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Informal Sector and Mobile Financial Services in Developing Countries: Does Financial Innovation Matter?

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Abstract

This paper investigates the impact of mobile financial services - MFS (mobile money, and mobile credit and savings) on the informal sector. Using both parametric and non-parametric methods on panel data from 101 emerging and developing countries over the period 2000-15, we find that MFS negatively affect the size of the informal sector. According to estimates derived from propensity score matching, MFS adoption decreases the informal sector size in a range of 2.4 – 4.3 percentage points of GDP. These formalization effects may stem from different possible transmission channels: improvement in credit access, increase in the productivity/profitability of informal firms attenuating subsistence constraints typical of entrepreneurship in the informal sector, as well as possible induced growth of firms already in the formal sector. The robustness of these results is supported by the use of an alternative estimation approach (instrumental variables). These findings lay the groundwork for the scarce literature on the macroeconomic impact of mobile financial services, a major dimension of the growing drive towards economic digitalization.

Keywords: Mobile financial services, Mobile money, Financial innovation, Digitalization, Informal sector, Developing countries

JEL classification: C26, E26, O33, G29, L96

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NON-TECHNICAL SUMMARY

The informal sector (at around 35% of GDP) remains an important challenge for emerging and developing (EMDCs) insofar as it may introduce significant microeconomic distortions, (competition, sectoral capital allocation, etc.), and macroeconomic losses in efficiency (lower productivity of labor and capital, disincentive to innovate and to scale up, increase in income inequality and poverty). A larger share of the informal sector is also associated with insufficient domestic resource mobilization and public spending to finance access to basic services (health, education), which are essential to reach sustainable development goals, or investment, notably in infrastructure, to facilitate economic diversification and integration in global value chains.

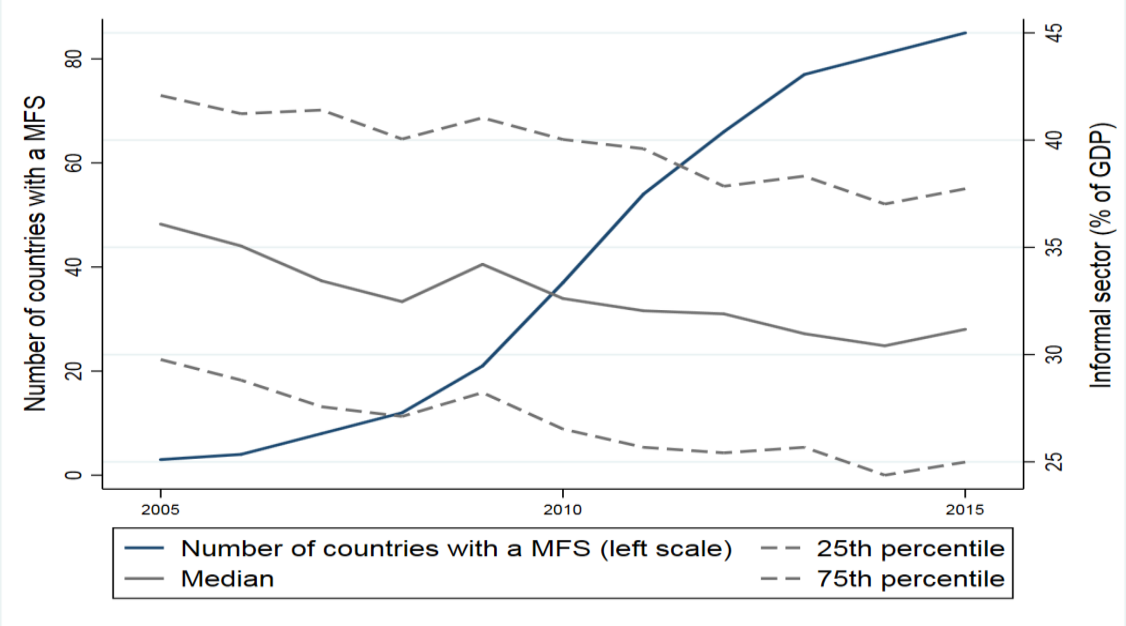
The choice to conduct economic activities in the informal sector is driven by a wide set of economic, financial and institutional motives. The first one may be a desire to avoid tax and social contributions. Low financial development and in particular poor access to credit may also favor remaining in the informal sector. International opportunities, such as openness to political, social and economic globalization, as well as regulatory and institutional quality may also affect the appetite for informal vs formal activities. Finally, the relative attractiveness of the informal sector vs the formal sector may depend on the business cycle itself, as the informal sector provides alternative income during times of economic downturns and high unemployment.

In parallel, mobile financial services (MFS) have been spreading rapidly in developing countries (see Figure below) with large informal financial sectors and low formal financial deepening and inclusion. As documented in the literature, these countries are characterized by a strong preference for cash transactions over other means of payment, low access to formal financial services for large segments of their populations and recourse to informal credit (and savings) to finance consumption and investment project instead of credit by formal banks and insurance. This very environment may have facilitated the rise of financial innovation in developing countries since the rise of Safaricom's M-Pesa in Kenya in 2007, with significant associated leapfrogging effects. Another noteworthy development has been the trend towards diversification of financial services offered by a growing array of providers (telecom operators, Fintech startups, banks themselves). From its initial focus on transactions as a means of payment, i.e. mobile money, MFS are increasingly offering credit services, and more recently, insurance services.

In our view, assessing the impact of mobile financial services on the informal economy therefore represents a research question of growing and significant interest, one that has received little attention so far. Our research goal is to determine the net effect of MFS adoption on the overall size of the informal sector and analyze some of its transmission channels.

To assess the net impact of mobile financial services on the informal sector, we draw on a panel data from 101 developing countries over the period 2000-15. Previous studies on the shadow economy have been plagued by complex national accounting measurement issues. However, our study use the recent IMF estimates (based on the night lights approach), which has the advantage of providing new insights on the relative size of the informal sector. We find that mobile financial services negatively affect the share of the shadow economy in economic activities. Based on non-parametric approach (propensity score matching), we show that MFS adoption significantly decreases the informal sector relative size in range of 2.4 – 4.3 % percentage points of GDP over the period of our study. Formalization effects may stem from different possible transmission channels: improvement in credit access, increase in the productivity/profitability of informal firms attenuating subsistence constraints typical of entrepreneurship in the informal sector, as well as possible induced growth of firms already in the formal sector. The robustness of these results is also supported by the use of an alternative estimation approach (instrumental variables). On balance, our findings lay the groundwork for the scarce literature on the macroeconomic impact of mobile financial services, a major dimension of the growing drive towards digitalization.

Informal sector distribution and mobile financial services (MFS) adoption in EMDCs



Mobile Financial Services (MFS) refer to the use of a mobile phone to access financial services like credit and savings, in addition to mobile money. EMDCs = Emerging and developing countries.
Sources: Informal sector (% of GDP) from Medina and Schneider (IMF, 2018), GSMA's Mobile money deployment tracker database and authors' calculations.

Secteur Informel et Développement des Services Financiers Mobiles : Quel est l'Impact de l'Innovation Financière?

