firms' increased liquidity, and an increased ability to establish creditworthiness using data generated by mobile financial services. Beck *et al*. (2018) have also documented the theoretical and empirical impacts of mobile money (M-Pesa) on firms' productivity. They point out that entrepreneurs are more willing to use mobile money as a means of payment to secure their transactions better and manage cash flows. Using mobile money also increases firms' probability of getting trade credit from their suppliers.

Our paper differs from Apeti and Edoh (2023) and Wandaogo *et al*. (2020) in five main ways. First, we use an instrumental variable method using the spatial lag of mobile money adoption in neighbouring countries as an instrument for mobile money. We also offer other alternative instruments for robustness purposes. Second, our estimation strategy uses three methods: IV-2SLS, system-GMM and the endogenous switching regression, thereby strengthening the robustness of the results. Third, contrary to Apeti and Edoh (2023), we find the impact of mobile money is larger for indirect tax revenues than for direct tax revenues. Fourth, we also look at the role of public services in the relationship between mobile money and tax revenue. The results indicate that the effect of mobile money on tax revenue strengthens with the provision of public services such as electricity. Finally, we identify corruption and international remittances as the potential channels through which mobile money affects tax revenue in developing countries.

The findings of our paper have important policy implications. Digital finance is a powerful tool for increasing tax revenues in developing countries. Our findings

[5] See also Apeti (2023)'s recent contribution on the subject.

also suggest that this positive impact could be further amplified if the deployment of mobile money services is linked to the provision of public services, such as access to electricity.

The rest of the paper is organised as follows. Section 2 identifies potential mechanisms for mobile money services to affect tax revenues. Section 3 details the empirical approach. The main results and further investigations for robustness checks purposes are reported in Section 4. Section 5 concludes.

2. How do mobile money services affect tax revenues?

This section thoroughly explains the potential transmission channels through which mobile money services theoretically influence non-resource tax revenue in EMDCs.

2.1 The channel of corruption

Policymakers and various international organisations committed to promoting transparency and good governance advocate that mobile phones, specifically mobile financial services, can be used as a social responsibility tool in the fight against corruption (Kanyam, Kostandini and Ferreira 2017). To this effect, Barasa (2021) studies the impact of mobile money on bribery payments in Kenya. He shows that adopting this mechanism for financial transactions results in a 3.1 percentage point reduction in bribe payments. More recently, Setor, Senyo and Addo (2021) also find that moving from cash transactions to digital payments reduces corruption by obviating the need for physical or face-to-face interactions between transacting parties. Limiting face-to-face interactions creates fewer opportunities for corrupt activities between taxpayers and tax or customs administration officials.

Several empirical studies have shown the negative effect of corruption on tax revenue (Gupta 2007; Besley and Persson 2014; Baum *et al*. 2017; Epaphra and Massawe 2017). Using a large sample of 105 countries, Gupta (2007) provides evidence for a strong negative relationship between tax collection performance and corruption. For Besley and Persson (2014), tax revenues are low in developing countries partly because corrupt systems of government face greater resistance to increasing their tax-raising power due to inefficiency issues, such as in the provision of public goods and services. Similarly, Baum *et al*. (2017) show that corruption negatively affects overall tax revenue and most of its components.

The negative correlation between corruption and tax revenue stems mainly from the impact of corruption on tax compliance and embezzlement. Digital finance will likely moderate that risk, reducing information asymmetries and improving transparency, traceability, and accountability between transacting parties.

From the above, it is thus possible to acknowledge the effect of mobile money services as a stimulating factor for the mobilisation of tax revenue transits through the impact of the reduction in corruption.

2.2 The informal economy channel

The informal economy is defined as the market-based and legal production of goods and services hidden from public authorities for monetary, regulatory or institutional reasons (Schneider, Buehn and Montenegro 2011). Informality is widely recognised in the literature as imposing constraints on fiscal performance, mainly because one of its underlying motives is the desire to evade taxes (Goel and Nelson 2016). Elgin and Uras (2013) demonstrate that a larger informal sector is associated with increased public debt and a higher probability of sovereign default. They argue that informality undermines tax revenues and public finances, leading to fiscal deficits and greater reliance on borrowing. Consequently, this weakened fiscal position compromises governments' ability to service their debt, increasing the risk of default.

Recent studies highlight that mobile payments have been a helpful tool in reducing informal economic activities (Jacolin *et al.* 2021; Syed *et al.* 2021). Syed *et al*. (2021) conclude that digital finance helps reduce the informal economy's growth in emerging South Asian countries, in particular by increasing financial inclusion. Specifically, Jacolin *et al*. (2021) show that mobile money is associated with a decrease in the size of the informal sector. The authors identify three transmission mechanisms through which mobile financial services negatively affect the informal economy: improvement in access to finance, growth of firms already in the formal sector, and improved productivity and profitability of informal firms (which increase the opportunity costs of staying in the small and less productive informal sector).

As a result, by reducing the informal sector's size, digital payment mechanisms play an essential role in mobilising tax revenues.

2.3 International remittances channel

Nan *et al*. (2021) and Ahmad, Green and Jiang (2020) review the literature on mobile financial services and their contribution to promoting financial inclusion and inclusive development, focusing on sub-Saharan Africa (SSA). They show that the adoption of mobile money has made it possible to increase the volume of remittances sent to countries in SSA. Similarly, Naito, Ismailov and Kimaro (2021) show that using mobile money increases the likelihood of remittances in Tanzania. This result is also confirmed by Riley (2018). Munyegera and Matsumoto (2016) stress that Ugandan households with mobile money accounts are more likely to receive remittances than their counterparts. This analysis aligns with Jack and Suri (2014), who show that mobile money users are more likely to receive funds transfers after exogenous shocks.[6]

[6] Also see Aron 2018.

The relationship between international remittances and tax revenue has been the subject of several studies in the last decades. Ebeke (2014) shows, for example, that international remittances widen host countries' fiscal space through their positive effects on the level and stability of government tax revenues. Using a large sample of countries, he underlines that remittances increase the level and strength of the government's tax revenue ratio in the presence of VAT. Similarly, Asatryan, Bittschi and Doerrenberg (2017) found that remittances positively affect VAT revenue. Abdih *et al*. (2012) examine the fiscal implications of remittances and the impact of remittances on government revenues in 17 remittance-dependent countries in the Middle East, North Africa, Central Asia, and the Caucasus. They notice a positive effect of remittance inflows on different components of tax revenues. Furthermore, Adams and Cuecuecha (2013) show that international remittances increase spending on investment goods like education, health and housing.

Drawing from the above discussion, we hypothesise that mobile money positively affects tax revenues in EMDCs, potentially mediated by the inflow of international remittances, decreased corruption, and a decline in the informal economy.

3. Research design

This section presents the econometric methodology that guides the empirical investigation of the impact of mobile money services on tax revenues in emerging markets and developing countries. Subsection 3.1 describes the data and the sample. Subsections 3.2 and 3.3 detail the empirical model and the identification strategy, respectively

3.1 Data and sample

3.1.1 Data sources

Our paper covers the period 1990 to 2021 and is based on a sample of 97 emerging markets and developing countries. The selected countries and the time period depend on data availability. The full sample of countries is provided in Appendix 1 (see Table A2). Data on tax revenue-related variables are collected from the UNU-WIDER Government Revenue Dataset. This is the most comprehensive database on tax revenue. It covers more than 160 countries and combines data from several sources. Data on mobile money adoption and type of mobile money service come from the GSM Association's Mobile Money Deployment Tracker database. The GSM Association is an organisation that represents the interests of mobile network operators worldwide. We test the robustness of our results using alternative mobile money measures (the number of registered MM accounts and the number of MM transactions per 1,000 adults, respectively) drawn from the IMF-Financial Access Survey (FAS) dataset. The data used to construct our instruments are sourced from the CEPII databases (Mayer and Zignago 2011; Conte, Cotterlaz and Mayer 2022) and the International Telecommunication Union (ITU). These include longitude and latitude data for countries' capitals and contiguity for the first source, and SMS volume for the second. The control variables for estimating Eq. (1) and other independent variables are taken from various databases, including the World Bank's World Development Indicators (WDI), Varieties of Democracy dataset (Coppedge *et al*. 2023), the database of political institutions (Scartascini, Cruz and Keefer 2021) and the World Bank's Informal Economy Database (Elgin *et al*. 2021). All variables and data sources used in this paper are presented in Appendix 1 (see Table A3). Table 3.1 provides summary statistics for the variables used in the baseline model.

Table 3.1 Summary statistics for the baseline model

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Non-resource tax revenue (% of GDP)	Percentage	2546	13.18	6.26	0.46	60.95
MM	Dummy variable	2546	0.25	0.43	0.00	1.00
GDP per capita	Logarithm	2546	7.74	1.06	5.25	11.12
NRA	Logarithm	2546	8.80	1.74	-0.45	14.24
Trade	Percentage	2546	77.40	46.49	9.96	437.33
Agriculture	Percentage	2546	17.16	12.11	0.03	64.67
Urban population	Percentage	2546	47.21	20.44	5.49	100.00
Political regime	Index	2546	2.52	6.06	-10.00	10.00

Source: Authors' own elaboration from collected data.

3.1.2 Some stylised facts

This subsection contains some stylised facts about tax revenue, mobile money and their potential relationship.

Since its first launch in the Philippines in 2001 and the successful introduction of M-Pesa in Kenya in 2007, mobile money services have experienced rapid growth across the developing world. By the end of 2021, mobile money services were available in 104 countries, up from 37 countries in 2010, according to GSMA's Mobile Money Deployment Tracker data. Our sample includes 76 out of the 104 mobile money countries. The spread of mobile money services has also led to an increase in the number of registered accounts, from 49.40 adults in 2010 to 1.41 billion adults in 2021.

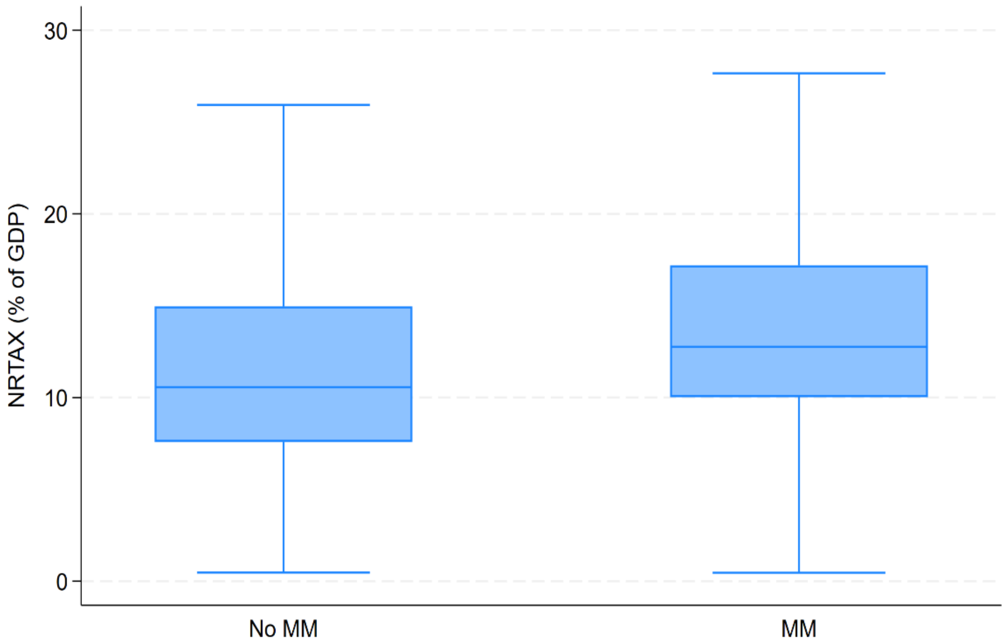
Initially designed for person-to-person (P2P), airtime top-ups (AT), cash-in (CI) and cash-out (CO) transactions, mobile money services have evolved significantly over time. This evolution has been driven by partnerships between mobile money operators[7] and various entities such as financial institutions, merchants and utility companies, resulting in a broader mobile money transaction mix that now includes bill payments, bulk disbursements, merchant payments or international remittances. In addition, some countries have introduced the option to pay for public services, taxes and utilities through mobile money. This type of transaction is known as 'person-to-government' (P2G) payments. As a result, mobile money is playing an increasingly important role in individuals' and businesses' daily transactions. This is reflected in the data for daily mobile money

[7] In 2021, there were 316 mobile money operators, compared to 111 in 2011 (GSMA Mobile Money Metrics).

transactions, which reached US$2.84 billion in 2021, compared to US$606,1 million in 2015 (GSMA Mobile Money Metrics). The existing types of mobile money services are listed and defined in Table A1 in Appendix 1.

A brief comparative analysis of tax revenue data indicates that the median of non-resource tax revenue in mobile money countries is 12.8 per cent of GDP, compared to 10.6 per cent in non-mobile money countries (see Figure 3.1). This observation indicates a potential correlation between adopting mobile money services and revenue mobilisation in developing countries.

Figure 3.1 Non-resource tax revenue (NRTAX) by mobile money adoption



Source: Authors' calculations based on data from the GSMA's Mobile Money Deployment Tracker and the UNU-WIDER Government Revenue Dataset.

3.2 Model specification

To examine the effect of mobile money on tax revenue, we estimate the following linear model relating tax revenue to its main determinants:

$$NRTAX_{i,t} = \alpha_0 + \beta MM_{i,t} + X'\delta + \varepsilon_{i,t} \qquad \text{Eq. (1)}$$

where $NRTAX_{i,t}$ denotes the non-resource tax revenue (in percentage of GDP) of country *i* in year *t*. Our focus is on non-resource tax revenues, as resource tax revenues are mainly dependent on commodity prices.[8] $MM_{i,t}$ is the dummy variable taking the value one from the year the mobile money service is launched in a given country *i*, and zero otherwise, as in Jacolin *et al*. (2021). We also assess the impact of the type of mobile money services using a dummy variable for each type. Table A1 in Appendix 1 describes the various mobile money services. X' represents a vector of control variables reflecting the main time-varying determinants of tax revenue. We follow the related literature to include GDP per capita, natural resource abundance, trade openness, agriculture sector, urban population and political regime. Fixed effects are included in the model to control for the unobserved heterogeneity.

