Technology Adoption and Leapfrogging: Racing for Mobile Payments*

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August 8, 2023

Abstract

Paying with a mobile phone is a cutting-edge innovation that is transforming the global payments landscape. Some developing countries have surprisingly overtaken advanced economies in adopting the mobile payment innovation. We construct a dynamic model with sequential payment innovations to explain this phenomenon, which uncovers how advanced economies' past success in adopting card-payment technology holds them back in the mobile-payment race. Our estimated model matches the cross-country adoption patterns of card and mobile payments and explains why advanced and developing countries favor different mobile payment solutions. Based on the model, we conduct quantitative analysis to assess welfare and policy implications.

Keywords: Technology Adoption, Payments, FinTech, Financial Development

JEL Classification: E4, G2, O3

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*We thank Mark Bils, Yiting Deng, Jeremy Greenwood, Apoorv Gupta, Kinda Hachem, Zhiguo He, Hugo Hopenhayn, Chang-Tai Hsieh, Chad Jones, Boyan Jovanovic, Pete Klenow, Dirk Krueger, Jane Li, Florin Maican, Nitya Nayar, Shumiao Ouyang, Zheng (Michael) Song, Pengfei Wang, Shang-Jin Wei, Kairong Xiao, Wei Xiong, Daniel Yi Xu and participants at various seminars and conferences for helpful comments, and Emily Emick and Brennan Merone for research assistance. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

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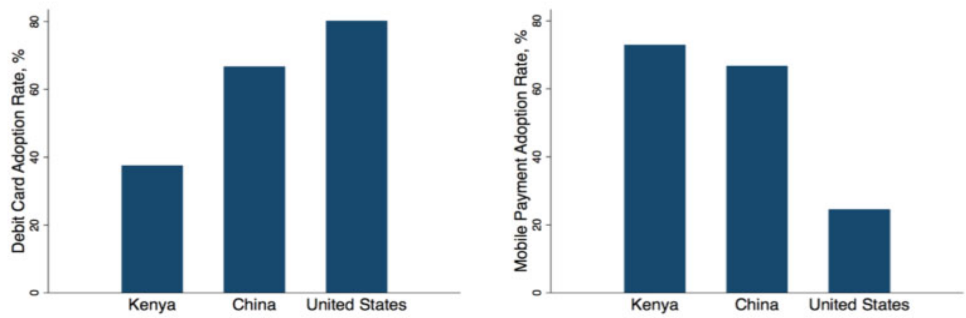
1 Introduction

The payments system is an essential financial technology infrastructure of the aggregate economy. With the successful launch of general-purpose credit cards in the late 1950s and debit cards in the mid-1980s, the United States has been one of the leading countries in deploying card payment technologies. However, the U.S. is falling behind in adopting the recent mobile-phone-based payment innovation (henceforth, "mobile payment").

In contrast, Kenya and China are front runners for mobile payment adoption. Within four years after being launched in 2007, mobile payment has been adopted by nearly 70% of Kenya's adult population (Jack and Suri, 2014). China also gained explosive growth in mobile payment usage in recent years. In 2017, a total of 276.8 billion mobile payment transactions were made in China, equivalent to 200 transactions per capita.[1]



(A) Card Payment Adoption Rate

(B) Mobile Payment Adoption Rate

Figure 1. Adoption of Card and Mobile Payments (2017)

Figure 1 compares the adoption of card and mobile payments in three countries: Kenya, China, and the U.S. Figures 1A and 1B report the percentage of the adult population (age 15 and above) having a debit card and using a mobile payment service, respectively.[2] As shown by the figures, while the U.S. boasts a higher card payment adoption rate, it has fallen far behind Kenya and China in mobile payment adoption.

These observations raise concerns about the efficiency and innovativeness of the U.S. payments system and lead to important questions. Why did developing countries lag in adopting card payments but some of them leapfrog in adopting mobile payments? Have advanced economies lost their leadership in the payment area? What government policies, if any, should be considered to facilitate mobile payment development?

[1] Source: *Statistical Yearbook of Payment and Settlement of China.*

[2] Sources: Global Financial Inclusion (Global Findex) Database of the World Bank, and eMarketer. See Internet Appendix II for the data details.

This paper addresses these questions. We first compile a novel dataset to examine the general adoption patterns of card and mobile payments across countries beyond the idiosyncratic cases of Kenya, China, and the U.S. We find that card payment adoption increases monotonically with per capita income. In contrast, the adoption of mobile payment shows a non-monotonic relationship with per capita income: increasing among low-income countries, decreasing among middle-income countries, and increasing again among high-income countries. Moreover, advanced economies and developing countries tend to adopt different mobile payment solutions. The former favor systems that are complementary to card usage, while the latter choose those that substitute for cards.