RÉSUMÉ

Cet article étudie l'impact des services financiers mobiles – SFM (moyen de paiements, crédit et épargne mobiles) sur le secteur informel. À partir d'un échantillon de 101 pays émergents et en développement sur la période de 2000-15, nous mettons en évidence l'existence d'une relation négative entre la diffusion de SFM et la part du secteur informel à l'aide d'approches paramétrique et non-paramétrique. L'approche d'appariement par les scores de propension relève une diminution de l'ordre de 2,4 à 4,3 points de pourcentage du secteur informel à la suite du lancement des SFM. Ces résultats découleraient à la fois des gains de productivité/rentabilité des firmes, d'un meilleur accès au crédit induits par l'utilisation des SFM et d'une croissance plus rapide du secteur formel, ces effets magnifiant le processus tendanciel de « formalisation » des économies. Nos résultats demeurent robustes à l'utilisation d'un estimateur alternatif (variables instrumentales). De manière générale, notre étude jette les bases d'une littérature, encore peu développée, sur l'impact macroéconomique des services financiers mobiles, une dimension majeure du mouvement croissant vers la numérisation ou « digitalisation » des échanges économiques.

Mots-clés : services financiers mobiles, innovation financière, digitalisation, secteur informel, pays en développement

Introduction

The informal economy (at around 35 % of GDP)[1] is often seen as an obstacle to development in emerging developing countries (EMDCs) insofar as it may introduce significant microeconomic distortions, (competition, sectoral capital allocation, etc.), and macroeconomic losses in efficiency (lower productivity of labor and capital, disincentive to innovate and to scale up, increase in income inequality and poverty). A larger share of the informal sector is also associated with insufficient domestic resource mobilization and public spending to finance access to basic services (health, education), which are essential to reach sustainable development goals, or investment, notably in infrastructure, to facilitate economic diversification and integration in global value chains.

Given the diversity of informal activities, the formalization process associated with economic growth is multifaceted and the efficiency of corrective policies to promote the formal sector a matter of debate (La Porta and Shleifer, 2014). One of the significant dilemma faced by policy makers is that the informal economy has also been shown to generate a significant source of income and economic inclusion to vulnerable segments of the population (women, ethnic minorities, migrants and refugees, poor). Public action is also hindered by poor quality data and studies on this topic have so far been plagued by complex national accounting measurement issues. However, the use of satellite data (night lights method) may provide new insights on the size of the informal sector (Henderson et al., 2012; Medina and Schneider, 2018).

In parallel, mobile financial services (MFS)[2] have been spreading rapidly in developing countries with large informal financial sectors and low formal financial deepening and inclusion. As documented by Guerineau and Jacolin (2014), these countries are characterized by a strong preference for cash transactions over other means of payment, low access to financial services for large segments of their populations and recourse to informal credit (and self-insurance) to finance consumption and investment project instead of credit by formal banks and insurance. Ironically, this environment may have facilitated the rise of financial innovation in developing countries since the rise of Safaricom's M-Pesa in Kenya in 2007, with significant associated leapfrogging effects. In these countries, MFS represent a rapid and cost-effective option to modernize financial

[1] Buehn and Schneider (2012) define the informal sector as all market-based legal production of good and services that escape inclusion in official account, taking aside illicit activities. It is expressed as a share of overall GDP. As discussed in Dell'anno (2016), based on this definition, the terms "*informal, shadow, underground, hidden, unofficial*" are often used synonymously and associated with terms such as economy, sectors, market or GDP or size.

[2] Mobile Financial Services (MFS) refer to the use of a mobile phone to access financial services like credit and savings, in addition to mobile money (GSMA, 2018).

transactions, for instance: ecommerce, direct wage payments to mobile accounts by employers, digitalization of payments among firms, social benefits by public authorities, and tax payments to tax administrations (Aron, 2018).

Another noteworthy development has been the trend towards diversification of financial services offered by a growing array of providers (telecom operators, Fintech startups, banks themselves). From its initial focus on transactions as a means of payment, i.e. mobile money, MFS are increasingly offering credit services, and more recently, insurance services. Financial digitalization is but one form of a towards economic digitalization, a fast-growing and multifaceted economic transformation driven by large network effects that affects both the business models of banks, telecom operators and other financial intermediaries and their relationship with the real sector of the economy.

In our view, assessing the impact of mobile financial services on the informal economy therefore represents a research question of growing and significant interest, one that has received little attention so far. Our research goal is to determine the net effect of MFS adoption on the overall size of the informal sector and analyze some of its transmission channels.

The choice to conduct economic activities in the informal sector is driven by a wide set of economic, financial and institutional motives. The first one may be a desire to avoid tax and social contributions (e.g. Djankov et al., 2010; Goel and Nelson, 2016; Mitra, 2017). Low financial development and in particular poor access to credit may also favor remaining in the informal sector (e.g. Blackburn et al., 2012; Bose et al., 2012; Berdiev and Saunoris, 2016). The attractiveness of the shadow economy may also be affected by the business cycle and the opportunities it creates in the formal sector (Schneider and Enste, 2000). International constraints, such as openness to political, social and economic globalization (e.g. Pham, 2017; Berdiev and Saunoris, 2018), as well as regulatory and institutional quality (administrative bureaucracy, corruption or quality of governmental or political institutions) may also drive the appetite for informal activities (e.g. 1998; Dabla-Norris et al., 2008; Dreher et al., 2009; Goel and Saurinos, 2014; Elbahnasawy et al., 2016).

To assess the net impact of mobile financial services on the informal sector, we draw on a panel data from 101 developing countries over the period 2000-15. We find that mobile financial services negatively affect the size of shadow economy. Based on non-parametric approach (propensity score matching), we show that MFS adoption significantly decreases the informal sector size in range of 2.4 – 4.3 % percentage points over the period of our study. Formalization effects may stem from different possible transmission channels: improvement in credit access, increase in the productivity/profitability of informal firms attenuating subsistence constraints typical of entrepreneurship in the informal sector, as well as possible induced growth of firms already in the formal sector.

The robustness of these results is also supported by the use of an alternative estimation approach (instrumental variables).

The remainder of the paper proceeds as follows. Section 2 analyses the transmission channels. Section 3 describes the data. Section 4 details empirical strategy. The empirical results are reported in Section 5, while Section 6 discusses the robustness checks. The final section concludes.

How do mobile financial services impact the shadow economy?

The literature on the economic impact of mobile financial services is scarce and focuses mostly on microeconomic implications. Jack et al. (2013), as well as Jack and Suri (2014), show that mobile money helps Kenyan households to share risks and smooth shocks. Suri and Jack (2016) find that access to mobile money lifted 2% of Kenyan households out of extreme poverty. Islam et al. (2017) highlight a positive effect of firms' mobile money use on firm investment. This impact is related to reduced transactional costs, increased firms' liquidity, and increased ability to establish credit worthiness by using data generated by mobile financial services use. Beck et al. (2018) have also documented theoretical and empirical impacts of MFS (M-Pesa) on firms' productivity. They point out that entrepreneurs are more willing to use MFS as means of payment to better secure their transactions, and better manage cash flows. The usage of mobile money also increases firms' probability of getting trade credit from their suppliers.[3]

Theoretically, the relationship between MFS adoption and the shadow economy could pass through three channels.