We first control for the level of development, measured by the lagged value of GDP per capita, as Crivelli and Gupta (2014) find strong evidence of a positive effect of income level on tax revenue performance. An increase in per capita income reflects, among other things, growing demand for public services and a higher degree of economic and institutional sophistication.

We consider the role of natural resources (or resource rents per capita) because natural resource abundance creates opportunities for rent-seeking when institutions are not strong, leading to a deterioration in the moral behaviour of taxpayers (Castañeda Rodríguez 2018). In addition, the resources bonanza crowds out income-generating activities such as entrepreneurship and investments (Torvik 2002; Mehlum, Moene and Torvik 2006), which would result in a reduced tax base. Standards arguments also suggest that resource rents reduce governments' incentives to invest in fiscal capacity (Masi, Savoia and Sen 2024).

We include a control variable for trade openness, defined as the total exports and imports divided by GDP. Previous studies have drawn mixed conclusions. On the one hand, the higher the level of trade, the more tax revenue is likely to be generated directly through tariffs, and indirectly through economic growth. On the other hand, trade barriers are low in countries characterised by a high degree of openness to international trade, so that tax revenues do not increase through the direct tariff channel (Crivelli and Gupta 2014; Gnangnon and Brun 2018).

Next, we account for the agricultural sector (measured by agriculture value added as a percentage of GDP), which is considered one of the most challenging sectors to tax, for well-documented reasons (Gupta 2007). Firstly, a large proportion of agricultural activity is carried out on a small scale. Second, much of small-scale agriculture is informal. Thirdly, there is a spatial spread of farming activities. Finally, agriculture is one of the most vulnerable sectors to exogenous shocks. These factors make the cost of verifying production and real income relatively high for tax administrations. As a result, many studies have highlighted

[8] Furthermore, in 4.2.4, we test the sensitivity of our results using the tax-to-GDP ratio (including resources-related taxes).

the negative impact of the agricultural sector on tax revenues (Gupta 2007; Baunsgaard and Keen 2010; Gnangnon and Brun 2018).

As a measure of the political regime, a proxy for the institutional framework, we use the Autocracy-Democracy Index. The index ranges from -10 to 10, with a value close to 10 indicating a democratic political regime and vice versa. Several studies stress that better institutional quality is associated with higher tax revenue, notably by improving the efficiency of tax administrations in mobilising tax revenues and increasing tax morale (Bird, Martinez-Vazquez and Torgler 2008).

Socio-demographic factors may also influence tax revenue. Regarding urbanisation, the theoretical relationship with tax revenue is unclear. Gupta (2007) demonstrates that the urban population has a positive impact on tax collection, reflecting the growth of industrial and service sectors relative to the agricultural sector. In addition, a high proportion of urban dwellers leads to lower tax compliance costs for tax authorities. In contrast, other studies report that urbanisation induces economies of scale in providing public goods and services, thereby reducing the need for public funding (Alesina and Wacziarg 1998).

3.3 Identification strategy

3.3.1 Estimation methods

The standard approach to estimating the effect of mobile money on tax revenue is to use ordinary least squares (OLS) regression. Although this approach indicates the correlation between the two variables, it is challenging to infer a causal effect from the adoption of mobile money services to tax revenue. The relationship between mobile money and tax revenue could be driven by reverse causality if higher tax revenues foster mobile money services deployment. In addition, our primary independent variable of interest (MM dummy variable) may also be subject to measurement error, leading to biased and inconsistent estimates of the effects of mobile money services on non-resource tax revenues. The challenge is to formulate an empirical strategy suitable for identifying the causal impact of mobile money services on tax revenue. We rely on three alternative identification strategies: the instrumental variables method (IV), the system generalised method of moments (SYS-GMM) in a dynamic setting and the endogenous switching regression (ESR) model.

3.3.2 A new instrumental variables strategy for mobile money adoption

Finding credible exogenous instruments for the adoption of mobile money services is challenging. Our instrumental strategy assumes that adopting mobile money services at the regional level, especially among neighbouring countries, may also induce the home country to adopt mobile money services. The intuition is that the spread of mobile money services in neighbouring countries may influence their adoption through peer imitation dynamics. The literature on the diffusion of technologies or innovations supports our intuition, suggesting that sharing information about the use of these services is a key driver in their spread. More specifically, the information shared by early adopters plays an important role in the adoption of new users. In other words, as the number of users increases, potential adopters who are geographically closer to them gain more exposure to the new technology, thereby bolstering the likelihood of adoption (Pulkki-Brännström and Stoneman 2013). Similarly, Comin, Dmitriev and Rossi-Hansberg (2012) emphasise that technology diffuses more slowly in locations that are further away from the early adopters.

Several anecdotal examples support our presumption that countries look to their neighbours' experiences when implementing mobile money services. For instance, after Kenya launched the M-Pesa mobile in March 2007, neighbouring Tanzania followed suit in April 2008 and Uganda in January 2009. There is a similar dynamic in Southeast Asia. After the launch of the GPay mobile money service in Bangladesh in August 2006, India introduced a similar service called Eko in July 2007. Figure 3.2 provides a graphical representation of the adoption of mobile money services over time and across countries, suggesting a spatial diffusion pattern.

To construct our instrument, we draw on research showing that geographic proximity matters in technology adoption (Conley and Udry 2010; Comin *et al*. 2012; Krishnan and Patnam 2014; Verkaart *et al*. 2017). The spatial weight matrix is a powerful tool for conceptualising spatial relationships in spatial econometric analysis. For the selection of the spatial weight matrix, we first use one based on geographical distance, defined as follows:

$$W_{ij}^{d} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases}, W_{ij}^{*d} = \frac{W_{ij}^{d}}{\sum_{j=1}^{n} W_{ij}^{d}}, \quad i \neq j \qquad \text{Eq. (2)}$$

where d_{ij} is the distance between the capitals (or the most populated cities if the capital is not the most populated city) of countries i and j, calculated by the position of latitude and longitude.[9] W_{ij}^{*d} is the row-standardised matrix so that the sum of elements in each row equals one. The matrix is based on the reciprocal distances of 213 countries. Eq. (2) shows that the greater the geographical distance between two capitals, the smaller their mutual influence.

[9] Data on the latitude and longitude of capitals are taken from Mayer and Zignago 2011.

To capture the process of the geographical adoption of mobile money, our instrument is defined as the spatial lag of mobile money adoption in neighbouring units:

$$MM\ Inst.(1)_{it} = \sum_j W_{ij}^d * MM_{j,t-1}, \quad i \neq j \qquad \text{Eq. (3)}$$

where $MM_{j,t-1}$ is a dummy variable that takes the value one if there is mobile money service in country *j* at time *t-1*, and zero otherwise. Since the matrix of distances is constant over time, time-variation in $MM\ Inst.(1)_{it}$ stems from the deployment of mobile money, as shown in Figure 3.1. Thus, our instrument can be interpreted as the weighted average (where W_{ij}^d are the weights) of neighbours' mobile money adoption (Anselin 2022). We use the same methodology to build instruments for implementing different mobile money services (see Table A1 in the Appendix).

As robustness tests, we also suggest four alternative instruments for mobile money adoption:

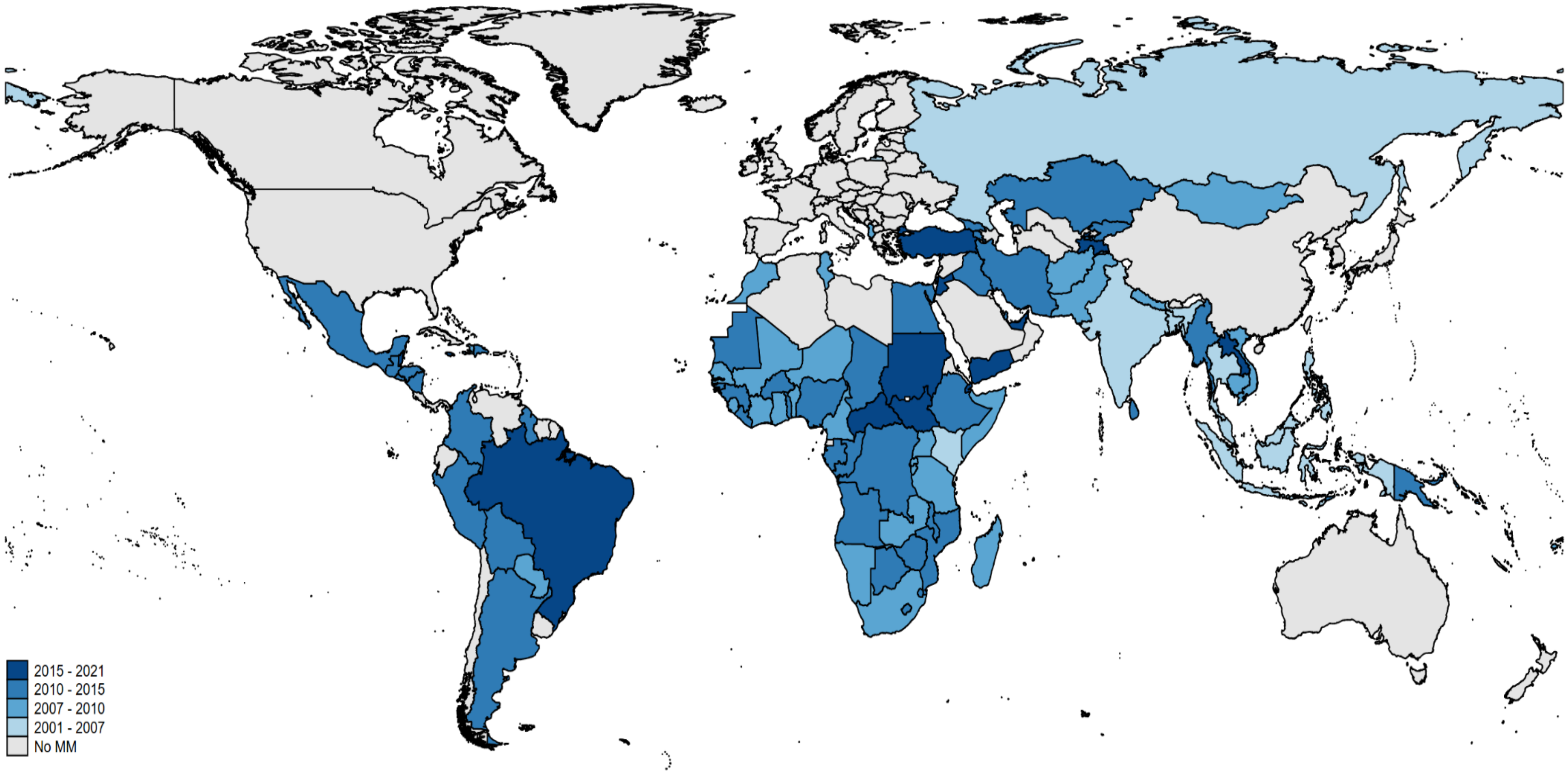
- A three-year moving average of the spatial lag of mobile money adoption using a geographical distance weight matrix.
- Another spatial lag of mobile money adoption using a k-nearest neighbour spatial matrix, where the k-nearest countries around a given country are weighted as one while the others are weighted as 0. We consider four nearest neighbours ($K = 4$) as suggested by Anselin (2003).
- The average proportion of neighbouring countries (with common borders[10]) that have adopted MM services (as in Wandaogo *et al*. 2022).
- The number of neighbouring countries (with common borders) that have adopted MM services and its lagged value.[11]

Based on the geographic weight matrix, Moran's I method is used to test the spatial correlation of mobile money deployment. Generally, Moran's I index is between -1 and 1, with a value greater than zero indicating a positive correlation and vice versa. It can be seen from Table A4 that the global Moran's indexes are mostly significantly positive between 2007 and 2021 at the 1 per cent level for the mobile money dummy variable and the different mobile money services. Thus, the adoption of mobile money has a significantly positive spatial correlation, which is suitable for modelling mobile money instruments with a spatial econometric analysis. Therefore, we assume that our instruments will positively influence the adoption of mobile money services but not the level of non-resource tax revenue

[10] Data on contiguity are obtained from Conte *et al*. 2022.

[11] Caselli and Reynaud (2020) use similar instruments for the adoption of fiscal rules.

Figure 3.2 Mobile money adoption across countries and time



Note: 'No MM' refers to non-mobile money countries.
Source: Authors' own elaboration based on data from the GSMA's Mobile Money Deployment Tracker.

4. Empirical results

This section reports the main findings of the estimation of the relationship between mobile money services and non-resources tax in EMDCs. This will be articulated around four subsections. First, we discuss the main findings on the impact of mobile money services on tax revenue. Second, we conduct further analyses for robustness purposes. Third, we address potential selection issues using the endogenous switching regression model. Finally, we empirically test the potential transmission channels identified in Section 2.

4.1 Baseline results

4.1.1 OLS estimations

We start by estimating Eq. (1) using OLS regressions. The results are reported in Table 4.1. Four separate models, with and without time-fixed effects or control variables, are estimated for non-resource tax revenue. Column 4 includes both fixed effects and control variables. Even without addressing endogeneity concerns, the results indicate that mobile money adoption is positively and significantly related to non-resource tax revenue in developing countries. Consistent with previous studies, we find that GDP per capita, trade openness, urban population and democracy are associated with higher tax revenues. Conversely, abundant natural resources and reliance on the agricultural sector reduce tax revenues.