We then construct a theory to explain the early success of advanced economies in adopting card payment, and how their advantage in card payment later hinders the adoption of mobile payment. In our model, three payment technologies–cash, card, and mobile–arrive sequentially. Newer technologies lower the variable costs of making payments, but they require a fixed cost to adopt. When card arrives after cash, high-income consumers adopt earlier because they spend more on purchases, and thus can save more on the variable costs of payments.[3] This explains the high adoption rate of card payments in rich countries. However, when mobile arrives after card, adoption incentives are different between existing card users and cash users. Because the incremental reduction in variable costs brought by mobile is smaller for card users than for cash users, the former face a higher income threshold to switch to mobile than the latter. As a result, the pre-mobile composition of cash and card users in each country leads to a non-monotonic relationship between mobile payment adoption and per capita income across countries. Moreover, to save on adoption costs, cash users favor mobile solutions that bypass card while card users prefer capitalizing on card. This explains why most developing countries choose Mobile Money (a card-substituting technology), whereas most advanced economies choose card-complementing mobile solutions such as Apple Pay.

Our estimated model matches cross-country adoption patterns of both card and mobile payments well. Based on the model, we conduct counterfactual and welfare analysis. We find that lagging behind in mobile payment adoption does not necessarily imply that advanced economies fall behind in overall payment efficiency, even though they may benefit less from the mobile payment innovation than some developing countries. Down the road, greater

[3] In our analysis, adopting card payment includes agents' decision to join the formal banking system combined with choosing card as the cost-effective payment solution.

technological progress in mobile payments are needed for advanced economies to catch up in the payment race, and we quantify welfare gains from introducing mobile payments across countries.

By focusing on the role of income heterogeneity, our benchmark model abstracts from market imperfections. We then embed payment innovations in a two-sided market setting to incorporate network externalities associated with payments. The payment market is two-sided, in which consumers and merchants jointly use each payment technology in transactions but bear separate costs. As underscored in Rochet and Tirole (2002, 2006) and the following two-sided market literature, a fundamental friction in the two-sided payment market is price coherence: Merchants typically do not price differentiate based on payment means. Consequently, consumers would not internalize the payment externalities they generate on merchants and through merchant pricing onto other consumers. Essentially, any consumer adopting a more efficient payment technology subsidizes those who do not. In our model setting, such externalities would affect the adoption and usage of new payment technologies. Nevertheless, we show that the main findings of our benchmark model continue to hold in the two-sided market setting, even though the market equilibrium is no longer socially optimal. We also find that certain policy interventions (e.g., subsidizing mobile payment adoption) can be welfare-enhancing in this two-sided market setting, and they may benefit developing and developed economies to different degrees.

Our paper contributes to several strands of literature. The first is the theories of payments. In recent years, a fast growing body of research (commonly known as the "two-sided market literature") has been developed for studying market structure and pricing of retail payments, especially card payments (e.g., Rochet and Tirole, 2002, 2006, 2011, Wright, 2003, 2012, Wang, 2010, Shy and Wang, 2011, Bedre-Defolie and Calvano, 2013, and Edelman and Wright, 2015). However, most of those studies assume a static environment and abstract from payment adoption decisions.[4]

The second is comparative studies on adoption and usage of payment innovations. While there is an abundance of literature studying domestic payment patterns (e.g., Rysman, 2007, Klee, 2008, Wang and Wolman, 2016 for the U.S.), cross-country studies are rather scarce. We fill this gap by compiling a novel dataset to study cross-country adoption patterns of mobile versus card payments. Our dataset includes both developed and developing economies,

[4] Among very few exceptions, Alvarez and Lippi (2009, 2017) and Li et al. (2020) study payment choices in dynamic settings, but they do not consider sequential innovations and leapfrogging.

which allows us to uncover and address the leapfrogging puzzle.

Our paper is also related to the literature on the rise of digital payments and FinTech payment firms. According to Berg et al. (2022), the rise of FinTech payment firms is one of the most significant changes to the financial industry over the last decade. This has had positive impacts on financial inclusion and welfare (e.g., Jack and Suri (2014) on mobile payments in Kenya and Muralidharan et al. (2016) on smartcard payments in India). Digital payment services provided by FinTech firms also transform the lending business (e.g., Parlour et al., 2021, Ghosh et al., 2021, Ouyang, 2021). Our paper complements those works in the sense that we take a structural approach to study how cost savings of different electronic payments affect payment efficiency and drive different adoption patterns across countries.

Our analysis also contributes to the literature of financial development. The trade-off between fixed and variable costs in our model is consistent with the mechanism of financial development studied in Greenwood and Jovanovic (1990). In their framework, agents need to pay a fixed adoption cost for accessing financial markets in order to gain a higher return. High-income agents are willing to pay for the access earlier and low-income agents wait until their incomes reach a threshold level. More recently, Philippon (2019) shows that the nature of fixed versus variable costs in robo-advising is likely to democratize access to financial services. Our model shares a similar insight but we extend it to sequential payment innovations to explain a novel cross-country leapfrogging pattern.

Finally, our finding that the incumbent technology curse can help explain the leapfrogging in mobile payment adoption echoes with previous studies in the literature on technology adoption. In a similar vein, studies have shown that in the presence of sequential innovations, some firms may get stuck with old technologies due to their past investments in technology-specific learning (e.g., Parente, 1994, Jovanovic and Nyarko, 1996, and Klenow, 1998). Our study extends this line of research to a new context where consumers make adoption decisions on sequential payment innovations.