The first transmission channel is a reduction the demand for cash. For La Porta and Shleifer (2014), informal firms are unproductive not only because their productivity is low and informal entrepreneurship is associated mostly with subsistence, but also because they use cash as the only means of payment. Therefore, moving from cash to digital payments (MFS as means of payment) promotes productivity/profitability, by reducing operational costs and making commercial transactions more secure, fluid and cheaper, as documented by Klapper (2017), and Beck et al. (2018). These efficiency gains increase the opportunity costs of staying in the small-scale and less productive informal sector.

Second, MFS may also affect the informal sector by improving access to credit, since informal MSMEs (which account for about 80 % of total MSMEs) and self-entrepreneurs

[3] Other studies have also looked at the impact of mobile money on resilience to climate shocks (Riley, 2018), antipoverty programs (Aker et al., 2016), agricultural outcomes (Aker and Ksoll, 2016), remittances (Munyegera and Matsumoto, 2016) or gender equality (Sekabira and Qaim, 2017).

usually report access to finance as the biggest obstacle they encounter (GPFI, 2018). Many digital financial services providers increasingly diversify their activities and combine mobile money and, credit, savings and insurance services to provide a full client relationship, similar to that of traditional banks. In addition, bundling these services with a wide array of non-bank services allows digital financial services providers to create an economic ecosystem, a powerful tool of client base and product use growth. Because it reaches out to previously unbanked populations in the informal sector, MFS encourage entrepreneurship and contribute to the empowerment of individuals or communities.

In so far as they generate large datasets on users (habits, credit history, ect.), MFS also facilitate credit access by reducing information asymmetries and improving transparency. [4] As is underlined in Klapper (2017), data analytics of digital transactions can help financial institutions create a qualifying credit score for MSMEs or self-employed entrepreneurs to start or expand their business in the formal sector.

Third, MFS may indirectly impact the shadow economy through formal sector growth, as the previous transmission mechanisms may also be applied to formal firms and they may be in a position to access MFS first, especially credit services. In particular, the improvement in productivity/profitability of formal firms induced by the use of MFS could be associated with an increase in hiring, thereby reducing the informal sector.

Finally, MFS can help decrease informal activities indirectly through the growth of formal sector, by boosting productivity/profitability, and hence reducing the opportunity benefits of informality. Access to mobile credit/savings can also strengthen the credibility of constrained MSMEs and self-entrepreneurs, helping them overcome the entry cost into the formal sector. In sum, the formalization effect of MFS services could therefore reflect both a transfer of informal firms to the formal sector and the formal sector own growth.

Data description

The purpose of our study is to examine the relationship between the development of MFS and the size of the informal economy in emerging and developing countries.

The informal sector

The definition and estimation of the size of the informal sector remains a source of debate within the economic literature. Several studies have defined and estimated the size of the informal sector, either excluding illicit activities, such as Medina and Schneider

[4] See Aron (2018) for more details.

(2018), Buehn and Schneider (2012), Elgin and Öztunali (2012) or including it (Alm and Embaye, 2013). In this paper, we adopt the former approach both for data availability reasons and a focus on domestic resources allocation, illicit activities being by nature neither authorized nor taxable.

The estimates of the size of the informal economy as a percentage of GDP are collected from Medina and Schneider (2018). These estimates are derived from a Multiple Indicators, Multiple Causes (MIMIC) approach. A particular type of structural equation model (SEM), the MIMIC model uses associations between different observable causes and impacts of an unobservable variable (the shadow economy), to estimate it. Unlike previous estimates that use GDP per capita and growth of GDP per capita as cause and indicator variables, Medina and Schneider (2018) use the "*night lights*" approach by Henderson et al. (2012) to capture economy activity, which relies on satellite data. They consequently provide a satisfactory response to the criticisms linked to the endogeneity problem of GDP associated with previous studies based on national accounting.

Based on these data, our initial sample covered 158 countries. We first excluded advanced economies (as defined by the IMF) given the low proportion the informal activities in these countries (on average less than 15% of GDP) and countries in conflict (Libya, Syria and Yemen). After eliminating countries with no data on control variables, our final sample consists of 101 countries over the period 2000-15, as reported in Table A1 (in appendix). The informal sector is on average equal to 34.2 % of GDP, with significant disparities between regions as shown in the Figure A1 (in appendix).

Mobile financial services (MFS)

Mobile Financial Services (MFS) refer to the use of a mobile phone to access financial services like credit and savings, in addition to mobile money (GSMA, 2018). These services can be accessed independently from access to internet.

A mobile money service denotes transferring money and making payments using mobile phone (GSMA, 2018). According to Aron (2017), page 7: "*the common characteristics of various definitions of mobile money are: it is electronic money issued on receipt of funds in an amount equal to the available monetary value; it is electronically recorded on a mobile device; the electronic value is redeemable for cash, and the electronic value may be accepted as a means of payment by parties other than the issuer (for example, for person-to-person transfers (P2P), retail payments and payment for services; government-to-person (G2P) transfers (and receipts); donor-to-person cash transfers; and business transfers (and receipts); and the electronic value is backed up by storage of equivalent funds in one or more banks depending on central banking or other regulations.*"

Launched in the Philippines in 2001, mobile money became widely known after its successful introduction in Kenya in 2007 (M-Pesa). According to Jack and Suri (2016), mobile money is used by at least one individual in 96% of Kenyan households and M-PESA, leading to a dramatic rise of financial inclusion of both households and MSMEs. By the end of 2015, 251 mobile money services were offered in 93, with Sub-Saharan Africa being the world's most dynamic market[5]. MFS represent 426.5 million registered accounts, associated with over one billion transactions per year and an average of 33 million transactions per day.

Mobile financial services are available in 72 of the 101 countries contained in our sample (see Table A1 in Appendix).[6] In our empirical approach, we measure mobile financial services by a dummy variable which takes the value one from the year the service is launched and zero otherwise. Data are collected from the GSMA's Mobile money deployment tracker database.

Econometric framework

We assume that the relationship between the informal sector size and the adoption of MFS is determined by the following linear equation:

$$Informal_{i,t} = \delta MFS_{i,t} + X'\beta + \mu_i + \epsilon_{i,t} \quad (1)$$

where $Informal_{i,t}$ denotes the size of informal sector (in percentage of GDP) of country i in year t. $MFS_{i,t}$ is the dummy variable taking the value one from the year the service is launched in country i, and zero otherwise. X' is a vector of exogenous variables. μ_i and $\epsilon_{i,t}$ are respectively an unobservable time invariant country specific effect and error term. The description and sources of the variables and summary statistics are reported in Tables A2 and A3.

Control variables

We include in our model the growth of GDP per capita in order to capture the possible impact of economic development on informal sector size. This variable also captures the business cycle (Medina and Schneider, 2018) and the long-term decrease of the informal sector induced by economic development (see Figure A1). We expect a negative relationship between economic activity and the informal sector. Schneider (2005, 2010) shows, for instance, that individuals and firms have a greater incentive to migrate from

[5] 127 services, against 36 in East Asia and Pacific, 9 in Europe and Central Asia, 31 in Latin America and the Caribbean, 16 in Middle East and North Africa, 40 in South Asia (Mobile money metrics, GSMA).