Table 4.1 Mobile money effect on non-resource tax revenue in EMDCs (OLS)

	(1)	(2)	(3)	(4)
	NRTAX (% GDP)			
MM	2.098***	0.715***	0.687***	0.620***
	(0.124)	(0.171)	(0.145)	(0.172)
GDP per capita			0.952***	0.973***
			(0.312)	(0.367)
NRA			-0.154**	-0.195***
			(0.072)	(0.070)
Trade			0.011***	0.011***
			(0.004)	(0.004)
Agriculture			-0.074***	-0.086***
			(0.014)	(0.015)
Urban population			0.118***	0.143***
			(0.016)	(0.017)
Political regime			0.035**	0.045***
			(0.016)	(0.016)
Observations	2,546	2,546	2,546	2,546
R-squared	0.862	0.870	0.878	0.879
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included.
Source: Authors' own elaboration from collected data.

4.1.2 2SLS estimations

Table 4.2 reports second stage instrumental variable estimates, which address the bias induced by the endogeneity of mobile money. Based on a geographical distance weight matrix, the spatial lag of mobile money is employed as an instrument to infer a causal effect of mobile money adoption on non-resource tax revenue. The first stage results are reported in Table A5 (see Appendix 2). The results reveal that our instrument is strongly correlated with mobile money deployment. We assess our instrument's validity and relevance using two diagnostic tests: (1) an under-identification test using the Kleibergen-Paap rk LM p-value and (2) a weak identification test using the Kleibergen-Paap rk Wald statistic. Under-identification tests the instrument's relevance with a rejection of the null hypothesis, indicating that the model is identified. Weak identification tests whether the instrument is only weakly correlated with the endogenous variable. The diagnostics statistics show that our instrumental strategy is strong. Kleibergen-Paap rk LM p-value suggests that the spatial lag of mobile money in neighbouring countries is an appropriate external instrument for mobile money adoption. The Kleibergen-Paap Wald F statistic (KP rk Wald F-value) is always much larger and well above the most demanding Stock-Yogo critical value of 16.38.

The IV-2SLS estimations confirm previous results from the OLS estimations regarding the effect of mobile money adoption on tax revenue. The coefficients' magnitude is much larger than that of Table 4.1, suggesting that the OLS coefficients were downward biased. Control variables remain significant with the same signs. These results highlight mobile money's causal solid impact on non-resource tax revenue.

Table 4.2 Instrumental variable estimates of the effects of mobile money on tax revenue

	(1)	(2)	(3)	(4)
	NRTAX (% GDP)			
MM	3.161***	4.676***	1.394***	4.290***
	(0.165)	(0.624)	(0.236)	(0.641)
GDP per capita			0.782**	1.947***
			(0.311)	(0.417)
NRA			-0.150**	-0.143**
			(0.071)	(0.072)
Trade			0.012***	0.013***
			(0.004)	(0.004)
Agriculture			-0.070***	-0.075***
			(0.013)	(0.015)
Urban population			0.089***	0.101***
			(0.017)	(0.019)
Political regime			0.027*	0.036**
			(0.016)	(0.017)
Observations	2,546	2,546	2,546	2,546
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
KP rk LM (p-value)	0.00	0.00	0.00	0.00
KP rk Wald F-value	3928	201.7	1519	172.7

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test.
Source: Authors' own elaboration from collected data.

4.2 Further investigations and robustness tests

In this section, we conduct further investigations and robustness tests using additional control variables and alternative measures of tax revenue and mobile money. We also employ alternative econometric specifications and instruments.

4.2.1 Additional control variables

In this subsection, we address concerns regarding how potentially omitted control variables influence the relationship between mobile money and tax revenue in EMDCs. Therefore, we refer to the related literature and control for inflation, female labour force participation, internet penetration, age dependency ratio, government ideology, human capital, foreign direct investment and foreign aid.

Inflation is expected to hurt tax revenue. Higher inflation rates can lead to lower tax revenue performance due to the phenomenon known as the Olivera-Tanzi effect. This phenomenon refers to the time lag between the incurrence of tax debt and the collection of tax revenues by the tax authorities.

Higher female labour force participation represents increased taxable income and consumption, raising labour and sales tax revenues in particular (Mahdavi 2008). There is also evidence that women are more likely to comply with paying their taxes, as they have stronger tax morale than men and pay more attention to ethical considerations (Torgler and Schaltegger 2005).

Recent studies also highlight that greater internet access improves tax collection. For example, internet access facilitates taxpayers' submission of tax-related information (where e-filing is possible) and tax administrations' treatment of such information, thereby reducing the costs for both the government and taxpayers and limiting fraud (Gnangnon and Brun 2018; Gnangnon 2022).

We control for the age dependency ratio. The age composition of the population's impact on tax revenue is ambiguous. On the one hand, the higher the dependency ratio, the greater the need for public social expenditure and tax revenues (Torgler and Schaltegger 2005). According to the life-cycle theory, on the other hand, retirees save more and work less, which translates into lower taxes on income and consumption (Mahdavi 2008).

We also examine the role of government ideology as several studies demonstrate that left-wing governments tend to tax more than others, mainly through taxes on income and capital or consumption taxes (Angelopoulos, Economides and Kammas 2012).

We also expect human capital to be positively associated with tax revenue. The more educated individuals are, the better they understand the importance of public interventions and policies that improve tax collection (Castañeda Rodríguez 2018). The level of education also determines the tax potential. Higher levels of education tend to lead to higher-paid jobs, thereby increasing income taxes. Moreover, a more educated workforce is often more productive, leading to higher corporate profits, which also contribute to higher corporate taxes.

Recent studies have also examined foreign direct investment's impact on tax revenues. Using a large sample of 172 countries, Gnangnon (2017) illustrates that the scale of FDI inflows influences this relationship. The author finds that below a threshold of 4.43 per cent, FDI inflows negatively affect non-resource tax revenue. More recently, Camara (2023) proves that FDI stimulates tax revenue in developing countries. However, this relationship was found to be insignificant in resource-exporting countries.

Studies investigating the impact of foreign aid on tax revenue are inconclusive. Some studies find that foreign aid hurts tax revenues (Gupta *et al.* 2004; Thornton 2014), while others conclude the opposite (Mascagni 2016).

Table 4.3 reports using additional control variables. We first included each variable individually (see columns 1 to 8) before estimating a specification including all the control variables (see column 9). The results of the first stage are reported in Table A6 in Appendix 2. Our results confirm the positive influence of left-wing governments on tax revenue (Table 4.3, columns 5 and 9). The findings also indicate that FDI inflows positively affect non-resource tax revenues (see Table 4.3, columns 7 and 9). Foreign aid exhibits a negative sign in column 8 but a positive sign when all control variables are included (see column 9). This suggests that the impact of foreign aid depends on some specific characteristics of the recipient countries. Mobile money adoption is consistently positive and significantly associated with tax revenues.

4.2.2 Types of mobile money services

As already mentioned, there has been a significant diversification of services in the mobile money industry. An overview of existing mobile money services is provided in Table A1 in Appendix 1. Exploring the effects of each MM service type represents a significant area of interest, given their potential to affect tax revenue differently. By allowing individuals or businesses to pay taxes, public services or bills (to government-owned utility companies) via mobile money, P2G payments help reduce administrative costs, as well as the risks associated with physical interactions and cash transactions (corruption, embezzlement of public funds, etc.). A case study in Kenya reveals that the digitalisation of P2G has increased transparency, accountability and traceability of funds collected, enabling public bodies to minimise fraud (GSMA 2017b). A study in the Cote d'Ivoire also shows that paying school fees through mobile money has significantly decreased the incidence of lost payments, fraud and theft (Frydrych, Scharwatt and Vonthron 2015).

Table 4.3 Additional control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NRTAX (% GDP)								
MM	4.613***	4.524***	2.913***	4.211***	4.103***	2.979***	4.184***	4.845***	3.403**
	(0.651)	(0.679)	(0.912)	(0.654)	(0.664)	(0.733)	(0.632)	(1.162)	(1.458)
GDP per capita	1.513***	2.089***	1.950***	1.925***	1.890***	1.538***	1.899***	2.349***	1.823***
	(0.423)	(0.432)	(0.468)	(0.416)	(0.420)	(0.442)	(0.413)	(0.507)	(0.610)
NRA	-0.160**	-0.157**	-0.152*	-0.151**	-0.147**	0.019	-0.154**	-0.150*	-0.043
	(0.073)	(0.074)	(0.092)	(0.072)	(0.072)	(0.093)	(0.074)	(0.085)	(0.125)
Trade	0.017***	0.013***	0.013***	0.013***	0.012***	0.013***	0.011***	0.014***	0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
Agriculture	-0.068***	-0.078***	-0.077***	-0.073***	-0.075***	-0.067***	-0.072***	-0.069***	-0.095***
	(0.015)	(0.015)	(0.018)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.018)
Urban population	0.096***	0.092***	0.101***	0.096***	0.097***	0.114***	0.101***	0.088***	0.049**
	(0.019)	(0.020)	(0.022)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.022)
Political regime	0.037**	0.038**	0.032*	0.036**	0.034*	0.002	0.034**	0.037**	0.026
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.020)
Inflation	-0.428								-3.090***
	(0.307)								(0.641)
FLFP		0.031**							0.021
		(0.015)							(0.018)
Internet			-0.015						-0.007
			(0.009)						(0.011)
Age dependency				-0.018					-0.018
				(0.011)					(0.014)
Government ideology (left)					0.557***				0.697***
					(0.185)				(0.208)
Education						0.021***			-0.006
						(0.005)			(0.007)
FDI							0.024***		0.066***
							(0.008)		(0.015)
ODA								-0.028*	0.052**
								(0.015)	(0.023)
Observations	2,394	2,546	2,231	2,546	2,546	2,166	2,535	2,344	1,679
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KP rk Wald F-value	153.5	165.5	80.11	171.1	164.4	116.7	173.4	58.58	26.35

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test.
Source: Authors' own elaboration from collected data.

Table 4.4 The types of mobile money services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	NRTAX (% GDP)										
	P2P	BP	P2G	G2P	OBP	AT	MP	IR	CI	CO	MM (div.)
MM (pr.)	4.693***	5.028***	4.459***	3.893***	3.906***	4.387***	4.855***	4.118***	4.338***	4.096***	
	(0.670)	(0.769)	(1.318)	(1.063)	(0.523)	(0.673)	(0.679)	(0.792)	(0.642)	(0.571)	
MM (div.)											4.835***
											(0.672)
GDP per capita	2.045***	1.902***	1.236***	1.321***	2.078***	1.940***	2.245***	1.389***	1.949***	2.007***	1.913***
	(0.425)	(0.422)	(0.386)	(0.376)	(0.413)	(0.419)	(0.438)	(0.381)	(0.416)	(0.409)	(0.404)
NRA	-0.136*	-0.131	-0.156**	-0.154**	-0.037	-0.116	-0.076	-0.137*	-0.148**	-0.148**	-0.115
	(0.074)	(0.082)	(0.076)	(0.073)	(0.079)	(0.078)	(0.073)	(0.077)	(0.073)	(0.072)	(0.072)
Trade	0.013***	0.011**	0.011***	0.011***	0.010**	0.012***	0.012***	0.010**	0.013***	0.014***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Agriculture	-0.074***	-0.064***	-0.068***	-0.083***	-0.058***	-0.071***	-0.066***	-0.055***	-0.075***	-0.072***	-0.066***
	(0.015)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
Urban population	0.096***	0.098***	0.140***	0.141***	0.125***	0.099***	0.094***	0.141***	0.101***	0.114***	0.112***
	(0.020)	(0.020)	(0.018)	(0.018)	(0.018)	(0.019)	(0.020)	(0.018)	(0.019)	(0.018)	(0.018)
Political regime	0.030*	0.039**	0.008	0.049***	0.032**	0.036**	0.045**	0.034*	0.036**	0.043**	0.034**
	(0.017)	(0.018)	(0.020)	(0.016)	(0.016)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KP rk Wald F-value	160.6	127.9	41.34	38.99	274	158.1	161.2	75.22	168.4	210.6	231.1

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. ‘KP rk LM (p-value)’ is the associated p-value of the Kleibergen-Paap under-identification test. ‘KP rk Wald F-value’ reports the Kleibergen-Paap Wald F statistic for the weak identification test.P2G, BP, P2G, G2P, OBP, AT, MP, IR, CI, and CO denote person-to-person payments, bill payments, person-to-government payments, government-to-person payment, Other bulk payments, airtime top-up, merchant payments, international remittances, cash-in and cash-out, respectively. MM (div) is the ratio of the number of MM services available to the number of existing services.
Source: Authors’ own elaboration from collected data.

The effects of transparency also apply to bills and merchant payments. Mobile money transactions generate financial records, which can help track merchants' sales more efficiently. This can potentially increase tax compliance, leading to higher tax revenues. Furthermore, international remittances via mobile money can increase consumption in the receiving country, thereby increasing sales tax revenues from higher consumption spending or corporate tax revenues from increased business activity.

Thus, we expect that each mobile money service has a positive effect on non-resource tax revenues, but in different ways. A mobile money service is measured as a dummy variable, taking the value one from the year the service is launched, and zero otherwise. We use the same approach as in Section 3.2.2 to construct an instrument for each type of mobile money service using a geographical distance weight matrix. Therefore, the instrument of each MM service corresponds to a spatial lag variable of the service in neighbouring units. Table 4.4 documents the estimated impact of each mobile money service on tax revenue. The first stage results are reported in Table A7 in Appendix 2. Looking at the magnitude of the estimated effect of each MM service, we find that bill payments, merchant payments, person-to-person payments, and person-to-government payments have a greater impact on non-resource tax revenues than the other six MM services (see Table 4.4, columns 2, 7, 1 and 3). These findings support that moving from cash transactions to digital payments contributes to enhanced transparency, accountability and traceability, thereby increasing tax revenues. In addition, a higher volume of person-to-person transactions can drive mobile money operator activity, potentially boosting corporate tax revenues. Governments can also collect more VAT on digital transactions.