The remainder of this paper is structured as follows. Section 2 provides the background of mobile payments and summarizes stylized facts regarding cross-country adoption patterns. Section 3 introduces the benchmark model and solves for the equilibrium. Section 4 estimates the model and explores model implications via counterfactual exercises. Section 5 conducts welfare and policy analysis. Section 6 extends the model to a two-sided setting with payment externalities. Section 7 provides additional robustness checks. Finally, Section 8 concludes.

2 Background and stylized facts

Following Crowe et al. (2010), we define a mobile payment to be a money payment made for a product or service through a mobile phone, regardless of whether the phone actually accesses the mobile network to make the payment. Mobile payment technology can also be used to send money from person to person.

The very first mobile payment transaction in the world can be traced back to 1997, when Coca-Cola in Helsinki came out with a beverage vending machine where users could pay for the beverage with just an SMS message.[5] Around the same time, the oil company Mobil also introduced a Radio Frequency Identification (RFID) device called Speedpass that allowed its users to pay for fuel at gas stations. These two earliest examples of mobile payment services were both based on SMS, and the payments were made through a mobile account that was linked to the user's device.

The mobile payment systems based on SMS then progressed with more user applications. In 2007, Vodafone launched one of the largest mobile payment systems in the world. It was based on SMS/USSD text messaging technology and offered various kinds of payment services. Vodafone launched this service in Kenya and Tanzania with the cooperation of local telecom operators.

The year 2011 witnessed major technology firms like Google and Apple entering the field of mobile payment. Google became the first major company to come up with a digital mobile wallet solution, Google Wallet. In 2014, Apple launched its own mobile payment service in the U.S. called Apple Pay (compatible with iPhone 6), which allowed the users to tap their phone against a contactless payment card terminal at the point of sale, paying instantly. In the wake of Apple Pay's success, Google and Samsung released their competing apps, Android Pay (later merged with Google Wallet and became Google Pay) and Samsung Pay, respectively.

As a cutting-edge payment innovation, mobile brings additional benefits compared with preceding card technologies, lowering both the adoption costs and variable costs of making payments. First, given that mobile phones had been widely adopted in most countries before the arrival of mobile payment, the fixed cost for adopting mobile payment is small

[5] Short Message Service (SMS) and Unstructured Supplementary Service Data (USSD) are two methods used by telecom companies to allow users to send and receive text messages. With SMS, messages are sent to SMS centers, which store the message and then transmit the message to the recipient. In contrast, USSD makes a direct connection between text message senders and recipients, making it more responsive.

for consumers and merchants. Second, mobile payment is fast, convenient, and more secure. Apple Pay, for example, enables the users to pay without unlocking their phones, and the Touch/Face ID of an iPhone adds extra security to authenticate a purchase. Apple Pay also encrypts payment information by a tokenization technology, thus enhancing privacy and reducing the risk of fraud. Moreover, as mobile payment technology becomes widespread, markets develop a system of complementary goods and services that further enhance users' benefits, such as financial planning, rewards programs, and price competition (Crowe et al. 2010).

2.1 Alternative mobile payment technologies

While there are many mobile payment solutions, they fall into two basic categories: either bypassing or complementing the existing bank-based payment card systems. We name them card-substituting and card-complementing mobile payments, respectively.[6] The former is mainly used in developing countries like Kenya, and the latter is popular in advanced economies like the U.S.

2.1.1 Card-substituting mobile payment

Card-substituting mobile payment is epitomized by Kenya's M-PESA model. M-PESA is a mobile payment service launched by Safaricom and Vodafone in Kenya in 2007. M-PESA users can deposit money into an account in their phones and send balances to other users by SMS text messages. Hence, they can use a mobile phone to deposit and withdraw money, pay for goods and services, and transfer money to other users. To deposit and withdraw money, M-PESA users rely on M-PESA agents (e.g., shops, gas stations, or post offices). These agents are the analogs of the ATMs and bank branches in the banking system, allowing the M-PESA operation to bypass the banking system.

Following the success in Kenya, M-PESA was emulated in many other developing countries. This category of mobile payment methods is defined as "Mobile Money" by the Global System for Mobile Communications Association (GSMA) that must meet the following four conditions. First, the payment method must include transferring money as well as making

[6] In our analysis, the adoption of card payment includes agents' decision to join the formal banking system combined with using card as the payment solution. In that sense, we could also name the two mobile payment categories bank-substituting and bank-complementing mobile payments, respectively.

and receiving payments using a mobile phone. Second, the payment method must be available to the unbanked (i.e., people who do not have access to a formal account at a financial institution). Third, the payment method must offer a network of physical transactional points (that can include agents) widely accessible to users. Fourth, mobile-banking-related payment services (such as Apple Pay and Google Wallet) that offer the mobile phone as just another channel to access a traditional banking product do not satisfy this definition of Mobile Money.

The global adoption of mobile money is concentrating in developing countries. In 2018, 45.6% mobile money users were in sub-Saharan Africa and 33.2% were in South Asia. Meanwhile, mobile money is barely relevant for developed countries.[7]

2.1.2 Card-complementing mobile payment

By contrast, card-complementing mobile payment systems are typically deployed in developed countries. The popular types, including those created by technology firms (e.g., Apple, Google, Samsung), rely heavily on banking and payment card networks. Because of their use of a proximity communication technology (e.g., NFC or QR codes), these payment types are often referred to as mobile proximity payment services.