[6] 21 countries are not covered by our study due to the unavailability of data on the informal sector or the control variables used for our empirical strategy.

the informal to formal sector at the top of the business cycle in order to seize business and job opportunities. We therefore expect a negative relationship between economic development and the informal sector.

Since tax evasion represents a major motive to operate in the informal sector, we include a variable capturing government size, measured by the amount of government spending. We find this measure to be an important decision variable decision for firms in developing countries, given the importance of the public sector both as a client and a major employer of the formal sector. Government spending may also provide a more trustworthy and forward looking picture for firms of governments financing needs, hence their anticipated tax burden, than past current tax burden ratios. A broad government with more resources may favour formal firms to ensure transparency and taxability. It could also have a crowding-out effect on private initiative and encourage informal activities (Berdiev and Saunoris, 2018). Its overall impact on the informal sector is therefore unclear.

Total investment is measured by total investment (or gross capital formation) as a proportion of GDP. Larger investment relative to GDP can be interpreted as sign of a dynamic economic. We therefore expect a negative relationship between total investment and the size of informal sector.

We use the new financial development index provided by Svirydzenka (2016) as a measure of financial development. This index has the advantage of taking into account all dimensions of financial development, namely: depth, accessibility (financial inclusion) and efficiency. Some studies show that an improvement in the development of financial sector is associated with a smaller informal sector size (Blackburn et al., 2012; Bose et al., 2012; Capasso and Jappelli, 2013), thanks to enhanced disclosure of information.

Like Moller and Wacker (2017), we measure infrastructure by the ratio of fixed telephone lines per 100 people.[7] Infrastructure is considered as an important driver of economic growth and development (Calderon and Serven, 2014). Improved infrastructure can contribute to the reduction of the informal sector by increasing firms' productivity and manufacturing output (Fedderke and Bogetic, 2009; Rud, 2012).

We also include in our model growth in the agricultural activities. Torgler and Schneider (2009), as well as Hassan and Schneider (2016) document that farmers are more likely to evade taxes than other professions and therefore to operate informally.

The informal sector may also be impacted by globalization negatively, as it increases exposure of local firms to best international practices, as shown by Berdiev and Saunoris

[7] Fixed telephone lines are poorly correlated with MFS adoption.

(2018). The social globalization index captures international interpersonal contacts, cultural proximity and information flows (through television, internet use and the presence of foreign population). Elgin (2013) shows that informal sector is lower in countries that experience high internet usage (also see Dreher, 2006; Goel et al., 2012; Cariolle et al., 2019). The political globalization index captures the diffusion of sound government policies. We expect a negative relationship between both control variables and the shadow economy.

Finally, we control for both institutional framework and trade environment. Following Dreher et al. (2009), as well as Buehn and Schneider (2012b), we include in our model an indicator apprehending corruption level, namely government integrity index.[8] Trade environment is measured by the trade freedom index[9] which assesses tariff and non-tariff barriers and how those impact imports and exports of goods and services (Elbahnasawy et al., 2016).

We first estimate Equation 1 using a fixed-effects model[10] in order to limit bias due to unobserved heterogeneity (i.e. unobserved effects that influence the underground economy). The results are discussed in the Section 5. In addition, we relax the linearity assumption of the relationship between the shadow economy and MFS adoption using a non-parametric approach based on propensity score matching (PSM).

The propensity score matching (PSM)

In this section, our main objective is to evaluate the impact of MFS adoption on the informal sector size (treated group), compared to countries that did not adopt MFS (control group).

Let $Informal_{1i}$ be the potential size of the informal sector in country i if MFS is adopted, and $Informal_{0i}$ the potential size of the informal sector in country i without MFS. Let MFS_i be the treatment variable, taking the value one from the year the service is adopted in country i, and zero otherwise. In addition, MFS adoption is conditional to a set of observed covariates X. Thus, for each country, we observe (MFS_i, IS_i, X), where $Informal_i$ is the realized outcome:

$$Informal_i = Informal_{0i} \; if \; MFS_i = 0 \; and \; Informal_i = IS_{1i} \; if \; MFS_i = 1 \quad (2)$$

Since it is not possible to observe the outcome of the treatment for both countries at the same time, we need to build a counterfactual by asking, for a country i with a MFS, what

[8] It ranges from 0 (very corrupt government) to 10 (very little corruption).
[9] It ranges from 0 (low trade freedom) to 100 (higher trade freedom).
[10] Hausman's test indicates a preference for the fixed-effects model (or within estimator) over the random-effects model.

would have been the informal sector size in the absence of MFS? Hence, the effect of MFS for a country i is given by:

$$\theta_i = IS_{1i} - IS_{0i} \qquad (3)$$

Then, the average treatment effect on the treat (ATT) defined as the mean of the difference in outcome (informal sector size) between the two groups (treated and control groups), is computed as follows:

$$ATT = E[Informal_{1i}|MFS_i = 1] - E[Informal_{0i}|\, MFS_i = 1] \qquad (4)$$

The ATT is based on two assumptions namely, the unconfoundedness assumption or conditional independence assumption (CIA) and the common support assumption (CSA). The CIA implies that the selection into the treatment group is only conditional to a set of observed covariates. In other words, after controlling-for these covariates, the treatment is independent of the potential outcome. Rosenbaum and Rubin (1983) define the propensity score - PS (or probability to adopt MFS) under the CIA as:

$$p(X) = pr(MFS = 1|X) \qquad (5)$$

where X is the vector of pre-treatment characteristics.

The CSA requires sufficient overlap in the characteristics of treated and control countries such that, for each country, the probability of the MFS adoption is comparable to the probability of non-adoption. The CSA is reflected by equation (6):

$$0 < pr(MFS = 1|X) < 1 \qquad (6)$$

When the two assumptions are met, the PSM estimator for ATT can be considered as unbiased.

Empirical results

This section presents the results of the impact of MFS adoption on the underground economy based on fixed-effects and PSM estimates.

Fixed effects estimates

We estimate three separate models for the shadow economy. The first includes all control variables, excepted institutional framework and trade environment, the second adds an institutional framework variable, and the third incorporates all control variables.

Table 1: Fixed-effects estimates

	(1) FE	(2) FE	(3) FE
Mobile financial services	**-1.027****	**-0.967****	**-0.936****
	(0.396)	**(0.387)**	**(0.375)**
GDP per capita	-0.133***	-0.135***	-0.136***
	(0.026)	(0.025)	(0.026)
Government spending	-0.036**	-0.037**	-0.034**
	(0.014)	(0.014)	(0.014)
Total investment	-0.071**	-0.075***	-0.071***
	(0.028)	(0.027)	(0.026)
Financial development index	-15.70***	-15.74***	-14.91***
	(3.691)	(3.519)	(3.426)
Infrastructure	-0.079	-0.072	-0.091
	(0.073)	(0.077)	(0.070)
Agriculture	-0.012	-0.011	-0.013
	(0.008)	(0.008)	(0.008)
Social globalization index	-0.391***	-0.371***	-0.329***
	(0.059)	(0.056)	(0.058)
Political globalization index	-0.033	-0.041	-0.032
	(0.040)	(0.037)	(0.037)
Government integrity		-0.079**	-0.080**
		(0.034)	(0.033)
Trade freedom			-0.046*
			(0.024)
Constant	66.67***	68.82***	68.87***
	(3.595)	(4.013)	(3.915)
Observations	1269	1269	1269
Countries	101	101	101
R^2 (within)	0.496	0.510	0.518
F-test	24.37***	23.50***	22.37***

Note: The sample goes from 2000 to 2015. The dependent variable is shadow economy (% of GDP). Robust standard errors are reported in brackets. (***, **, *) indicate significance at the 1 %, 5 % and 10 % level.