Finally, we investigate the association between a diversified mobile money service structure and tax revenue. We assume that the more diversified the mobile money industry is in terms of available services, the more likely it is for a country to collect more taxes due to the cumulative positive effects of each MM service. The MM service diversification indicator is measured by the ratio of the number of services available in a country to the total number of existing services (i.e., ten). Its instrument is the simple average of the instrument's value for each MM service. Our finding shows that tax revenue increases as the structure of MM services becomes more diverse (see Table 4.4, column 11). This suggests that a more diversified structure of mobile money services can cover a broader range of individuals' or firms' daily activities, thereby contributing to improved tax collection.

4.2.3 The role of public services

Next, we look at the role of public services in the relationship between mobile money and tax revenues. Recent studies underline the importance of providing public services to incentivise tax compliance (Blimpo *et al.* 2018; Okunogbe and

Santoro 2023). Blimpo *et al*. (2018) show that providing social infrastructure such as reliable electricity positively affects tax revenue in developing countries. Relying on this literature, we re-estimate Eq. (1), including a public service variable and its interaction term with mobile money. We use three alternative measures for public services: access to electricity, access to water and access to infrastructure (proxied by the fixed telephone lines as in Moller and Wacker 2017). Each variable is instrumented by its lagged value. The instrument for the interaction term is constructed by interacting the instrument for mobile money adoption with the instrument for the public service variable. In Table 4.5, we present the results obtained from the analysis.[12]

We find that the joint effect of mobile money and public services is positively significant. Regarding the net effect of the interaction term, the results show a significant positive impact for the three specifications. The net effect can only be determined if the coefficients associated with the primary variable (mobile money) and the interaction term are both significant. In the case of access to electricity, the net effect is 4.54.[13] This implies that improving access to electricity and its associated benefits for mobile money may result in higher tax revenue. Marginal effects further demonstrate that, as the provision of public services increases, mobile money's impact on tax revenues rises. In terms of policy, the findings suggest that to fully leverage the potential of mobile money (and thus increase tax revenues), it is essential to complement its development with other policy measures, such as providing public services.

[12] The results of the first stage are available upon request from the authors.

[13] The net effect of 4.54 is computed as $(2.811 + [0.025 * 68.61])$, where 2.811 is the unconditional coefficient value of mobile money, 0.025 is the conditional coefficient of the interaction term between mobile money and access to electricity, and 68.61 is the mean value of access to electricity.

Table 4.5 The role of public services

	(1)	(2)	(3)
		NRTAX (% GDP)	
MM	2.811***	2.306***	4.417***
	(0.701)	(0.775)	(0.742)
Electricity	0.036**		
	(0.014)		
Water		0.021	
		(0.027)	
Infrastructure			0.009
			(0.022)
MM*Electricity	0.025**		
	(0.011)		
MM*Water		0.039***	
		(0.015)	
MM*Infrastructure			0.128**
			(0.054)
GDP per capita	1.381***	2.612***	1.743***
	(0.486)	(0.626)	(0.488)
NRA	-0.192**	0.095	-0.147
	(0.078)	(0.112)	(0.099)
Trade	0.017***	0.022***	0.014***
	(0.005)	(0.006)	(0.005)
Agriculture	-0.021	-0.046*	-0.079***
	(0.018)	(0.026)	(0.015)
Urban population	0.027	-0.076**	0.087***
	(0.027)	(0.035)	(0.022)
Political regime	-0.031	0.066**	0.046**
	(0.022)	(0.032)	(0.019)
Observations	2,178	1,711	2,458
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00
KP rk Wald F-value	12.35	14.65	14.48
Marginal effect			
Mean	4.538***	5.428***	5.479***
	(1.259)	(1.156)	(1.035)
Percentiles			
10	3.194***	4.292***	4.369***
	(0.801)	(0.856)	(0.665)
25 %	3.747***	4.806***	4.444***
	(0.975)	(0.978)	(0.685)
50 %	4.928***	5.729***	4.920***
	(1.407)	(1.249)	(0.834)
75 %	5.308***	6.043***	6.078***
	(1.555)	(1.350)	(1.266)
90 %	5.328***	6.196***	7.493***
	(1.562)	(1.401)	(1.842)

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test.
Source: Authors' own elaboration from collected data.

4.2.4 Tax decomposition and alternative measures of tax revenue

In this section, we conduct a disaggregated analysis by examining the effect of mobile money on non-resource components of tax revenue. First, we explore the link between direct (indirect) tax revenue (also expressed as a percentage of GDP) and mobile money adoption. Second, we investigate whether mobile money affects personal income taxes, non-resource corporate taxes, VAT and trade taxes. The results are detailed in Table A8 in Appendix 2. Contrary to Apeti and Edoh (2023), our findings support that mobile money has a greater impact on indirect tax revenue than direct tax revenues (see Table A8, columns 1 and 2). This is not surprising, given that bill payments, merchant payments, and international remittances are among the mobile money services that have a more pronounced effect on tax revenues. Consequently, they are more likely to contribute to the rise of indirect tax revenues like sales taxes, VAT or taxes on international transactions.

Next, we perform sensitivity and falsification tests on our dependent variable. First, we employ a ratio of non-resource tax revenue as a percentage of GDP purchasing power parity (PPP). Second, we consider the ratio of tax revenue (including resource-related tax revenue) as a percentage of GDP. Finally, we replace our dependent variable with resource-related tax revenue to test whether our main finding is specific to non-resource tax revenue or whether it is just a spurious correlation. The results of these analyses are shown in Table A9 in Appendix 2. Our main finding remains robust to the sensitivity tests (see Table A8, columns 1 and 2). More importantly, the falsification test (with an insignificant coefficient for mobile money) confirms that our main result is specific to non-resource tax revenues and not a more general effect that would apply to any outcome variable (see Table A9, column 3).

4.2.5 Alternative instruments for mobile money adoption

As mentioned in 3.2.2, we have constructed alternative instruments of mobile money adoption to check whether our results are driven by the methodology used to generate the geographical distance weight matrix. We therefore test our results sequentially, using as an instrument for mobile money adoption: (1) the three-year moving average of the spatial lag of mobile money adoption in neighbouring countries based on the geographical distance weight matrix; (2) the spatial lag of mobile money adoption based on the 4-nearest weight matrix; (3) the average proportion of neighbouring MM countries as in Wandaogo *et al*. 2022; (4) the number of neighbouring MM countries and its lagged value.[14] The results are presented in Table A10. The diagnostic test and the results of the first stage confirm the validity of our alternative instruments for mobile money adoption. Our main finding remains robust: mobile money adoption increases tax revenues.

[14] Caselli and Reynaud (2020) use a similar approach in a study examining the adoption of fiscal rules.

4.2.6 Considering sample heterogeneity

Next, we assess the robustness of our results by excluding from the sample countries where the number of mobile money accounts per adult exceeds 50 per cent in 2021,[15] aiming to determine whether this subset of countries drives our findings. We also perform sub-sample estimations looking at the impact of mobile money adoption in low-income countries (LICs) and non-low-income countries (non-LICs). Table A11[16] in Appendix 2 outlines the results obtained from these analyses. Our main result remains unchanged when excluding countries with intensive mobile money use (see Table A11, column 1). More importantly, the magnitude of coefficients suggests that mobile money has a more pronounced positive effect on tax revenue in low-income countries (see Table A11, columns 2 and 3).

4.2.7 Alternative measures of mobile money and system-GMM

We also check the robustness of our main results using alternative measures of mobile money, namely the number of registered mobile money accounts per 1,000 adults and the number of mobile money transactions per 1,000 adults, both expressed in logarithms. We re-estimate Eq. (1) using these alternative measures via 2SLS, with the volume of SMS sent as an instrument. Mobile money transactions are mainly made via SMS. Therefore, the volume of SMS appears to be a suitable instrument for measuring the use of mobile money, as it is exogenous to tax revenues. The results from the estimations are reported in Table A12 (see columns 1 to 4). The findings corroborate the previous conclusions, as we observe a positive effect of the mobile money usage variables on tax revenues.

We also explore another alternative approach to address the endogeneity concerns and the potential persistence of our dependent variable using a dynamic framework (i.e., adding the one-year lagged value of non-resource tax revenue to the set of regressors in Eq. (1)). We thus complement the instrumental variable approach with the system-GMM method proposed by Blundell and Bond (1998). The results are reported in columns 5 to 7 of Table A12. Before discussing the estimates, it is important to note that standard diagnostic tests validate the adequacy of the model. The lagged value of non-resource tax revenues is significant in all specifications, confirming the persistence of tax revenue over time. The two-step system-GMM estimates confirm the results obtained with the 2SLS estimator: mobile money continues to impact tax revenue positively.

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[15] Data come from the World Bank's Global Findex Database 2021. This includes Gabon, Ghana, Kenya, Mongolia, Thailand, Uganda and Zimbabwe.

[16] The results of the first stage are available upon request from the authors.

4.3 Endogenous switching regression model

As the IV-2SLS could produce biased results in the presence of selection bias (Ertefaie *et al*. 2016; Canan, Lesko and Lau 2017), we test the robustness of our results using an ESR model. Selection bias could arise, for example, from the fact that observable factors (such as level of development) affect both mobile money adoption and tax revenues. We prefer the ESR model rather than the propensity score matching (PSM) method to account for selection bias from both observable and unobservable factors. More details on the endogenous switching regression approach are given in Appendix 3.

The average treatment effects on the treated (ATT) estimates from the ESR model are shown in Table 4.6. The findings reveal that adopting mobile money services significantly increases tax revenues by 9.2 per cent. Regarding income level, the results show that introducing mobile money services tends to increase tax revenues by 14.3 per cent in low-income countries and 3 per cent in non-low-income countries.[17] These results are consistent with our earlier findings and confirm that digital finance plays an important role in increasing tax revenues in developing countries.

Table 4.6 ESR-based average treatment effects on the treated (ATT) of mobile money on tax revenue

	(1) Mean NRTAX (% of GDP) MM countries	(2) Non-MM countries	(3) ATT	(4) t-Value	(5) Change (%)
Full sample	14.094	12.904	1.190	29.34***	9.22
	(0.132)	(0.114)			
LICs	10.767	9.423	1.344	10.29***	14.26
	(0.132)	(0.101)			
Non-LICs	15.557	15.106	0.451	4.01***	3.00
	(0.162)	(0.126)			

Note: Standard errors are in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. ‘LICS’ and ‘Non-LICs’ refer to low-income countries and non-low-income countries, respectively.
Source: Authors’ own elaboration from collected data.

[17] Estimates of the selection and outcome equations for LICs and non-LICs are available from the authors upon request.

4.4 Potential transmission channels

Although our results support the conclusion that adopting mobile money services affects tax revenues, they do not show how this effect is transmitted. In this section, we conduct a mediation analysis, drawing on the methodologies proposed by Baron and Kenny (1986), Imai, Keele and Tingley (2010) and VanderWeele (2015), to empirically investigate the potential pathways through which mobile money influences tax revenues. This paper's core idea is that mobile money's impact on non-resource tax revenues passes through the inflow of international remittances, the reduction of corruption and the decline of the informal economy, as highlighted in Section 2. These potential transmission channels are referred to as mediators.

The approach considered here allows for the decomposition of the total effect of mobile money on tax revenue into a direct effect (i.e., the main effect of mobile money on non-resource taxes not through the mediator) and an indirect effect (i.e., the effect of mobile money on non-resource taxes through the mediator). Our analysis is divided into two complementary parts in order to provide a comprehensive overview of the mediation process. The first part focuses on individual mediators, examining their specific role in the relationship between mobile money and tax revenue. In the second part, we take a broader approach, exploring the combined influence of all mediators as a group.

Our mediation analysis primarily follows the traditional approach developed by Baron and Kenny (1986). This method involves fitting two linear model regressions: one for the mediator and another for the outcome using structural equation modelling. Direct, indirect, and total effects are then estimated as a function of coefficients derived from these regressions. Building on this methodology, we simultaneously estimate i) the impacts of MM on the mediator (model 1) and ii) the direct effect of mobile money on tax revenue while controlling for the mediator (model 2).

$$Model\ 1: \quad Mediator_i = \alpha_1 + \beta_1 MM_i + \upsilon_i \qquad \text{Eq. (10)}$$

$$Model\ 2: \quad NRTAX_i = \alpha_2 + \beta_2 Mediator_i + \beta_3 MM_i + \varepsilon_i \qquad \text{Eq. (11)}$$

where $Mediator_i$ represents alternatively remittance inflows, corruption and the informal sector. We first assume that there is no interaction between mobile money and the mediator, implying that the effect of mobile money on tax revenue through the mediator is additive and does not depend on the mediator's level. The estimated mediation effect (or indirect effect) is, therefore, calculated as the product of β_1 and β_2. This term also reflects the magnitude of the mediation, which essentially depends on the extent to which mobile money affects the mediator and the extent to which the mediator impacts non-resources taxes. β_3

represents the direct effect. Finally, the total effect is given by the sum of the direct and indirect effects: $\beta_3 + (\beta_1 * \beta_2)$.[18]

To measure corruption, we use the political corruption index from the Varieties of Democracy (V-Dem) Dataset (Coppedge *et al*. 2023). This indicator ranges from 0 (less corrupt) to 1 (more corrupt). The political corruption index includes measures of six different types of corruption, covering various areas and levels of the political sphere and distinguishing between executive, legislative and judicial corruption. As a measure of the informal sector, we use Elgin *et al*.'s (2021) estimates of the size of the informal economy as a percentage of GDP. These estimates are derived from a multiple indicators, multiple causes (MIMIC) approach. The informal economy is defined as the market-based and legal production of goods and services hidden from public authorities for monetary, regulatory or institutional reasons (Schneider *et al*. 2011). Data on remittance inflows (as a percentage of GDP) come from the World Bank's WDI database.