As a leading example, Apple Pay was launched in 2014 as one of the first mobile wallets – apps that enable people to connect credit cards, debit cards, and bank accounts to mobile devices to send and receive money. Among all the mobile wallet competitors, Apple Pay boasts the largest user adoption and market coverage. Originally launched in the U.S., Apple Pay has been deployed in dozens of countries in a few years, most of which are developed countries.[8]

2.2 Data and stylized facts

To study the global adoption pattern of mobile payments, we assembled a novel dataset on debit card and mobile payment adoption in 94 countries.[9] The countries in our sample

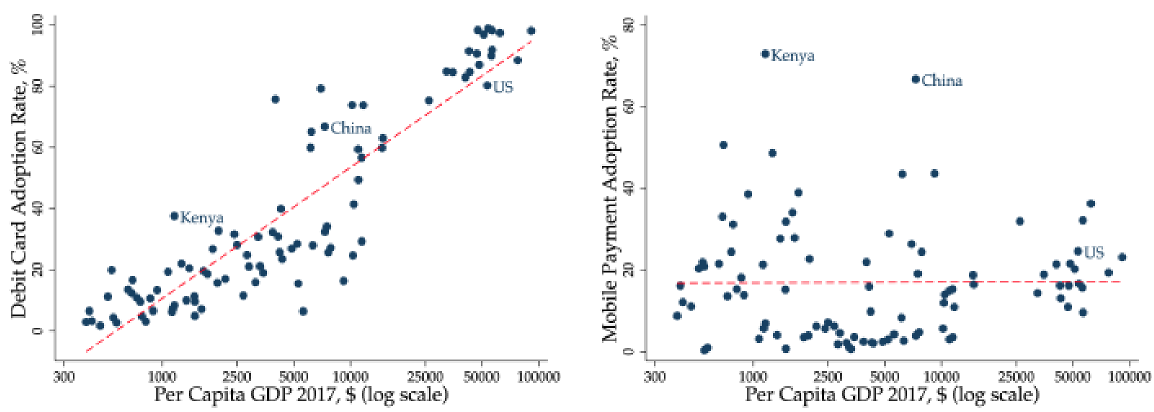
[7]See Figure A1 in Internet Appendix I for the global adoption of mobile money in 2018. Data source: GSMA (2018), "State of the Industry Report on Mobile Money."

[8]See Figure A2 in Internet Appendix I for the global deployment of Apple Pay in 2020. Data source: https://en.wikipedia.org/wiki/Apple Pay#Supported countries.

[9]Debit card ownership is a good measure of consumers who have become banked and have access to either debit or credit card technology because credit card users almost surely own debit cards. For robustness checks, we redid the empirical analysis using an alternative measure from the World Bank dataset on the percentage

accounted for 91.4% of world GDP in 2017.

Our data are drawn from the following sources (See Internet Appendix II for more details). First, the data on the adoption rates of card-substituting mobile payment services in 2017 are based on the Global Financial Inclusion (Global Findex) Database of the World Bank, which surveyed 76 countries with a visible presence of Mobile Money payment services. Second, the data on the adoption rates of card-complementing mobile payments around 2017, gathered from eMarketer, cover 23 countries with a visible presence of mobile proximity payment services. Merging the two mobile payment data sources yields a sample of 94 countries, including five countries covered in both data sources. We also collect the adoption rates of debit cards for the 94 countries in 2017 from the Global Findex Database of the World Bank. Finally, we obtain the data on per capita GDP and other variables for each country in our sample from the World Bank.



(A) Debit Card Adoption (B) Mobile Payment Adoption

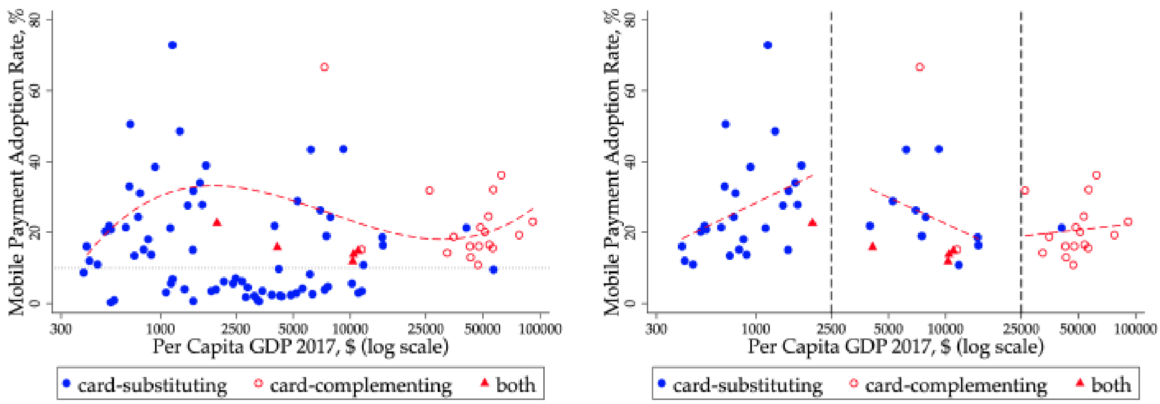
Figure 2. Card and Mobile Payment Adoption across Countries

Figure 2 plots the adoption rates of debit card and mobile payments against log per capita GDP in 2017. Fitting a simple linear regression line to the data shows that debit card adoption increases with per capita GDP across countries, while there appears no clear relationship between mobile payment adoption and per capita GDP.[10]

of the adult population (age 15 and above) using a debit or credit card to make a purchase in the past year and the results are very similar.