The regression results are reported in Table 1. The coefficient of MFS adoption is negative and significant at the 5 % level (columns 1 to 3). This confirms our hypothesis of a negative relationship between informality and MFS adoption.

Propensity score matching results

We estimate the propensity score (PS) using a logit model with MFS adoption as the dependent variable). To estimate the PS, we rely on the literature (GSMA, 2016b; Mothobi and Grzybowski, 2017; Della Peruta, 2018; Aron, 2018) to identify the set of variables that may likely to influence both MFS adoption and informality. These include: mobile phone market share (the ratio of mobile phones subscription in country i to that of his region), income level (measured by the logarithm of household consumption per capita), financial development (domestic credit to private sector), investment freedom, rule of law, inflation, social globalization index, labor force participation rate, urban population growth, and education level (mean years of schooling).

Table 2: Logit estimate of the propensity score

Dependent variable	Mobile financial services (dummy variable)
Mobile phone market share	0.055***
	(0.012)
Households consumption	-0.876***
	(0.154)
Financial development	0.026***
	(0.005)
Investment Freedom	0.018***
	(0.005)
Rule of Law	-1.217***
	(0.177)
Inflation	-0.007
	(0.013)
Social globalization index	0.049***
	(0.014)
Labor force	0.029***
	(0.007)
Urban population growth	0.149***
	(0.044)
Level of education	-0.031
	(0.044)
Observations	1104
Pseudo R^2	0.155
Model χ^2	149.45***
Log likelihood ratio	-591.25

Note: The sample goes from 2000 to 2015. The dependent variable is MFS adoption. Robust standard errors are reported in brackets. (***, **, *) indicate significance at the 1 %, 5 %, 10 %. Unreported constant included. All independent variables are one-year lagged, excepted investment freedom and rule of law.

Table 2 reports the estimates of the propensity score model. Our results show that the main drivers of MFS adoption are the mobile phone market share, income level, financial development, investment freedom, rule of law, social globalization, labor force, and urban population growth. The positive correlation between the probability of the adoption of MFS and regional market share confirms that the emergence of MFS is fundamentally linked to the mobile phone market’s size (GSMA, 2016a). MFS are more available in low- and middle-income countries as they are considered as low-cost solutions, and hence more appealing to low-income populations (GSMA, 2016b) than to high income populations with high consumption levels and high access to a variety of means of payments. Financial deepening, investment freedom, and the quality of institutional framework (proxied by rule of law) also provide important incentives for MFS adoption. This confirms earlier results that restrictive regulatory environments and investment barriers are negatively correlated with MFS adoption (Pénicaud, 2013; Evans and Pirchio, 2014). Labor force participation and the urbanization rate both have a positive effect on the deployment of MFS since their transactions are mostly from urban to rural areas, and fulfil a need for distant payments (Buku and Meredith, 2013; Della Peruta, 2018). Macroeconomic stability (proxied by the inflation rate) is not significant, as some countries (Argentina, Democratic Republic of the Congo, or Malawi) with an average inflation rate of 10 %, have nonetheless decided to adopt MFS. The education level is also not significant, suggesting that the use of MFS is simple enough to be accessible to the less educated populations, already familiar with the use of mobile phone applications.

Based on the propensity score estimates, we can match treated and untreated countries using four different matching algorithms for robustness purposes. First, under the N-nearest-neighbour matching, each treated *i* is matched with untreated *j* with close PS. Following Minea and Tapsoba (2014), and Balima et al. (2017), we consider the nearest (N = 1), the two-nearest (N = 2), and the three-nearest (N = 3). The second method is the radius or caliper matching (Dehejia and Wahba, 2002), which matches each treated *i* with untreated *j* that falls within radius *r*. We use the PS to define a medium (r = 0.1), a small (r = 0.05) and a wide (r = 0.2) radius.[11] Third, we use the kernel matching developed by Heckman et al. (1998), which matches each treat *i* with all untreated, with weights inversely proportional to the gap between the treated and control observations. We employ the Eparnecknikov function in this paper. The fourth algorithm is the local linear matching, which is similar to the kernel matching but includes a linear term in the weighting function.[12]

First, the quality of matching appears satisfactory according to standard assessment tools. Figure 1 presents the distribution of the estimated of the PS for the two groups and the region of common support. A visual inspection of the density distributions (Caliendo and Kopeinig, 2008) indicates that the common support assumption is satisfied: all the treated observations and the untreated observations were within the region of common support. In other words, there is sufficient overlap in the distribution of the PS for MFS adopters and non-adopters. Table 3 presents result from covariate balancing tests, which reveals that the standardized mean difference for overall

[11] Following Austin (2011), we define medium radius as 0.2 of the standard deviation of the logit of the propensity score. The wide radius and small radius are set equal to two and a half the medium radius, respectively (Lin, 2010).
[12] The default bandwidth (0.06) is used for the kernel and local linear regression matching.

covariates used in the estimation process of PSM reduces from 28.0 % before matching to a range of 3.6 – 5.7 % after matching. The total bias also decreases by 79.6 – 87 % depending on the matching methods. These values are greater than the 20 %, critical value suggested by Rosenbaum and Rubin (1985).

The second diagnostic tool used is the pseudo-R^2 (defined as the difference between the pseudo-R^2 for the matched and for the unmatched samples) from the logit estimation of the conditional probabilities of the adoption of MFS. The results show that the pseudo-R^2 is very close to zero after matching for all matching algorithms, suggesting that there are no systematic differences in the distribution of covariates between the MFS adopters and non-adopters after matching. The p-values of likelihood ratio test highlight the joint significance of all covariates in the logit model after matching, but not before matching. In sum, the low pseudo-R^2, low mean standardized bias, high total bias reduction, and insignificant p-values of the likelihood ratio test after matching indicate that the specification of the propensity score estimation process has successfully balanced the distribution of covariates between MFS adopters and non-adopters.

Figure 1: Distribution of the estimated propensity score and the region of common support

The PSM yields significant insights on how the adoption of MFS affects the underground economy. The four matching algorithms show that the adoption of MFS has a negative and significant (at the 1 % level) impact on the share of informal sector activities in range of 2.4 – 4.3 % percentage points, depending on the matching algorithm. Our results show that improvement in firms' productivity/profitability and access to credit stemming from

MFS use (Section 2) represent significant incentives for MSMEs or self-employed entrepreneurs to enter the formal sector and translate into tangible formalization effects. Our findings may also reflect the growth of the formal sector. These results are all the more remarkable as the diffusion of this financial innovation is both in terms of geographic coverage, product diversification (credit, savings and insurance) and client base. Possible cross effects with other forms of economic digitalization may also unfold and amplify these effects, suggesting that further formalization effects may be on the way.