Table 4.7 reports the results from the mediation analysis for individual mediators, where 'proportion mediated' refers to the extent to which each potential mediator (or channel) mediates the total effect of mobile money on tax revenue. Looking at the top of Table 4.7 (i.e., the estimates for model 1), the results show that corruption and the informal economy decrease significantly, while the inflow of remittances increases with the adoption of mobile money services. These findings, on the one hand, confirm the conclusions of Barasa (2021), who highlights the role of digital finance in bribe payments. On the other hand, they reinforce the findings of Jacolin *et al*. (2021), who suggest that mobile money is associated with a smaller size of the informal sector in developing countries, and those of Munyegera and Matsumoto (2016) and Apiors and Suzuki (2018) on remittances.

In line with model 2, the results show that all mediators significantly impact non-resource taxes. In particular, increased corruption and the shadow economy lead to decreased tax revenues, as Besley and Persson (2014) and Elgin and Uras (2013) suggested. In contrast, the inflow of remittances consistently positively affects non-resource tax revenues, which aligns with Asatryan *et al*. (2017) and Ebeke (2014).

We also report the decomposition of total effects (TE), which indicate statistically significant natural direct effects (NDE) and natural indirect effects (NIE). The ratio of the mediating effect to the total effect is 19.2 per cent for remittances, suggesting that 19.2 per cent of the impact of mobile money on tax revenue is achieved through remittance inflows when it is considered as the single mediator. Our results also suggest that informality and corruption mediated 12.4 per cent

[18] Imai *et al*. (2010) demonstrate that when both outcome and mediator are modelled using linear regression, and there is no interaction between treatment and mediator, both classical approach and causal mediation analysis using the potential-outcomes framework yield identical results.

and 8.7 per cent of the relationship between tax revenue and mobile money, respectively.

Table 4.7 Results of mediation analysis based on individual mediators

	(1) Remittances	(2) Corruption	(3) Informal economy
Dependent variable: mediator variable			
MM	0.572***	-0.014**	-1.852***
	(0.218)	(0.006)	(0.067)
Dependent variable: NRTAX (% GDP)			
MM	0.629**	1.552***	1.273***
	(0.283)	(0.254)	(0.294)
Mediator variable	0.262***	-10.601***	-0.097***
	(0.027)	(0.454)	(0.011)
Effect decomposition			
NIE	0.150***	0.148**	0.180***
	(0.058)	(0.060)	(0.022)
NDE	0.629**	1.552***	1.273***
	(0.283)	(0.254)	(0.294)
TE	0.779***	1.701***	1.453***
	(0.284)	(0.259)	(0.297)
Proportion mediated	0.192**	0.087**	0.124***
	(0.096)	(0.035)	(0.027)
Observations	2,292	2,546	2,297

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'NIE', 'NDE', and 'TE' refer to natural indirect effect, natural direct effect and total effect, respectively. 'Proportion mediated' refers to the ratio of NIE to TE.
Source: Authors' own elaboration from collected data.

When the no-interaction assumption is relaxed,[19] the interaction terms between mobile money and each mediator are only significant for corruption. In this case, the percentage mediated increases from 8.7 per cent to 10.2 per cent when corruption is considered as the only mediator. This suggests that the impact of mobile money on non-resource tax revenue through corruption varies with the level of corruption.

[19] This is done by adding the interaction term between the mobile money variable and the mediator to Model 2. The results for this analysis are available from the authors upon request.

Table 4.8 Results of mediation analysis incorporating all mediators

	(1) Remittances	(2) Corruption	(3) Informal economy	(4) NRTAX (% GDP)
MM	1.796*** (0.158)	-0.032*** (0.004)	-1.881*** (0.063)	1.277*** (0.136)
Remittances				0.161*** (0.020)
Corruption				-4.234*** (0.796)
Informal economy				-0.300*** (0.034)
Effect decomposition				
NIE	0.289*** (0.042)	0.136*** (0.032)	0.565*** (0.069)	0.990*** (0.086)
NDE				1.277*** (0.136)
TE				2.267*** (0.120)
Proportion mediated				0.437
Observations	2,292	2,292	2,292	2,292

Note: Robust standard errors in parentheses. Unreported constant included. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Breusch–Pagan test of independence: $\chi^2(6) = 48.56***$. 'NIE', 'NDE', and 'TE' refer to natural indirect effect, natural direct effect and total effect, respectively. 'Proportion mediated' refers to the ratio of NIE to TE.
Source: Authors' own elaboration from collected data.

So far, we have assumed that each mediator's linear regression is independent of the others. However, it is important to acknowledge that our mediators may be related and, therefore, have correlated error terms. To check this, we perform a Breucsh-Pagan test of independence of error terms of the regressions. The results reject the null hypothesis (see note below Table 4.8), suggesting that the residuals of the mediator regressions are indeed correlated. We then employ the seemingly unrelated regressions (Zellner and Huang 1962), which simultaneously estimate a system of linear regressions, to account for the correlated residuals across the models. Estimates derived from the seemingly unrelated regressions allow us to compute the total, direct and indirect effects when all mediators are considered as a group. The results are reported in Table 4.8. Our findings suggest that 43.7 per cent of the total effect of mobile money on tax revenue is mediated by a reduction in corruption and informality and an increase in the inflow of international remittances. This means that our three channels are capturing close to 50 per cent of the total effect of mobile money services on non-resource tax revenues.

5. Conclusion

This paper investigates whether the rapid expansion of mobile money services influences tax revenue in emerging markets and developing countries. For that purpose, we use a large sample of 97 countries from 1990 to 2021. We contribute to the existing literature in several ways: i) we focus our analysis on the relationship between non-resource tax revenue and mobile money services; ii) we rely mainly on the instrumental variables method using five alternative instruments for mobile money; iii) we investigate the role of public services on the mobile money–tax revenue nexus; iv) we discuss and test empirically the potential transmission mechanisms through which mobile money affects non-resource tax revenue in the developing world.

Our results suggest adopting mobile money leads to more non-resource tax revenue in EMDCs, and this positive effect tends to be more significant in low-income countries. We also provide evidence that bill payments (BP), merchant payments (MP), person-to-person payments (P2P), and person-to-government payments (P2G) have a greater impact on tax revenue than other types of mobile money services. We also demonstrate that the provision of public services, such as electricity, improves the positive effect of mobile money on tax revenues. The positive impact of mobile money services on tax revenue stems from the decline of the informal sector, international remittances inflow, and corruption control.

From these findings, we can offer a policy toolkit to increase tax revenue in EMDCs. The first step should be to encourage deploying digital financial services in countries where they are not yet available. Second, EMDCs would benefit from investing more in telecommunications infrastructure to enable mobile money operators to reach the maximum number of people and thus broaden the tax base. Along the same line, diversifying the mobile money services range, which is associated with more tax revenue, should be accelerated. Third, digital finance-related gains will only be effective if policymakers improve financial literacy and strengthen consumer protection to mitigate some risks (subscription and identity fraud, SIM swap, fake currency, commissions and internal frauds, etc.). Finally, mobile money alone is insufficient; its deployment must be accompanied by other development policies, such as improving access to public services. Only under these conditions can developing countries fully realise the leapfrogging effects associated with digital finance.

Appendices

Appendix 1 List of countries and description of variables

Table A1.1 Types of mobile money services

MM service	Definition
Person-to-person (P2P) transfers	Domestic transfers between individuals.
Bill payment (BP)	Payment made by an individual either from their mobile money account to a biller or a billing organisation via a mobile money platform in exchange for services provided.
Person-to-government (P2G) transfers	Money transfers from individuals or companies to governments, including agencies and other local, state and national institutions.
Government-to-person (G2P) payment	Payment from a government to a person's mobile money account.
Other bulk payment (OBP)	Payment made by an organisation to an individual's mobile wallet via a mobile money platform.
Airtime top-up (AT)	Buying airtime using mobile money, usually funded from a mobile money account.
Merchant payment (MP)	Payment made from a mobile wallet to a retail merchant via a mobile money platform in exchange for goods and services.
International remittances (IR)	Cross-border money transfers from one person to another.
Cash-in (CI)	The process by which a customer credits their accounts. This is usually done through an agent who collects the cash and credits the customer's mobile money account.
Cash-out (CO)	The process by which a customer withdraws cash from their mobile money account. This is usually done through an agent who gives the customer cash in exchange for a transfer from the customer's mobile money account.

Source: Authors' version, based on the GSMA Mobile Money Glossary (2021) pp.75-79

Table A1.2 List of countries

Albania (2010)	**El Salvador (2011)**	Libya	**Senegal (2008)**
Algeria	**Eswatini (2011)**	**Madagascar (2010)**	**Sierra Leone (2010)**
Angola (2014)	**Fiji (2010)**	**Malaysia (2007)**	**Singapore (2013)**
Azerbaijan	**Gabon (2012)**	**Mauritania (2013)**	**Solomon Islands (2013)**
Bangladesh (2006)	**Gambia (2016)**	**Mauritius (2019)**	**South Africa (2009)**
Benin (2010)	**Georgia (2013)**	**Mexico (2012)**	Sri Lanka
Bhutan	**Ghana (2009)**	Moldova	**Sudan (2016)**
Botswana (2011)	**Guatemala (2011)**	**Mongolia (2010)**	**Tajikistan (2019)**
Bulgaria	**Guinea (2012)**	**Morocco (2010)**	**Tanzania (2008)**
Burkina Faso (2012)	**Guinea-Bissau (2012)**	**Mozambique (2011)**	**Thailand (2004)**
Burundi (2010)	**Guyana (2013)**	**Namibia (2010)**	**Timor-Leste (2014)**
Cambodia (2009)	**Haiti (2010)**	**Nepal (2009)**	**Togo (2013)**
Cameroon (2010)	**Honduras (2011)**	**Niger (2010)**	**Tunisia (2010)**
Chad (2012)	Hungary	**Nigeria (2011)**	**Turkey (2016)**
Chile	**India (2007)**	North Macedonia	**Uganda (2009)**
China	**Indonesia (2007)**	**Pakistan (2009)**	Ukraine
Comoros (2019)	**Iran (2011)**	Panama	**United Arab Emirates (2019)**
(Democratic Republic of) Congo (2012)	**Jamaica (2016)**	**Papua New Guinea (2011)**	Uruguay
(Republic of) Congo (2011)	**Jordan (2016)**	**Paraguay (2010)**	Uzbekistan
Costa Rica	**Kazakhstan (2015)**	**Peru (2015)**	**Vietnam (2010)**
Cote d'Ivoire (2008)	**Kenya (2007)**	**Philippines (2001)**	**Zambia (2009)**
Croatia	**Kyrgyz Republic (2014)**	Poland	**Zimbabwe (2011)**
Dominican Republic (2014)	**Lao PDR (2018)**	Romania	
Ecuador	Lebanon	**Rwanda (2009)**	
Egypt (2013)	**Lesotho (2012)**	Saudi Arabia	

Source: GSMA (Mobile Money Deployment Tracker). Countries in bold have adopted mobile money services, with the year of the first service launch shown in parentheses.

Table A1.3 Description of variables and data sources

Variables	Definition	Source
Dependent variables		
NRTAX	Non-resource tax revenue, excluding social contributions (% of GDP)	UNU-WIDER Government Revenue Dataset (GRD)
NRDT	Direct taxes, excluding social contributions and resource revenue (% of GDP)	
NRIT	Non-resource component of indirect tax (% of GDP)	
PT	Total income, capital gains, and profit taxes on individuals (% of GDP)	
NRCT	Total income and profit taxes on corporations, excluding taxes on resource firms (% of GDP)	
VAT	Value-added tax (% of GDP)	
TT	Total taxes on international trade, including both import and export taxes	
TR	Total tax revenue, including resource tax (% of GDP)	
RT	Resource tax (% of GDP)	
NRTAX (% GDP, PPP)	Non-resource tax revenue, excluding social contributions (% of GDP at purchasing power parity (PPP))	Authors' calculations based on data from the UNU-WIDER GRD and the World Bank's World Development Indicators (WDI) databases
Variables of interest		
MM	Dummy variable taking the value one from the year a country adopts mobile money service and zero otherwise	Authors' calculations based on data from the GSMA's Mobile Money Deployment Tracker
MM (pr.)	Dummy variable for the MM services (see Table A1 for the definition of MM services)	
MM (div.)	The MM services diversification indicator is measured as the ratio of the number of MM services adopted by a given country to the total number of existing MM services (year-on-year)	
LogMMAc	Number of registered mobile money accounts per 1,000 adults (in logarithm)	IMF-Financial Access Survey (FAS)
LogMMT	Number of mobile money transactions per 1,000 adults (in logarithm)	
Other independent variables		
GDP per capita	Natural logarithm of gross domestic product per capita (in constant 2015 US$)	WDI

NRA	Natural resource abundance is measured as total natural resource rents per capita (in logarithm)	Authors' calculations based on data from the World Bank's WDI database
Trade	Trade openness is measured as the sum of exports and imports of goods and services (% of GDP)	
Agriculture	Agriculture, value added (% of GDP)	WDI
Urban population	Urban population (% of total population)	
Political regime	The political regime is measured by the Autocracy-Democracy Index	Varieties of Democracy (V-Dem) Dataset v13 (Coppedge *et al*. 2023)
Inflation	Logarithmic transformation of the inflation rate: log(100 + growth rate of consumer price index (CPI))	Authors' calculations based on data from the World Bank's WDI database
FLFP	The female labour force participation rate is measured as the percentage of the female population (aged 15 and over) that is economically active	WDI
Internet	Individuals using the internet (% of the population)	
Age dependency	The ratio of dependents (under 15 or over 64) to the working-age population (15–64)	
Government ideology (left)	A dummy variable equal to one if government ideology is left	Authors' calculations based on data from the Database of Political Institutions 2020 (Scartascini *et al.* 2021)
Education	School enrolment, primary (% gross)	WDI
FDI	Foreign direct investment, net inflows (% of GDP)	
ODA	Net official development assistance received (% of GNI)	
Electricity	Access to electricity (% of total population)	
Water	People with at least basic access to drinking water (% of population)	
Infrastructure	Fixed telephone lines (per 100 people)	
Instruments		
MM inst. (1)	Spatial lag of mobile money adoption using a spatial geographical distance weight matrix	Authors' calculations based on data from Mayer and Zignago (2011), Conte *et al*. (2022) and the GSMA's Mobile Money Deployment Tracker
MM inst. (1)_MA	Spatial lag of mobile money adoption using a spatial geographical distance weight matrix (3-year moving average)	
MM inst. (2)	Spatial lag of mobile money adoption using k-nearest neighbour spatial matrix	

MM inst. (3)	The average proportion of neighbouring countries (with common borders) that have adopted MM	
MM inst. (4)	Number of neighbouring countries (with common borders) that have adopted MM	
LogSMS	Total SMS sent (in logarithm)	International Telecommunication Union (ITU)
Mediator variables		
Remittances	Personal remittances received (% of GDP)	WDI
Corruption	Corruption index	Varieties of Democracy (V-Dem) Dataset v13 (Coppedge *et al*. 2023)
Informal economy	Multiple indicators multiple causes model-based (MIMIC) estimates of informal output (% of official GDP)	Informal economy database (Elgin *et al.* 2021)

Source: Authors' own elaboration from collected data.