[10]The regression results are reported in Table A1 of Internet Appendix III, where per capita GDP is found statistically significant in the card adoption regression but not in the mobile adoption regression. The card adoption model also shows a good fit for the data (adjusted $R^2 = 0.81$) while the mobile adoption model shows a poor fit (adjusted $R^2 = -0.01$).

However, some subtle patterns of mobile payment adoption emerge as we delve further into the data. First, we distinguish mobile payment technologies used in each country in our sample. As shown in Figure 3A, most countries in the highest income group adopt card-complementing mobile payments, while most other countries choose card-substituting ones. Also, considering that mobile payment is a fairly recent technological innovation, it is possible that some countries may not have fully introduced it due to information or coordination frictions. We then leave out the observations that have a very low adoption rate (i.e., <10%)[11] and fit the remaining data with a smooth nonparametric curve.[12] It becomes evident that mobile payment adoption displays a non-monotonic relationship with per capita GDP.



(A) Nonparametric fit

(B) Linear fit

Figure 3. Cross-Country Mobile Payment Adoption

Informed by the nonparametric fitting and countries' adoption of different mobile payment technologies, we divide the sample into three income groups: low-income countries (per capita GDP $<$ \$2,500), middle-income countries (\$2,500 $\leq$ per capita GDP $\leq$ \$25,000), and high-income countries (per capita GDP $>$ \$25,000). We then add back a linear regression line to each income-country group. The results are shown in Figure 3B and corroborate the non-monotonic relationship between mobile payment adoption and per capita income: increasing among low-income countries, decreasing among middle-income countries, and increasing again among high-income countries. The regression results are reported in Internet

[11] Removing observations with mobile payment adoption rates below 10% only affects countries from the Global Findex Database that use Mobile Money payment services. Presumably, the eMarketer dataset on mobile proximity payment adoption has already applied a similar rule.

[12] The nonparametric fitting curve is based on kernel-weighted local polynomial smoothing using the Epanechnikov kernel function.

Appendix III and are robust to using a nonlinear regression model or excluding two outlier countries (Kenya and China) with exceptionally high mobile payment adoption rates (see Tables A1-A2 in Internet Appendix III). The results also show that the non-monotonic mobile payment adoption pattern continues to hold after controlling for a variety of additional factors (see Tables A3-A4 in Internet Appendix III).

To sum up, the data suggests the following stylized facts about cross-country adoption patterns of card and mobile payments:

1. *Positive relationship between per capita income and card adoption.* – The adoption of card payments increases with per capita income across countries.

2. *Non-monotonic relationship between per capita income and mobile payment adoption.* – The adoption of mobile payments increases with per capita income among low- and high-income countries, but decreases with per capita income among middle-income countries.

3. *Overtaking in mobile payment adoption.* – Some low-income countries overtake high-income countries in adopting mobile payments.

4. *Different mobile payment technology choices across countries.* – Low- and middle-income countries primarily adopt card-substituting mobile payment technologies, while high-income countries adopt card-complementing ones.

In the rest of the paper, we construct a theory to explain these stylized facts and conduct welfare and policy analyses.

3 Model

In this section, we provide a model to explain the stylized facts about cross-country payment technology adoption patterns. We first outline the model setup in Section 3.1 and then characterize the equilibrium in Section 3.2.

3.1 Setup

Our model studies the adoption of payment technologies across countries. In each country, three payment technologies arrive sequentially, in the order of cash, card, and mobile.

Cash is a traditional paper payment technology, accessible to everyone in an economy.[13] Using cash incurs a cost τ_h per dollar of transaction, which includes handling, safekeeping, and fraud expenses. In contrast, card and mobile are electronic payment technologies, each of which requires a fixed cost of adoption but lowers variable costs of doing transactions comparing with cash. We denote k_d and k_m as the one-time fixed adoption costs associated with card and mobile, respectively. Those include all tangible and intangible costs that consumers may have to incur for joining banking or mobile payment networks plus the costs of acquiring the hardware and software for making electronic transactions.[14] It is natural to assume $k_d > k_m$.[15] The variable costs associated with using card and mobile are denoted as τ_d and τ_m per dollar of transaction, respectively. To capture the technology progress between cash, card, and mobile, we assume $\tau_h > \tau_d > \tau_m$.[16]

Time is discrete with an infinite horizon. We consider an economy where agents' incomes are exogenous and heterogeneous (e.g., due to differences in productivity). Without loss of generality, we assume that income I_t at date t follows an exponential distribution across the population in the economy, with the cumulative distribution function (cdf) $G_t(I_t) = 1 - \exp(-I_t/\lambda_t)$. The exponential distribution has been shown fitting income distributions well (e.g., see Dragulescu and Yakovenko, 2001). Figure 4 presents an example of fitting the U.S. household income distribution in 2017 with an exponential distribution.[17] Note that the exponential distribution has the mean λ_t and a fixed Gini coefficient at 0.5. Assuming an exponential income distribution allows our benchmark model to focus on the effect of per

[13] One could also assume a fixed adoption cost for cash. But given cash is the only payment option before electronic ones, its adoption is guaranteed, with the adoption cost paid by adopters or subsidized by the government.