In order to ensure the robustness of our matching estimations, we also need to check for possible hidden bias due to unobserved variables that may influence MFS adoption. As suggested by Rosenbaum (2002), we use of a sensitivity analysis called bounding approach (Rosenbaum bounds – rbounds) to address this issue. The critical thresholds of gamma (Γ), beyond which the causal inference of significant MFS adoption impact may be questionable, are reported in Table 4.[13] The critical values of gamma (Γ) range from 1.65-1.75 to 2.15-2.25. These cutting points are largely in line with the literature (Rosenbaum, 2002; DiPrete and Gangl, 2004)[14], suggesting that the estimated average treatment effects of MFS adoption on the informal sector are robust, even in the presence of unobserved heterogeneity.

[13] For instance, the critical value of 1.90-2.00 (radius matching) suggests that if countries that have the same X-vector differ in their odds by a factor of 90-100 %, the negative and significant impact of MFS adoption on the shadow economy may be questionable.
[14] Tipping critical levels usually range between 1.1 and 2.2.

Table 3: Matching quality indicators before and after matching

Matching algorithm		Pseudo R^2		LR χ^2		$p > \chi^2$		Mean standardized bias		Total % bias reduction
		Before matching	After matching	Before matching	After matching	Before matching	After matching	Before matching	After matching	
Nearest neighbors matching	N = 1	0.154	0.009	214.92	9.35	0.000	0.499	28.0	4.3	84.64
	N = 2	0.154	0.009	214.92	8.87	0.000	0.535	28.0	4.9	82.50
	N = 3	0.154	0.009	214.92	8.63	0.000	0.567	28.0	5.2	81.43
Radius matching	r = 0.045	0.154	0.007	214.92	7.33	0.000	0.694	28.0	4.3	84.64
	r = 0.09	0.154	0.006	214.92	5.97	0.000	0.802	28.0	3.6	87.14
	r = 0.18	0.154	0.011	214.92	10.70	0.000	0.381	28.0	5.7	79.64
Kernel matching	Bw = 0.06	0.154	0.007	214.92	7.03	0.000	0.722	28.0	4.1	85.36
Local linear matching	Bw = 0.06	0.154	0.009	214.92	9.35	0.000	0.499	28.0	4.3	84.64

Source: Author's calculations.

Table 4: PSM estimates of the impact of MFS adoption on the informal sector and sensitivity analysis

	Nearest neighbor matching			Radius matching			Kernel matching	Local linear matching
	N = 1	N = 2	N = 3	r = 0.045	r = 0.09	r = 0.18	Bw = 0.06	Bw = 0.06
Mobile financial service (ATT)	**-4.278*** (1.154)**	**-4.152*** (1.097)**	**-4.078*** (1.051)**	**-3.391*** (0.838)**	**-2.946*** (0.772)**	**-2.378*** (0.680)**	**-3.336*** (0.835)**	**-3,133*** (0.859)**
Critical level of hidden bias (Γ)	1.70-1.75	1.95-2.05	2.15-2.25	2.05-2.15	1.90-2.00	1.65-1.75	2.00-2.10	2.00-2.10
Number of observations	1104	1104	1104	1104	1104	1104	1104	1104
Bootstrap replications	500	500	500	500	500	500	500	500

Note: Bootstrapped standard errors are reported in brackets. (***, **, *) indicate significance at the 1%, 5%, 10% level.

Robustness checks

The relationship between the size of informal sector and MFS adoption may be endogenous given possible omitted variables bias, measurement errors or reverse causality. Since the shadow economy is associated with a strong preference for cash because it is untraceable (Williams and Schneider, 2016), the prevalence of a large informal sector represents a largely untapped market for financial services and hence strong incentives to develop financial innovations like MFS. The early and rapid growth of MFS in emerging and developing countries points out to such reverse causality effects. Moreover, since the PSM method leads to unbiased estimates only when the selection into the treatment is based the observed, we confirm our results by an alternative estimation approach using instrumental variables estimator (2SLS) to control for unobservable factors.

The main challenge is to find a suitable instrument to isolate the causal effect of the MFS adoption on informal activities. Our first instrument is the mobile phone subscription ratio (per 100 people), as the deployment of MFS is fundamentally linked to the mobile phone market's dynamism (GSMA, 2016a). We use urban population (as a % of total population) as a second instrument in so far as MFS transactions are mostly from urban to rural areas (Della Peruta, 2018).

We also estimate three separate models for the shadow economy as before. The results are reported in Table 5. We assess the validity and the relevance of our instruments using three diagnostic tests. First, we use the under-identification test by Kleibergen-Paap (2006) to check whether the equation is identified (i.e., that the instruments are correlated with the endogenous variable). Second, we employ the weak-identification test by Kleibergen-Paap (2006) to examine whether the instruments are only weakly correlated with the endogenous regressor. Finally, we use the over-identification test by Hansen (1982) in order to check whether the orthogonality conditions are valid. The results of these tests, which are reported at the bottom of Table 4, show that the instruments used are valid and relevant.

The empirical results of the instrumental variables point in the same direction as previously: the MFS adoption lead to lower informal activities (Table 5, columns 1 to 3). All coefficients are significant at the 1 % level.

Table 5: Instrumental variable regressions

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Mobile financial services	**-5.226***** **(1.270)**	**-5.844***** **(1.332)**	**-4.628***** **(1.334)**			
MFS (providers)				**-1.954***** **(0.482)**	**-2.132***** **(0.494)**	**-1.634***** **(0.484)**
GDP per capita	-0.130* (0.066)	-0.120* (0.066)	-0.118* (0.065)	-0.121* (0.068)	-0.112* (0.067)	-0.111* (0.066)
Government spending	0.086*** (0.014)	0.088*** (0.014)	0.088*** (0.014)	0.089*** (0.014)	0.091*** (0.014)	0.090*** (0.014)
Total investment	-0.230*** (0.025)	-0.229*** (0.026)	-0.232*** (0.025)	-0.242*** (0.026)	-0.242*** (0.027)	-0.242*** (0.026)
Financial development index	-8.295*** (2.925)	-6.463** (2.890)	-7.166** (2.809)	-10.200*** (2.986)	-8.944*** (2.961)	-9.172*** (2.868)
Infrastructure	-0.258*** (0.039)	-0.242*** (0.039)	-0.257*** (0.040)	-0.272*** (0.040)	-0.260*** (0.041)	-0.274*** (0.041)
Agriculture	-0.006 (0.029)	-0.008 (0.029)	-0.011 (0.029)	-0.011 (0.030)	-0.013 (0.030)	-0.015 (0.029)
Social globalization index	-0.166*** (0.031)	-0.116*** (0.037)	-0.101*** (0.037)	-0.149*** (0.031)	-0.109*** (0.037)	-0.091** (0.038)
Political globalization index	-0.011 (0.019)	-0.012 (0.020)	-0.010 (0.020)	0.012 (0.023)	0.0132 (0.024)	0.010 (0.023)
Government integrity		-0.083*** (0.031)	-0.071** (0.030)		-0.065** (0.030)	-0.056* (0.029)
Trade freedom			-0.057*** (0.022)			-0.067*** (0.022)
Constant	51.17*** (2.668)	50.37*** (2.666)	52.69*** (2.603)	48.45*** (2.796)	47.58*** (2.810)	50.94*** (2.716)
Observations	1269	1269	1269	1269	1269	1269
Countries	101	101	101	101	101	101
R^2 (centered)	0.349	0.344	0.364	0.289	0.274	0.323
Under id test: KP LM statistic	245.8	235.7	217.9	186.3	179.1	157.4
Weak id test: KP LM statistic	186.6	176.2	167.1	110.9	106.4	90.65
Over id test: Hansen j statistic	0.298	0.470	0.166	0.951	1.254	0.532
Hansen j-test (p-value)	0.585	0.493	0.684	0.330	0.263	0.466