Appendix 2 Descriptive statistics and empirical results

Table A2.1 Global spatial correlation – Moran's I

Year	MM	P2P	BP	P2G	G2P	OBP	AT	MP	IR	CI	CO
2001	-0.004	-0.004	-0.004	-0.004		-0.004	-0.004	-0.004	-0.004		
2002	-0.005	-0.005	-0.005	-0.004		-0.004	-0.005	-0.005	-0.005	-0.004	
2003	-0.005	-0.005	-0.005	-0.004		-0.004	-0.005	-0.005	-0.005	-0.004	
2004	-0.001	-0.001	-0.001	-0.004	-0.004	-0.004	-0.001	-0.005	-0.005	-0.001	0.003
2005	-0.001	-0.001	-0.001	-0.004	-0.004	-0.004	-0.001	-0.005	-0.005	-0.001	0.003
2006	0.006	-0.001	0.006	-0.004	-0.001	-0.001	0.006	-0.005	-0.005	0.006	0.011
2007	0.048***	0.043***	0.048***	-0.005	-0.001	-0.004	0.048***	0.000	-0.003	0.048***	0.056***
2008	0.033***	0.029**	0.033***	0.010	0.000	0.004	0.033***	0.005	0.000	0.033***	0.037***
2009	0.073***	0.068***	0.074***	0.052***	0.008	0.051***	0.074***	0.048***	0.042***	0.073***	0.077***
2010	0.072***	0.072***	0.056***	0.034***	-0.003	0.062***	0.067***	0.048***	0.049***	0.072***	0.079***
2011	0.077***	0.077***	0.060***	0.036***	0.010	0.075***	0.070***	0.069***	0.051***	0.069***	0.069***
2012	0.130***	0.130***	0.121***	0.035***	0.009	0.136***	0.126***	0.125***	0.064***	0.121***	0.123***
2013	0.138***	0.138***	0.128***	0.027**	0.009	0.143***	0.134***	0.126***	0.072***	0.138***	0.140***
2014	0.140***	0.140***	0.125***	0.034***	0.013	0.146***	0.136***	0.131***	0.082***	0.140***	0.145***
2015	0.149***	0.149***	0.134***	0.034***	0.013	0.148***	0.138***	0.133***	0.089***	0.149***	0.154***
2016	0.148***	0.148***	0.127***	0.048***	0.022*	0.149***	0.138***	0.137***	0.089***	0.148***	0.159***
2017	0.148***	0.148***	0.127***	0.067***	0.022*	0.156***	0.138***	0.137***	0.094***	0.148***	0.159***
2018	0.156***	0.156***	0.131***	0.092***	0.094***	0.152***	0.150***	0.151***	0.108***	0.156***	0.167***
2019	0.173***	0.173***	0.153***	0.100***	0.086***	0.160***	0.167***	0.174***	0.166***	0.172***	0.181***
2020	0.178***	0.178***	0.158***	0.100***	0.086***	0.167***	0.171***	0.178***	0.164***	0.178***	0.186***
2021	0.188***	0.188***	0.162***	0.100***	0.073***	0.179***	0.182***	0.191***	0.164***	0.188***	0.197***

Note: (***, **; *) denote the 1, 5 and 10 per cent significance levels, respectively.
Source: Authors' own elaboration from collected data.

Table A2.2 First stage results for Table 4.2

	(1)	(2)	(3)	(4)
	MM			
MM inst. (1)	1.498***	1.223***	1.461***	1.135***
	(0.024)	(0.086)	(0.037)	(0.086)
GDP per capita			-0.167***	-0.216***
			(0.031)	(0.033)
NRA			-0.002	-0.010
			(0.008)	(0.008)
Trade			-0.000	-0.000
			(0.000)	(0.000)
Agriculture			-0.001	-0.001
			(0.001)	(0.001)
Urban population			0.011***	0.009***
			(0.002)	(0.002)
Political regime			0.002	0.001
			(0.002)	(0.002)
Observations	2,546	2,546	2,546	2,546
R-squared	0.699	0.703	0.708	0.713
Countries	97	97	97	97
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. MM inst. (1) denotes the spatial lag of mobile money using a geographical distance weight matrix.
Source: Authors' own elaboration from collected data.

Table A2.3 First stage regression results for Table 4.3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					MM				
MM inst. (1)	1.138***	1.124***	0.919***	1.113***	1.110***	1.113***	1.154***	0.751***	0.713***
	(0.092)	(0.087)	(0.103)	(0.085)	(0.087)	(0.103)	(0.088)	(0.098)	(0.139)
GDP per capita	-0.248***	-0.220***	-0.172***	-0.217***	-0.218***	-0.234***	-0.202***	-0.244***	-0.188***
	(0.034)	(0.033)	(0.040)	(0.032)	(0.032)	(0.037)	(0.033)	(0.033)	(0.051)
NRA	-0.010	-0.009	-0.005	-0.012	-0.010	-0.011	-0.012	-0.013	-0.007
	(0.009)	(0.008)	(0.012)	(0.008)	(0.008)	(0.011)	(0.009)	(0.008)	(0.015)
Trade	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.001***	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture	-0.001	-0.000	0.002	-0.000	-0.001	0.000	-0.000	-0.000	0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Urban population	0.007***	0.009***	0.010***	0.008***	0.008***	0.006***	0.010***	0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Political. regime	0.000	0.001	-0.001	0.001	0.001	0.002	0.002	-0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Inflation	0.119***								0.202**
	(0.022)								(0.080)
FLFP		-0.001							-0.003
		(0.001)							(0.002)
Internet			-0.005***						-0.004***
			(0.001)						(0.001)
Age dependency				-0.004***					-0.003**
				(0.001)					(0.002)
Government ideology (left)					0.066***				0.015
					(0.017)				(0.022)
Education						0.002***			0.002**
						(0.000)			(0.001)
FDI							0.001		0.001
							(0.001)		(0.002)
ODA								-0.002***	-0.005***
								(0.001)	(0.002)
Observations	2,394	2,546	2,231	2,546	2,546	2,166	2,535	2,344	1,679
R-squared	0.721	0.713	0.728	0.715	0.715	0.711	0.715	0.731	0.739
Countries	97	97	97	97	97	94	97	92	89
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. MM inst. (1) denotes the spatial lag of mobile money using a geographical distance weight matrix. Source: Authors' own elaboration from collected data.

Table A2.4 First stage regression results for Table 4.4

	(1) P2P	(2) BP	(3) P2G	(4) G2P	(5) OBP	(6) AT	(7) MP	(8) IR	(9) CI	(10) CO	(11) MM (div.)
MM (pr.) Inst.	1.119***	1.030***	0.867***	0.993***	1.396***	1.094***	1.124***	1.060***	1.124***	1.211***	
	(0.088)	(0.091)	(0.135)	(0.159)	(0.084)	(0.087)	(0.089)	(0.122)	(0.087)	(0.083)	
MM (div.) Inst.											1.224***
											(0.081)
GDP per capita	-0.214***	-0.176***	-0.069**	-0.101***	-0.212***	-0.207***	-0.222***	-0.124***	-0.214***	-0.239***	-0.174***
	(0.033)	(0.034)	(0.031)	(0.027)	(0.033)	(0.033)	(0.035)	(0.033)	(0.033)	(0.032)	(0.026)
NRA	-0.011	-0.012	-0.009	-0.011**	-0.037***	-0.016*	-0.021**	-0.013	-0.009	-0.011	-0.014**
	(0.008)	(0.009)	(0.007)	(0.005)	(0.007)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)
Trade	-0.000	0.000	0.000	0.000	0.001**	-0.000	-0.000	0.001*	-0.000	-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)
Agriculture	-0.001	-0.002*	-0.004***	-0.000	-0.005***	-0.001	-0.002	-0.007***	-0.000	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Urban population	0.009***	0.008***	0.002	0.002	0.003*	0.009***	0.009***	0.001	0.009***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Political regime	0.002	0.000	0.007***	-0.002	0.001	0.001	-0.001	0.002	0.001	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546	2,546
R-squared	0.714	0.683	0.545	0.464	0.661	0.702	0.684	0.571	0.712	0.709	0.730
Countries	97	97	97	97	97	97	97	97	97	97	97
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. MM (pr.) Inst. denotes the spatial lag of each type of mobile money service using a geographical distance weight matrix. MM (div.) Inst. is the simple average of the instrument's value for each MM service.

Source: Authors' own elaboration from collected data.

Table A2.5 Tax decomposition

	(1)	(2)	(3)	(4)	(5)	(6)
	NRDT	NRIT	PT	NRCT	VAT	TT
MM	1.925***	2.477***	1.545***	1.683***	1.092***	1.436***
	(0.373)	(0.535)	(0.235)	(0.229)	(0.264)	(0.393)
GDP per capita	2.045***	0.564*	1.373***	1.127***	0.434*	0.263
	(0.234)	(0.294)	(0.195)	(0.213)	(0.246)	(0.191)
NRA	0.006	-0.249***	0.039	0.090**	0.093	-0.121***
	(0.050)	(0.052)	(0.031)	(0.036)	(0.082)	(0.045)
Trade	0.006***	0.017***	0.001	0.002	0.007***	0.004**
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Agriculture	0.001	-0.079***	-0.003	-0.002	-0.045***	-0.010
	(0.008)	(0.010)	(0.006)	(0.006)	(0.013)	(0.008)
Urban population	0.067***	0.027*	0.019**	0.064***	-0.054***	0.027**
	(0.011)	(0.014)	(0.009)	(0.009)	(0.015)	(0.011)
Political regime	0.024***	-0.006	0.011	0.034***	-0.013	0.019**
	(0.009)	(0.012)	(0.008)	(0.008)	(0.022)	(0.008)
Observations	2,288	2,315	1,891	1,668	1,484	2,348
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
KP rk Wald F-value	158.6	156.8	140	139.4	140	157.3

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 percent levels. Unreported constant included. ‘KP rk LM (p-value)’ is the associated p-value of the Kleibergen-Paap under-identification test. ‘KP rk Wald F-value’ reports the Kleibergen-Paap Wald F statistic for the weak identification test. The results of the first stage are available upon request from the authors. ‘NRDT’, ‘NRIT’, and ‘NRCT’ refer to non-components of direct tax revenue, indirect tax revenue, and corporate tax revenues, respectively. ‘PT’, ‘VAT’, and ‘TT’ refer to personal income taxes, value-added tax, and trade taxes, respectively. All are expressed as a percentage of GDP.
Source: Authors’ own elaboration from collected data.

Table A2.6 Alternative measures of tax revenue and falsification test

	(1)	(2)	(3)
	NRTAX (% GDP, PPP)	TR (% GDP)	RT (% GDP)
MM	1.513***	4.438***	-0.234
	(0.274)	(0.699)	(0.248)
GDP per capita	0.837***	2.842***	0.573***
	(0.195)	(0.433)	(0.170)
NRA	-0.054*	-0.082	0.113***
	(0.031)	(0.074)	(0.033)
Trade	0.005**	0.026***	0.010***
	(0.002)	(0.005)	(0.003)
Agriculture	-0.020***	-0.103***	-0.023***
	(0.007)	(0.016)	(0.006)
Urban population	0.051***	0.030	-0.059***
	(0.009)	(0.021)	(0.009)
Political regime	0.004	0.023	-0.012**
	(0.008)	(0.019)	(0.006)
Observations	2,546	2,462	2,412
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00
KP rk Wald F-value	172.7	156.1	154

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test. The results of the first stage are available upon request from the authors. 'TR' is the ratio of tax revenue (including resource-related tax revenues). 'RT' refers to the ratio of resource tax revenues.
Source: Authors' own elaboration from collected data.