[14] Learning costs (e.g., learning about using different payment technologies and evaluating the associated benefits and risks) could be a major component of the adoption costs. Learning requires both time and efforts. While lower-income agents may face lower opportunity costs for their time, they may be confronted with higher effort costs. Therefore, lower-income agents do not necessarily face a lower learning cost for adopting new technologies. In our analysis, we assume agents face the same adoption cost.

[15] In our model context, k_d includes the costs of being banked plus choosing card as the payment instrument, which can be much higher than k_m, the cost of joining a mobile payment network (e.g., Mobile Money). The costs of adopting mobile payment do not have to include the costs of adopting a mobile phone given most consumers have already adopted a mobile phone for communication needs.

[16] The assumption $\tau_d > \tau_m$ captures the technology progress between card and mobile. Violating this assumption would yield a mobile payment adoption pattern different from the data. Note that if $\tau_d \leq \tau_m$, card users would never have incentives to adopt mobile payment. Still, some cash users may adopt mobile payment if k_m is sufficiently smaller than k_d, but they will later switch from mobile to card when their incomes grow sufficiently high.

[17] Source: The U.S. Census Bureau's 2017 Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) Research File, which reports household income in \$2,500 increments up to \$100,000.

capita income while keeping the income inequality fixed, and we show later that our findings are robust under alternative distributional assumptions with flexible Gini coefficients.[18] Over time, each agent's income grows at a constant rate g, i.e., $I_{t+1} = I_t(1+g)$, as does the mean income of the economy, i.e., $\lambda_{t+1} = \lambda_t(1+g)$. We normalize the population size to unity.

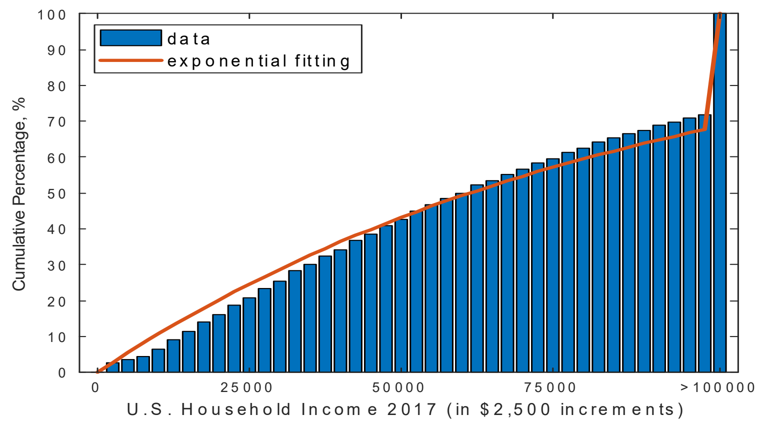


Figure 4. Exponential Income Distribution

An agent has a linear utility $u = c$, where c is her consumption. We assume there is no storage technology, and thus each agent consumes all her income net of payment costs each period. We also assume payment services and merchant services are provided via competitive markets. A consumer always uses her favorite payment technology and the private cost to the consumer equals the social cost.[19] In Sections 6 and 7, we will relax these assumptions and introduce market imperfections in the analysis for robustness checks.

3.2 Equilibrium

Based on the model setup, we derive the equilibrium adoption patterns of cash, card, and mobile payment technologies as they arrive sequentially in an economy.

3.2.1 Cash payment

Cash is the only payment technology in the economy before the arrival of electronic payments. Since cash is accessible to everyone, its adoption rate is 100%. In such an economy, the value

[18] In Section 7.2, we extend the analysis by assuming a log-logistic income distribution and allow for country-specific Gini coefficients, and the findings are very similar.

[19] Note that one could also assume that a fraction ψ of each consumer's spending has to be paid with cash even after the consumer has adopted electronic payments. In that case, some consumers would use multiple payment means, and we can rescale all variable costs of payment by a factor of $(1-\psi)$ and the analysis is intact.

function V_h of an agent depends on her income I_t, and can be written as

$$V_h(I_t) = (1 - \tau_h)I_t + \beta V_h(I_{t+1}),$$

$$\text{where} \quad I_{t+1} = I_t(1 + g)$$

and β is the discount rate.

Accordingly, $V_h(I_{t+1}) = (1 + g)V_h(I_t)$, and we derive

$$V_h(I_t) = \frac{(1 - \tau_h)\, I_t}{1 - \beta(1 + g)}. \tag{1}$$

3.2.2 Card payment

At date T_d, the payment card technology arrives.[20] Each agent then compares card and cash technologies and decides whether to adopt card.