Note: The sample goes from 2000 to 2015. The dependent variable is shadow economy (% of GDP). MFS dummy variable and MFS providers are treated as endogenous variables, and they are instrumented via mobile phone subscription and urban population. Regional fixed effects are included in each specification. Robust standard errors are reported in brackets. (***, **, *) indicate statistical significance at the 1 %, 5 %, and 10 % level.

In addition, we test whether our results are sensitive to the measure of MFS using the number of MFS providers as an alternative indicator. The number of MFS providers refers to the number of institutions (mobile phone operators and/or financial institutions) offering digital financial services year-by-year. The correlation rate between this variable and mobile money indicator is 65 % and significant at the 1% level. The results are reported in Table 5 (columns 4 to 6). Our results remain valid. More specifically, in response to a 10 % increase in the standard deviation of MFS providers, the standard deviation of shadow economy decreases in range of 2,7 – 3,6 % (Table 4, columns 4 to 6).[15]

Finally, our findings also highlight other drivers of shadow economy,Economic development , tax burden proxied by government spending, total investment, financial development, infrastructure, social globalization, government integrity, and trade freedom all favour the development of the formal sector over the informal one.

Conclusion

This paper investigates whether and to what extent financial innovation such as mobile financial services may affect the size of the informal sector, which represent a large share of economic activity in developing countries. This research question has received little attention so far but, in our view, may have important macroeconomic repercussions as it may be a driver of financial development and growth, as well as a tool to increase mobilization of domestic resources.

Using a panel data from 101 emerging and countries over the period 2000-15, we find that MFS negatively affect the size of the informal sector. Based on non-parametric approach (propensity score matching), we show that MFS adoption significantly decreases the informal sector size in range of 2.4 – 4.3 % percentage points. Formalization effects may stem from different possible transmission channels: improvement in credit access, increase in the productivity/profitability of informal firms attenuating subsistence constraints typical of entrepreneurship in the informal sector, as well as possible induced growth of firms already in the formal sector. The robustness of these results is also supported by the use of an alternative estimation approach (instrumental variables). Our study confirms that economic and financial development, infrastructure, trade freedom, as well as the quality of governance, also have a positive impact on the attractiveness of the formal sector over the informal sector.

These findings lay the groundwork for the literature on the MFS' macroeconomic implications, which has received little attention so far. As financial digitalization intensifies, we expect associated macroeconomic effects to increase, calling for more research on its overall impact on inclusive economic development and domestic resource mobilization. The ongoing diversification of MFS, combined with the digitalization of

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[15] The standardized is calculated by $\beta_X = \alpha_X \frac{\delta_X}{\delta_Y}$, where α_X, δ_X and δ_Y are the initial estimated coefficient, the standard deviation of MFS providers, and the standard deviation of the informal sector, respectively.

other economic transactions (tax, wages, etc.) may also entail additional cumulative cross-effects along the road.

They may also provide substantial inputs to the current debate on institutional quality and regulation of mobile financial services. First, MFS contribute to strengthen transparency of economic activity and financial transactions: digitization makes domestic corruption more difficult. Second, like any financial innovation, MFS have created new types of fraud (fake currency deposits, phishing, SIM swaps, etc.). This shows that regulatory environments are important enablers of MFS growth.

Further research is needed to determine how these new financial institutions affect financial stability. The jury may still be out on whether MFS are complements or competitors to banking systems and micro finance and whether their impact on financial development and international integration is stabilizing or not. But the significance of this issue certainly grows as exponentially as MFS services themselves, calling for more regulatory vigilance and monitoring to make these services a net contributor to sustainable development.

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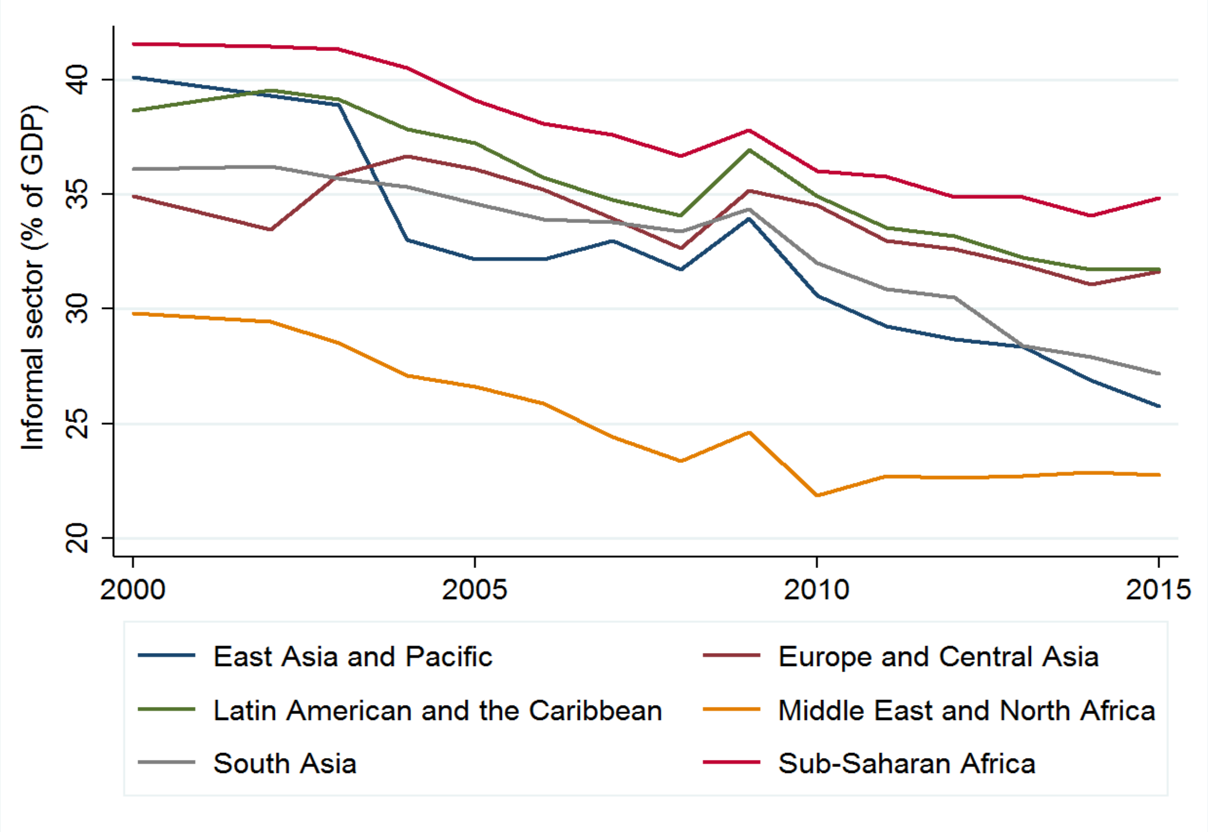
Figure and tables

(i) Figure

Figure A1: Informal shadow in developing countries, 2000-2015



This Figure provides information on the evolution of the informal sector across regions and over time.