Table A2.7 Alternative instruments for mobile money adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1st-stage	2nd-stage	1st-stage	2nd-stage	1st-stage	2nd-stage	1st-stage	2nd-stage	1st-stage	2nd-stage
	MM	NRTAX (% GDP)	MM	NRTAX (% GDP)	MM	NRTAX (% GDP)	MM	NRTAX (% GDP)	MM	NRTAX (% GDP)
MM inst. (i)	1.217***		0.386***		0.441***		0.052***		0.055***	
	(0.088)		(0.032)		(0.038)		(0.006)		(0.007)	
MM		4.330***		4.264***		4.976***		4.341***		4.212***
		(0.629)		(0.724)		(0.805)		(0.964)		(0.896)
GDP per capita	-0.224***	1.957***	-0.237***	1.940***	-0.218***	2.666***	-0.299***	2.475***	-0.304***	2.412***
	(0.034)	(0.435)	(0.032)	(0.433)	(0.035)	(0.472)	(0.039)	(0.451)	(0.038)	(0.435)
NRA	-0.013	-0.138*	-0.006	-0.144**	-0.003	-0.211**	-0.004	-0.217**	-0.005	-0.195**
	(0.009)	(0.077)	(0.009)	(0.072)	(0.009)	(0.087)	(0.009)	(0.086)	(0.008)	(0.085)
Trade	-0.000	0.012***	-0.000	0.013***	0.000	0.012**	-0.000	0.012**	-0.000	0.011**
	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)	(0.005)	(0.000)	(0.005)	(0.000)	(0.005)
Agriculture	-0.000	-0.077***	-0.001	-0.075***	-0.002**	-0.081***	-0.002*	-0.083***	-0.002*	-0.085***
	(0.001)	(0.014)	(0.001)	(0.015)	(0.001)	(0.015)	(0.001)	(0.015)	(0.001)	(0.015)
Urban population	0.009***	0.096***	0.010***	0.101***	0.006***	0.070***	0.010***	0.078***	0.009***	0.080***
	(0.002)	(0.020)	(0.002)	(0.020)	(0.002)	(0.023)	(0.002)	(0.024)	(0.002)	(0.024)
Political regime	0.000	0.041**	0.000	0.036**	0.005***	0.020	0.005**	0.022	0.005**	0.023
	(0.002)	(0.017)	(0.002)	(0.017)	(0.002)	(0.019)	(0.002)	(0.018)	(0.002)	(0.018)
Observations	2,480	2,480	2,546	2546	2,291	2,291	2,291	2,291	2,292	2,292
R-squared	0.713		0.710		0.715		0.699		0.700	
Countries	97		97		88		88		88	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM (p-value)		0.00		0.00		0.00		0.00		0.00
KP rk Wald F-value		190.8		141.7		132.9		66.84		71.30

Note: Robust standard errors in parentheses. (***, **, *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test. Mobile money adoption instruments: three-year moving average of the spatial lag variable of mobile money adoption on neighbouring countries using geographical distance weight matrix in column (1); the spatial lag variable of mobile money adoption using 4-nearest neighbouring weight matrix in column (3); the average proportion of neighbouring MM countries in column (5); the number of neighbouring MM countries in column (7); and the lag value of the number of neighbouring MM countries in column (9).
Source: Authors' own elaboration from collected data.

Table A2.8 Sub-sample analyses

	(1)	(2)	(3)
	NRTAX (% GDP)		
	Excl. top-account countries	LICs	Non-LICs
MM	4.789***	1.941***	1.272***
	(0.697)	(0.321)	(0.407)
GDP per capita	2.055***	3.251***	-0.265
	(0.448)	(0.624)	(0.424)
NRA	-0.138*	-0.468***	-0.034
	(0.074)	(0.105)	(0.093)
Trade	0.013***	0.010	0.005
	(0.004)	(0.007)	(0.005)
Agriculture	-0.059***	-0.036**	-0.103***
	(0.015)	(0.015)	(0.035)
Urban population	0.107***	0.073**	0.085***
	(0.020)	(0.030)	(0.023)
Political regime	0.028	0.049***	-0.026
	(0.019)	(0.018)	(0.024)
Observations	2,375	974	1,568
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
KP rk LM (p-value)	0.00	0.00	0.00
KP rk Wald F-value	161.4	732.4	605.2

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. ‘KP rk LM (p-value)’ is the associated p-value of the Kleibergen-Paap under-identification test. ‘KP rk Wald F-value’ reports the Kleibergen-Paap Wald F statistic for the weak identification test.
Source: Authors’ own elaboration from collected data.

Table A2.9 Alternative measures of mobile money and estimation method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IV-2SLS				SYS-GMM		
	1st-stage	2nd-stage	1st-stage	2nd-stage			
	LogMMAc	NRTAX (% GDP)	LogMMT	NRTAX (% GDP)	NRTAX (% GDP)		
LogSMS	0.447***		0.569***				
	(0.098)		(0.134)				
NRTAX $_{t-1}$					0.835***	0.793***	0.808***
					(0.033)	(0.074)	(0.077)
MM					0.303**		
					(0.135)		
LogMMAc		0.745***				0.287**	
		(0.258)				(0.123)	
LogMMT				0.773***			0.185**
				(0.246)			(0.079)
Observations	249	249	255	255	2,490	268	270
R-squared	0.681		0.796				
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP rk LM (p-value)		0.00		0.00			
KP rk Wald F-value		20.65		18.05			
Countries	43	43	45	45	97	41	41
AR (2) test					0.138	0.518	0.487
Hansen test					0.351	0.459	0.566
Instruments					68	35	35

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels. Unreported constant included. 'KP rk LM (p-value)' is the associated p-value of the Kleibergen-Paap under-identification test. 'KP rk Wald F-value' reports the Kleibergen-Paap Wald F statistic for the weak identification test. AR (2) reports *p*-values for the null hypothesis that the errors in the first difference regression exhibit no second-order serial correlation. Hansen test reports p-values for the null hypothesis that the instruments.
Source: Authors' own elaboration from collected data.

Appendix 3 Endogenous switching regression model

The decision to adopt mobile money services can be viewed as a standard binary choice problem based on maximising an underlying utility function. Let M^* denote the difference between the expected benefits of adoption (B_{iA}) and non-adoption (B_{iN}) of mobile money services, such that a country *i* decides to adopt mobile money services if $M^* = B_{iA} - B_{iN} > 0$. MM^* cannot be observed, but can be modelled as follows:

$$M_i^* = X_i'\alpha + \mu_i \text{ with } M_i = \begin{cases} 1 & if\ M_1^* > 0 \\ 0 & otherwise \end{cases} \qquad \text{Eq. (3.1)}$$

where M is a binary variable that equals one for country *i* if it adopts MM services and zero otherwise. X is a vector of observed factors (covariates) that influence the decision to adopt MM. α represents a vector of parameters to be estimated, and μ is an error term that captures measurement errors and unobserved factors.

The ESR model consists of two stages. The first stage is a selection equation for adopting mobile money services, as Eq. (3.1) shows. In the second stage, two regime equations for the adoption and non-adoption of mobile money services can be specified for the outcome of interest. The model is outlined as follows:

$$Regime\ 1{:} \quad Y_{1i} = Z_i'\beta_1 + \eta_{1i} \quad if \quad M_i = 1 \qquad \text{Eq. (3.2a)}$$

$$Regime\ 2{:} \quad Y_{2i} = Z_i'\beta_2 + \eta_{2i} \quad if \quad M_i = 0 \qquad \text{Eq. (3.2b)}$$

where Y_i is the outcome of interest (i.e., non-resource tax revenue) for MM countries (regime 1) and non-MM countries (regime 2). The vector Z_i' consists of exogenous variables that may influence tax revenue (as in Eq. (1)). A trivariate normal distribution with zero mean and constant variance is assumed for the three error terms μ_i, η_{1i} and η_{2i}. While the variables in the X_i' and Z_i' vectors may overlap, proper identification requires at least one variable in the X_i' vector that does not appear not in the Z_i' vector. Therefore, the selection Eq. (3.1) is estimated based on all explanatory variables outlined in the outcome equations (as in Eq. (1)) plus one instrument. Mobile money adoption is instrumented as in subsection 3.3.2. Specifications (3.2a) and (3.2b) consider observable factors (via the Z_i' vector) to reduce selection bias. However, unobservable factors may still lead to a correlation between the error terms in the selection and outcome equations (i.e., corr $(\mu_i, \eta_i) \neq 0$). The ESR model addresses selection bias due to unobservable factors (which may bias the estimation of parameters β_1 et β_2) by predicting the inverse Mills ratios λ_{1i} et λ_{2i} for MM service adoption and non-adoption, respectively, from Eq. (3.1), and including them in the corresponding outcome equations:

$$Regime\ 1: \quad Y_{1i} = Z_i'\beta_1 + \lambda_{1i}\delta_1 + \eta_{1i} \quad if \quad M_i = 1$$
Eq. (3.3a)

$$Regime\ 2: \quad Y_{2i} = Z_i'\beta_2 + \lambda_{2i}\delta_2 + \eta_{2i} \quad if \quad M_i = 0$$
Eq. (3.3b)

where δ_1 and δ_2 are the parameters of the inverse Mills ratios. Following Lokskin and Sajaia (2004), we use the full information maximum likelihood (FIML) to estimate the selection and outcomes equations simultaneously. The coefficients derived from the ESR model can then be used to compute two outcomes. For a country that has introduced the MM service, the (observed) expected value of tax revenue is given by:

$$E(Y_{1i}|M_i = 1) = Z_i'\beta_1 + \lambda_{1i}\delta_1$$
Eq. (3.4a)

In the counterfactual scenario, the (unobserved) expected value of tax revenue is given by:

$$E(Y_{2i}|M_i = 1) = Z_i'\beta_2 + \lambda_{1i}\delta_2$$
Eq. (3.4b)

Thus, the unbiased average treatment effects (ATT) on treated is:

$$ATT = E(Y_{1i}|M_i = 1) - E(Y_{2i}|M_i = 1) = Z_i'(\beta_1 - \beta_2) + \lambda_{1i}(\delta_1 - \delta_2)$$
Eq. (3.5)

The results of the ESR model for the full sample are presented in Table A13. Column (1) reports the estimated coefficients and standard errors of the selection equation, while the outcome equations are presented in columns (2) and (3). From the selection equation, we find that countries with a high GDP per capita or a larger agricultural sector are less likely to adopt mobile money services. The political regime (i.e., democracy) positively affects the probability of mobile money adoption. The estimates in columns (2) and (3) show that some variables, such as trade openness, political regime, agriculture and urbanisation, have the same signs in both outcome equations: positive for the first two variables and negative for the others. The results also reveal that GDP per capita (resp. resource abundance) did not significantly influence tax revenues in non-MM countries (resp. MM countries).

The signs and significance of the estimated covariance between the error term in the selection equation and the error terms in the outcome equations (ρ_1 and ρ_2, respectively) have economic interpretations, as emphasised by Abdulai and Huffman 2014; Lokshin and Sajaia 2004. First, ρ_1 and ρ_2 are statistically significant, indicating the presence of selection bias. This confirms that both observable and unobservable factors influence the countries' decisions to adopt mobile money services, and the outcomes. Second, since ρ_1 and ρ_2 are negative, there is what Fuglie and Bosch (1995) call 'hierarchical sorting' so that countries in regime 1 (MM adoption) have above-average tax revenues in both regimes but are better off in regime 1. Those in regime 2 have below-average tax revenues but are better off in regime 1.

Table A3 Estimation results of ESR for the selections and outcome equations

	(1)	(2)	(3)
		NRTAX (% GDP)	
	Selection equation	MM countries	Non-MM countries
GDP per capita	-0.532***	1.293**	0.430
	(0.093)	(0.595)	(0.276)
NRA	-0.024	0.133	-0.385***
	(0.026)	(0.195)	(0.071)
Trade	-0.001	0.031***	0.018***
	(0.001)	(0.009)	(0.003)
Agriculture	-0.028***	-0.235***	-0.226***
	(0.006)	(0.041)	(0.020)
Urban population	0.004	-0.125***	-0.058***
	(0.004)	(0.020)	(0.010)
Political regime	0.035***	0.263***	0.257***
	(0.008)	(0.053)	(0.023)
MM inst.	6.196***		
	(0.234)		
$\ln\sigma_1$		1.652***	
		(0.009)	
ρ_1		-0.168**	
		(0.071)	
$\ln\sigma_2$			1.628***
			(0.005)
ρ_2			-0.159**
			(0.077)
Wald test of independent equations	9.856***		
Log-likelihood	-8,384.24		

Note: Robust standard errors in parentheses. (***, **, and *) indicate significance at 1, 5 and 10 per cent levels.
Source: Authors' own elaboration from collected data.