At any date $t \geq T_d$, the value function V_d of an agent who has income I_t and has adopted card can be written as

$$V_d(I_t) = (1 - \tau_d)I_t + \beta V_d(I_{t+1}),$$

which yields

$$V_d(I_t) = \frac{(1 - \tau_d)\, I_t}{1 - \beta(1 + g)}. \tag{2}$$

The availability of the card technology also changes the value function of cash users because it adds an option of adopting card in the future. Therefore, the value function of an agent who has income I_t and decides to continue using cash at date t would be

$$V_h(I_t) = (1 - \tau_h)I_t + \beta \max\{V_h(I_{t+1}), V_d(I_{t+1}) - k_d\}. \tag{3}$$

At any date $t \geq T_d$, an agent would adopt card if and only if

$$V_d(I_t) - k_d \geq V_h(I_t). \tag{4}$$

Therefore, Eqs. (2), (3), and (4) pin down the minimum income level I_d for card adoption,

[20] Given that everyone has access to cash, whether the arrival of card technology is anticipated or not does not affect the analysis.

which requires

$$\frac{(1-\tau_d)\,I_d}{1-\beta(1+g)} - k_d = (1-\tau_h)I_d + \beta[\frac{(1-\tau_d)\,(1+g)I_d}{1-\beta(1+g)} - k_d].$$

Accordingly, an agent would have adopted card by date $t \geq T_d$ if and only if her income satisfies that

$$I_t \geq I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}. \tag{5}$$

The intuition of condition (5) is straightforward: An agent would adopt card if the flow benefit of adoption $(\tau_h - \tau_d)I_t$ can cover the flow cost $(1-\beta)k_d$.

The card payment adoption rate, $F_{d,t}$, is determined as

$$F_{d,t} = 1 - G_t(I_d) = \exp\left(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_t}\right). \tag{6}$$

It follows immediately from Eq. (6) that the payment card adoption rate increases with per capita income (i.e., $\partial F_{d,t}/\partial \lambda_t > 0$).

3.2.3 Mobile payment

Mobile payment arrives after card as an unanticipated shock.[21] In the subsequent analysis, we start with a scenario where only a card-substituting mobile payment technology (e.g., Mobile Money) is introduced, and we then proceed to another scenario where a card-complementing mobile payment technology (e.g., Apple Pay) becomes available.

A card-substituting mobile payment technology. At date $T_m > T_d$, a card-substituting mobile payment technology arrives. This mobile payment technology allows users to replace or bypass the card technology, with a lower marginal cost $\tau_m < \tau_d < \tau_h$ and a lower fixed cost $k_m < k_d$. Each agent then compares three payment technologies (i.e., cash, card, and mobile) to make the adoption decision.

At any date $t \geq T_m$, the value function V_m of an agent who has income I_t and has adopted mobile can be written as

$$V_m(I_t) = (1-\tau_m)I_t + \beta V_m(I_{t+1}),$$

[21] This is a simplifying assumption, and we will relax it in Section 7.1 to consider anticipated arrival of mobile payments.

which yields

$$V_m(I_t) = \frac{(1-\tau_m)\, I_t}{1-\beta(1+g)}. \tag{7}$$

Because mobile is a superior payment technology than card, (i.e., $\tau_m < \tau_d$ and $k_m < k_d$), an agent who has not adopted card by date $T_m - 1$ (i.e., $I_{T_m-1} < I_d$) would no longer consider adopting card at date T_m and afterwards. Instead, they would adopt mobile payment at a date $t \geq T_m$ whenever

$$V_m(I_t) - k_m \geq V_h(I_t), \tag{8}$$

where the value function of a cash user $V_h(I_t)$ now becomes

$$V_h(I_t) = (1-\tau_h)I_t + \beta \max\{V_h(I_{t+1}), V_m(I_{t+1}) - k_m\}. \tag{9}$$

Equations (7), (8), and (9) then pin down the minimum income level I_m for mobile payment adoption:

$$I_t \geq I_m = \frac{(1-\beta)k_m}{(\tau_h - \tau_m)}. \tag{10}$$

Given $\tau_m < \tau_d < \tau_h$ and $k_m < k_d$, Eqs. (5) and (10) imply $I_m < I_d$, so the fraction of agents who have switched from cash to mobile by date $t \geq T_m$ is

$$\begin{aligned} F_{h\to m,t} &= G_{T_m-1}(I_d) - G_t(I_m) = \exp(-I_m/\lambda_t) - \exp(-I_d/\lambda_{T_m-1}) \\ &= \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m-1}}). \end{aligned} \tag{11}$$

An agent who has adopted card by date $T_m - 1$ (i.e., $I_{T_m-1} \geq I_d$) would adopt mobile payment at a date $t \geq T_m$ whenever

$$V_m(I_t) - k_m \geq V_d(I_t), \tag{12}$$

where the value function of a card user now becomes

$$V_d(I_t) = (1-\tau_d)I_t + \beta \max\{V_d(I_{t+1}), V_m(I_{t+1}) - k_m\}. \tag{13}$$

Equations (7), (12), and (13) pin down the income level I'_m above which agents would switch from card to mobile payment to be

$$I_t \geq I'_m = \frac{(1-\beta)k_m}{(\tau_d - \tau_m)}. \tag{14}$$

Hence, the fraction of agents who have switched from card to mobile by date $t \geq T_m$ is

$$\begin{aligned} F_{d\to m,t} &= 1 - G_t(I'_m) = \exp(-I'_m/\lambda_t) \\ &= \exp(-\frac{(1-\beta)k_m}{(\tau_d - \tau_m)\lambda_t}) \end{aligned} \tag{15}$$

as long as some card adopters have not adopted mobile (i.e., $F_{d\to m,t} < F_{d,T_m-1}$). Otherwise, $F_{d\to m,t} = F_{d,T_m-1}$.