Sources: Medina and Schneider (2018) and authors' own calculations.

(ii) Tables

Table A1: List of countries

Sub-Saharan Africa	Latin America & the Caribbean	Europe & Central Asia	Middle East & North Africa	East Asia & Pacific	South Asia
Benin (2010)	Argentina (2013)	Albania	Algeria	Cambodia (2009)	Bangladesh (2006)
Botswana (2011)	Bahamas	Armenia (2012)	Bahrain	Fiji (2010)	Bhutan
Burkina Faso (2012)	Belize	Azerbaijan	Egypt (2013)	Indonesia (2007)	India (2007)
Burundi (2010)	Bolivia (2013)	Bosnia and Herzegovina	Iran (2011)	Malaysia (2007)	Nepal (2009)
Cameroon (2010)	Brazil (2013)	Bulgaria	Jordan	Mongolia (2010)	Pakistan (2009)
Cape Verde	Chile	Croatia	Kuwait	Philippines (2001)	Sri Lanka (2012)
Central African Republic	Colombia (2011)	Georgia (2013)	Morocco (2010)	Thailand (2004)	
Chad (2012)	Costa Rica	Hungary	Oman	Vietnam (2010)	
Congo, Dem. Rep. (2012)	Dominican Republic (2014)	Kazakhstan	Saudi Arabia		
Congo, Rep. (2011)	Ecuador	Kyrgyz Republic (2014)	Tunisia (2010)		
Cote d'Ivoire (2008)	El Salvador (2011)	Moldova	United Arab Emirates		
Ethiopia (2013)	Guatemala (2011)	Poland			
Gabon (2012)	Guyana (2013)	Romania (2014)			
Gambia	Honduras (2011)	Russia (2002)			
Ghana (2009)	Jamaica	Tajikistan			
Guinea (2012)	Mexico (2012)	Turkey (2012)			
Guinea-Bissau (2010)	Nicaragua (2011)	Ukraine			
Kenya (2007)	Paraguay (2010)				
Lesotho (2012)	Peru (2015)				
Madagascar (2010)	Suriname				
Malawi (2012)	Uruguay				
Mali (2010)	Venezuela				
Mauritania (2013)					
Mauritius					
Mozambique (2011)					
Namibia (2010)					
Niger (2010)					
Nigeria (2011)					
Rwanda (2009)					
Senegal (2008)					
Sierra Leone (2010)					
South Africa (2009)					
Swaziland (2011)					
Tanzania (2008)					
Togo (2013)					
Uganda (2009)					
Zambia (2009)					

Note: This table provides information for the sample countries. The launch year of the first mobile money service is reported in brackets.
Source: Mobile money deployment tracker, GSMA.

Table A2: Description of the variables

Variables	Description	Sources
Informal	Informal sector (% of GDP)	Medina and Schneider (2018)
Mobile financial services (MFS)	Dummy variable that takes the value one in the year the service is launched and zero otherwise	Authors' calculations & Mobile money deployment tracker (GSMA)
MFS providers	Number of operators	
Mobile phone subscription	Mobile phone subscription per 100 people	WDI-World Bank
Mobile phone market share	Mobile phone market share at the regional level	Authors' calculations & WDI-World Bank
Growth GDP per capita	Percentage change in GDP per capita (year-on-year)	WDI-World Bank
Households consumption	Households consumption per capita	WDI-World Bank
Government spending	Level of government spending	Heritage Foundation
Total Investment	Gross capital formation (% of GDP)	WEO-IMF
Financial Development	Financial development index	Svirydzenka (2016)
	Domestic credit to private (% of GDP)	WDI-World Bank
Inflation	Average consumer prices (percent change)	WEO-IMF
Infrastructure	Fixed telephone lines per 100 people	WDI-World Bank
Agriculture	Agriculture added value (annual growth)	
Social Globalization	Interpersonal contact, cultural proximity and information flows	Dreher (2006) & Gygli et al. (2018)
Political Globalization	Diffusion of sound government policies	
Labor force	Labor force participation rate (% of adult population)	WDI-World Bank
Urban population growth	Percentage change in urban population (year-on-year)	
Urban population	Urban population (% of total population)	
Education level	Mean years of schooling (people aged 25 years and above)	UNDP
Government integrity	Level of corruption	Heritage Foundation
Investment Freedom	Absence of investment restrictions	
Trade Freedom	Absence of trade restrictions	
Rule of law	Index of agents' confidence in and abide on the rules of society	WGI-World Bank

Table A3: summary statistics

Variable	Unit	Obs.	Mean	Std. Dev.	Min	Max
Informal sector	Percentage	1269	34,05	10,14	12,02	69,01
Mobile financial services	Dummy variable	1269	0,31	0,46	0,00	1,00
MFS providers	Number of providers	1269	0,74	1,71	0,00	18,00
Mobile phone subscription	Percentage	1269	66,78	45,95	0,00	200,93
Mobile phone market share	Percentage	1269	6,39	11,71	0,00	86,38
Growth GDP per capita	Percentage	1269	2,66	4,01	-36,83	33,03
Households consumption	Logarithm	1178	7,51	1,06	5,22	10,58
Government spending	Index	1269	73,43	16,76	0,00	97,60
Total investment	Percentage	1269	24,39	8,45	4,86	73,04
Financial development index	Index	1269	0,24	0,15	0,00	0,71
Domestic credit	Percentage	1249	34,24	23,51	0,56	126,73
Inflation	Percentage	1267	6,69	9,10	-3,47	221,49
Infrastructure	Percentage	1269	11,35	10,73	0,00	43,39
Agriculture	Percentage	1269	2,86	7,95	-45,35	55,62
Social globalization	Index	1269	52,27	14,75	10,87	81,38
Political globalization	Index	1269	69,29	15,42	15,93	95,31
Labor force participation	Percentage	1269	63,42	10,87	39,15	89,05
Urban population growth	Percentage	1269	2,55	1,87	-2,70	14,68
Urban population	Percentage	1269	52,20	20,89	8,25	98,34
Education	Percentage	1264	7,08	2,79	1,20	12,70
Government integrity	Index	1269	32,90	12,87	0,00	90,00
Rule of law	Index	1269	-0,39	0,61	-1,92	1,45
Trade freedom	Index	1269	68,92	12,86	0,00	89,20
Investment freedom	Index	1269	49,82	17,51	0,00	90,00

Note: The sample period goes from 2000 to 2015. “Unit” denotes the measurement units of the regression variables. “Obs.” denotes the number of observations for the respective variable. The last four columns show the mean, standard deviation, minimum and maximum.