References

Abdih, M.Y.; Barajas, M.A.; Chami, M.R. and Ebeke, M.C. (2012) *Remittances Channel and Fiscal Impact in the Middle East, North Africa, and Central Asia*, International Monetary Fund

Abdulai, A. and Huffman, W. (2014) 'The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application', *Land Economics* 90.1: 26–43

Adams Jr, R.H. and Cuecuecha, A. (2013) 'The Impact of Remittances on Investment and Poverty in Ghana', *World Development 50*, 24–40

Ahmad, A.H.; Green, C. and Jiang, F. (2020) 'Mobile Money, Financial Inclusion and Development: A Review with Reference to African Experience', *Journal of Economic Surveys* 34.4: 753–792

Alesina, A. and Wacziarg, R. (1998) 'Openness, Country Size and Government', *Journal of Public Economics* 69.3: 305–321

Angelopoulos, K.; Economides, G. and Kammas, P. (2012) 'Does Cabinet Ideology Matter for the Structure of Tax Policies?', *European Journal of Political Economy* 28.4: 620–635

Anselin, L. (2022) 'Spatial Econometrics', in S.J. Rey and R.S. Franklin (eds.), *Handbook of Spatial Analysis in the Social Sciences*, Edward Elgar Publishing: 101–122

Anselin, L. (2003) *GeoDa 0.9 User's Guide*, Spatial Analysis Laboratory (SAL), Department of Agricultural and Consumer Economics, University of Illinois, Urbana-Champaign, IL

Apeti, A.E. (2023) 'Household Welfare in the Digital Age: Assessing the Effect of Mobile Money on Household Consumption Volatility in Developing Countries', *World Development* 161(C): 106110

Apeti, A.E. and Edoh, E.D. (2023) 'Tax Revenue and Mobile Money in Developing Countries', *Journal of Development Economics* 161: 103014

Apiors, E.K. and Suzuki, A. (2018) 'Mobile Money, Individuals' Payments, Remittances, and Investments: Evidence from the Ashanti Region, Ghana', *Sustainability* 10.5, Article 5

Aron, J. (2018) 'Mobile Money and the Economy: A Review of the Evidence', *The World Bank Research Observer* 33.2 : 135–188

Asatryan, Z.; Bittschi, B. and Doerrenberg, P. (2017) ‘Remittances and Public Finances: Evidence from Oil-price Shocks’, *Journal of Public Economics* 155: 122–137

Avom, D.; Bangaké, C. and Ndoya, H. (2023) ‘Do Financial Innovations Improve Financial Inclusion? Evidence from Mobile Money Adoption in Africa’, *Technological Forecasting and Social Change* 190*:* 122451

Barasa, L. (2021) *Mobile Money Payment: An Antidote to Petty Corruption?* Research Paper 453, African Economic Research Consortium

Baron, R.M. and Kenny, D.A. (1986) ‘The Moderator–mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations’, *Journal of Personality and Social Psychology* 51.6: 1173–1182

Baum, M.A.; Gupta, M.S.; Kimani, E. and Tapsoba, M.S.J. (2017) ‘Corruption, Taxes and Compliance’, *eJournal of Tax Research* 15.2: 190–216

Baunsgaard, T. and Keen, M. (2010) ‘Tax Revenue and (or?) Trade Liberalization’, *Journal of Public Economics* 94.9: 563–577

Beck, T.; Pamuk, H.; Ramrattan, R. and Uras, B.R. (2018) ‘Payment Instruments, Finance and Development’, *Journal of Development Economics* 133: 162–186

Besley, T. and Persson, T. (2014) ‘Why Do Developing Countries Tax So Little?’, *Journal of Economic Perspectives* 28.4: 99–120

Bird, R.M.; Martinez-Vazquez, J. and Torgler, B. (2008) ‘Tax Effort in Developing Countries and High Income Countries: The Impact of Corruption, Voice and Accountability’, *Economic Analysis and Policy* 38.1: 55–71

Blimpo, M.; Mensah, J.T.; Opalo, K.O. and Shi, R. (2018) Electricity Provision and Tax Mobilization in Africa, *World Bank Policy Research Working Paper* 8408

Blundell, R. and Bond, S. (1998) ‘Initial Conditions and Moment Restrictions in Dynamic Panel Data Models’, *Journal of Econometrics* 87.1: 115–143

Camara, A. (2023) ‘The Effect of Foreign Direct Investment on Tax Revenue’, *Comparative Economic Studies* 65.1: 168–190

Canan, C.; Lesko, C. and Lau, B. (2017) ‘Instrumental Variable Analyses and Selection Bias’, *Epidemiology* 28.3: 396

Caselli, F. and Reynaud, J. (2020) ‘Do Fiscal Rules Cause Better Fiscal Balances? A New Instrumental Variable Strategy’, *European Journal of Political Economy* 63: 101873

Castañeda Rodríguez, V.M. (2018) 'Tax Determinants Revisited. An Unbalanced Data Panel Analysis', *Journal of Applied Economics* 21.1: 1–24

Comin, D.A.; Dmitriev, M. and Rossi-Hansberg, E. (2012) *The Spatial Diffusion of Technology*, Working Paper 18534, National Bureau of Economic Research

Conley, T.G. and Udry, C.R. (2010) 'Learning about a New Technology: Pineapple in Ghana', *American Economic Review* 100.1: 35–69

Conte, M.; Cotterlaz, P. and Mayer, T. (2022) *The CEPII Gravity Database*, Working Papers 2022-05, CEPII Research Center

Coppedge, M. *et al*. (2023) 'V-Dem [Country-Year/Country-Date] Dataset v13', Varieties of Democracy (V-Dem) Project

Crivelli, E. and Gupta, S. (2014) 'Resource Blessing, Revenue Curse? Domestic Revenue Effort in Resource-rich Countries', *European Journal of Political Economy* 35: 88–101

Ebeke, C.H. (2014) 'Do International Remittances Affect the Level and the Volatility of Government Tax Revenues?', *Journal of International Development* 26.7: 1039–1053

Elgin, C. and Uras, B.R. (2013) 'Public Debt, Sovereign Default Risk and Shadow Economy', *Journal of Financial Stability* 9.4: 628–640

Elgin, C.; Kose, M.A.; Ohnsorge, F. and Yu, S. (2021) *Understanding Informality*, SSRN Scholarly Paper 3916568

Epaphra, M. and Massawe, J. (2017) 'Corruption, Governance and Tax Revenues in Africa', *Business and Economic Horizons* 13.4: 439–467

Ertefaie, A.; Small, D.; Flory, J. and Hennessy, S. (2016) 'Selection Bias When Using Instrumental Variable Methods to Compare Two Treatments But More Than Two Treatments Are Available', *The International Journal of Biostatistics* 12.1: 219–232

Frydrych, F.; Scharwatt, C. and Vonthron, N. (2015) *Paying School Fees with Mobile Money in Côte d'Ivoire: A Public-Private Partnership to Achieve Greater Efficiency*, GSM Association

Fuglie, K.O. and Bosch, D.J. (1995) 'Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis', *American Journal of Agricultural Economics* 77.4: 891–900

Gnangnon, S.K. (2022) 'Internet, Participation in International Trade, and Tax Revenue Instability', *Journal of Economic Integration* 37.2: 267–315

Gnangnon, S.K. (2017) 'Impact of Foreign Direct Investment (FDI) Inflows on Non-resource Tax and Corporate Tax Revenue', *Economics Bulletin* 37.4: 2890–2904

Gnangnon, S.K. and Brun, J.-F. (2019) 'Internet and the Structure of Public Revenue: Resource Revenue Versus Non-resource Revenue', *Journal of Economic Structures* 8.1: 1

Gnangnon, S.K. and Brun, J.-F. (2018) 'Impact of Bridging the Internet Gap on Public Revenue Mobilization', *Information Economics and Policy* 43: 23–33

Goel, R.K. and Nelson, M.A. (2016) 'Shining a Light on the Shadows: Identifying Robust Determinants of the Shadow Economy', *Economic Modelling* 58: 351–364

GSMA (2017a) *State of the Industry Report on Mobile Money, Decade Edition: 2006–2016*, GSM Association

GSMA (2017b) *Person-to-Government (P2G) Payment Digitalisation: Lessons from Kenya*, GSM Association

Gupta A.S. (2007) *Determinants of Tax Revenue Efforts in Developing Countries*, IMF Working Paper WP/07/184

Gupta, A.S.; Clements, B.; Pivovarsky, A. and Tiongson, E. (2004) 'Foreign Aid and Revenue Response: Does the Composition of Aid Matter?', in S. Gupta; B. Clements and G. Inchauste (eds.), *Helping Countries Develop: The Role of Fiscal Policy*, Washington: International Monetary Fund

Hjort, J. and Poulsen, J. (2019) 'The Arrival of Fast Internet and Employment in Africa', *American Economic Review* 109.3: 1032–1079

Imai, K.; Keele, L. and Tingley, D. (2010) 'A General Approach to Causal Mediation Analysis', *Psychological Methods* 15.4: 309–334

Islam, A.; Muzi, S. and Rodriguez Meza, J.L. (2018) 'Does Mobile Money Use Increase Firm's Investment? Evidence from Enterprise Surveys in Kenya, Uganda, and Tanzania', *Small Business Economics* 51: 687–708

Jack, W. and Suri, T. (2014) 'Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution', *American Economic Review* 104.1: 183–223

Jack, W.; Ray, A. and Suri, T. (2013) 'Transaction Networks: Evidence from Mobile Money in Kenya', *American Economic Review* 103.3: 356–361

Jacolin, L.; Keneck Massil, J. and Noah, A. (2021) 'Informal Sector and Mobile Financial Services in Emerging and Developing Countries: Does Financial Innovation Matter?', *The World Economy* 44.9: 2703–2737

Kanyam, D.A.; Kostandini, G. and Ferreira, S. (2017) 'The Mobile Phone Revolution: Have Mobile Phones and the Internet Reduced Corruption in Sub-Saharan Africa?', *World Development* 99: 271–284

Krishnan, P. and Patnam, M. (2014) 'Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?', *American Journal of Agricultural Economics* 96.1: 308–327

Lokshin, M. and Sajaia, Z. (2004) 'Maximum Likelihood Estimation of Endogenous Switching Regression Models', *The Stata Journal* 4.3: 282–289

Mahdavi, S. (2008) 'The Level and Composition of Tax Revenue in Developing Countries: Evidence from Unbalanced Panel Data', *International Review of Economics & Finance* 17.4: 607–617

Mascagni, G. (2016) 'Aid and Taxation in Ethiopia', *The Journal of Development Studies* 52.12: 1744–1758

Mascagni, G.; Dom, R.; Santoro, F. and Mukama, D. (2023) 'The VAT in Practice: Equity, Enforcement, and Complexity', *International Tax and Public Finance* 30.2: 525–563

Mascagni, G.; Mengistu, A.T. and Woldeyes, F. B. (2021) 'Can ICTs Increase Tax Compliance? Evidence on Taxpayer Responses to Technological Innovation in Ethiopia', *Journal of Economic Behavior & Organization* 189: 172–193

Masi, T.; Savoia, A. and Sen, K. (2024) 'Is there a Fiscal Resource Curse? Resource Rents, Fiscal Capacity and Political Institutions in Developing Economies', *World Development* 177: 106532

Mayer, T. and Zignago, S. (2011) *Notes on CEPII's Distances Measures: The GeoDist Database*, SSRN Scholarly Paper 1994531

Mehlum, H.; Moene, K. and Torvik, R. (2006) 'Institutions and the Resource Curse', *The Economic Journal* 116.508: 1–20

Moller, L.C. and Wacker, K.M. (2017) 'Explaining Ethiopia's Growth Acceleration – The Role of Infrastructure and Macroeconomic Policy', *World Development* 96: 198–215

Moore, M., and Prichard, W. (2020) 'How Can Governments of Low-Income Countries Collect More Tax Revenue?', in K. Hujo (ed.), *The Politics of Domestic*

Resource Mobilization for Social Development, Springer International Publishing: 109–138

Munyegera, G.K. and Matsumoto, T. (2016) ‘Mobile Money, Remittances, and Household Welfare: Panel Evidence from Rural Uganda’, *World Development* 79: 127–137

Naito, H.; Ismailov, A. and Kimaro, A.B. (2021) ‘The Effect of Mobile Money on Borrowing and Saving: Evidence from Tanzania’, *World Development Perspectives* 23: 100342

Nan, W. (Vince); Zhu, X. (Christina) and Lynne Markus, M. (2021) ‘What We Know and Don’t Know about the Socioeconomic Impacts of Mobile Money in Sub-Saharan Africa: A Systematic Literature Review’, *The Electronic Journal of Information Systems in Developing Countries* 87.2: e12155

Okunogbe, O. and Santoro, F. (2023) ‘Increasing Tax Collection in African Countries: The Role of Information Technology’, *Journal of African Economies*, 32.Supplement_1: i57–i83

Pulkki-Brännström, A.-M. and Stoneman, P. (2013) ‘On the Patterns and Determinants of the Global Diffusion of New Technologies’, *Research Policy* 42.10: 1768–1779

Riley, E. (2018) ‘Mobile Money and Risk Sharing Against Village Shocks’, *Journal of Development Economics* 135: 43–58

Scartascini, C.; Cruz, C. and Keefer, P. (2021) *The Database of Political Institutions 2020 (DPI2020)*, IDB Publications

Schneider, F.; Buehn, A. and Montenegro, C.E. (2011) ‘Shadow Economies All Over the World: New Estimates for 162 Countries from 1999 to 2007’, in F. Schneider (ed.), *Handbook on the Shadow Economy*, Edward Elgar Publishing

Setor, T.K.; Senyo, P.K. and Addo, A. (2021) ‘Do Digital Payment Transactions Reduce Corruption? Evidence from Developing Countries’, *Telematics and Informatics* 60: 101577

Suri, T. and Jack, W. (2016) ‘The Long-run Poverty and Gender Impacts of Mobile Money’, *Science* 354.6317: 1288–1292

Syed, A.A.; Ahmed, F.; Kamal, M.A. and Trinidad Segovia, J.E. (2021) ‘Assessing the Role of Digital Finance on Shadow Economy and Financial Instability: An Empirical Analysis of Selected South Asian Countries’, *Mathematics* 9.23, Article 23

Thornton, J. (2014) ‘Does Foreign Aid Reduce Tax Revenue? Further Evidence’, *Applied Economics* 46.4: 359–373

Torgler, B. and Schaltegger, C.A. (2005) *Tax Morale and Fiscal Policy*, Working Paper 2005–30, CREMA Working Paper

Torvik, R. (2002) ‘Natural Resources, Rent Seeking and Welfare’, *Journal of Development Economics* 67.2: 455–470

VanderWeele, T. (2015) *Explanation in Causal Inference: Methods for Mediation and Interaction,* Oxford University Press

Verkaart, S.; Munyua, B.G.; Mausch, K. and Michler, J. D. (2017) ‘Welfare Impacts of Improved Chickpea Adoption: A Pathway for Rural Development in Ethiopia?’, *Food Policy* 66: 50–61

Wandaogo, A.-A.; Sawadogo, F. and Lastunen, J. (2022) *Does the Adoption of Peer-to-government Mobile Payments Improve Tax Revenue Mobilization in Developing Countries?* Working Paper 2022/18, WIDER Working Paper

Zellner, A. and Huang, D.S. (1962) ‘Further Properties of Efficient Estimators for Seemingly Unrelated Regression Equations’, *International Economic Review* 3.3: 300–313

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