Combining Eqs. (11) and (15), the total fraction of agents who have adopted mobile payments by date $t \geq T_m$ is

$$\begin{aligned} F_{m,t} &= F_{h\to m,t} + F_{d\to m,t} = \exp(-I_m/\lambda_t) - \exp(-I_d/\lambda_{T_m-1}) + \exp(-I'_m/\lambda_t) \\ &= \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m-1}}) + \exp(-\frac{(1-\beta)k_m}{(\tau_d - \tau_m)\lambda_t}) \end{aligned} \tag{16}$$

as long as $F_{d\to m,t} < F_{d,T_m-1}$. Otherwise, $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h-\tau_m)\lambda_t})$. This result unveils the following subtle relationship between the mobile payment adoption rate and per capita income:

1. To trace how the mobile payment adoption evolves in a country over time, one can take the value of λ_{T_m-1} as given, so Eq. (16) yields $\partial F_{m,t}/\lambda_t > 0$. This suggests that a country's mobile payment adoption rate increases over time as more agents switch from cash or card to mobile due to their income growth.

2. To make a cross-country comparison at a point in time, however, one needs to take into account $\lambda_{T_m-1} = \lambda_t/(1+g)^{t-T_m+1}$. Accordingly, Eq. (16) can be written as

$$F_{m,t} = \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d(1+g)^{t-T_m+1}}{(\tau_h - \tau_d)\lambda_t}) + \exp(-\frac{(1-\beta)k_m}{(\tau_d - \tau_m)\lambda_t}).$$

   In light of this expression, the sign of $\partial F_{m,t}/\lambda_t$ depends on the level of λ_t. The fraction of cash-mobile switchers (as captured by the first two terms) could decrease in λ_t if λ_t is sufficiently large. That is because in a country with a larger λ_t, more agents would have been locked in by card when the mobile arrives. In contrast, the fraction of card-mobile switchers (as captured by the third term) always increases in λ_t. Therefore, the mobile payment adoption rate may display a non-monotonic relationship with per capita income across countries.

3. In the long run, due to income growth, all the card adopters would eventually switch to mobile (i.e., $F_{d\to m,t} = F_{d,T_m-1}$). We then have $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h-\tau_m)\lambda_t})$, in which case the mobile payment adoption rate becomes strictly increasing in per capita income across countries (i.e., $\partial F_{m,t}/\partial\lambda_t > 0$).

The discussion makes it clear that $F_{d\to m,T_m} < F_{d,T_m-1}$ is a necessary condition for the leapfrogging of mobile payment adoption to occur at T_m. According to Eqs. (6) and (15), this requires $\frac{k_m}{\tau_d-\tau_m} > \frac{k_d(1+g)}{\tau_h-\tau_d}$, which ensures $I'_m > I_d(1+g)$. Therefore, given $\lambda_{T_m} = (1+g)$ λ_{T_m-1}, only a fraction of the consumers who have adopted card by $T_m - 1$ would cross the income threshold for adopting mobile at T_m. If this condition is violated, the cost savings of mobile payment relative to card would be so large that all card users switch to mobile at T_m. As a result, the cross-country mobile adoption would display a rank-preserving pattern, that is, a country with a higher per capita income (and thus a higher card adoption rate) would always have a higher mobile adoption rate.

A card-complementing mobile payment technology. We now extend the model to consider another scenario where a card-complementing mobile payment solution becomes available at T_m. As an add-on upgrade to the existing card technology, this card-complementing mobile payment technology allows a card adopter to pay an upgrading cost k_m^a to get the mobile payment feature that lowers the variable cost of payments (i.e., $\tau_h > \tau_d > \tau_m$). This add-on technology requires a lower fixed cost than adopting the card-substituting mobile payment method (i.e., $k_m^a < k_m$). If offered both mobile payment technologies, agents who have adopted card before T_m would prefer adopting the card-complementing mobile payment technology because $k_m^a < k_m$, while agents who have not adopted card would bypass card and adopt the card-substituting mobile payment technology because $k_m < k_d + k_m^a$.

If card-complementing mobile payment is the only option offered in the economy, card users solve the value function:

$$V_d(I_t) = (1-\tau_d)I_t + \beta \max\{V_d(I_{t+1}), V_m(I_{t+1}) - k_m^a\}. \tag{17}$$

This yields the income threshold I_m^a for adoption:

$$I_t \geq I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}, \tag{18}$$

a result analogous to Eq. (14). Hence, the fraction of mobile adopters by date $t \geq T_m$ is

$$F_{m,t} = F_{d\to m,t} = \exp(-\frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)\lambda_t}), \tag{19}$$

which increases with per capita income across countries.

Alternatively, if both card-complementing and card-substituting mobile payments are offered in the economy, agents who switch from cash to mobile would choose the card-substituting technology. Their fraction is given by Eq. (11) above. Adding the card-mobile switchers given by Eq. (19), the total fraction of mobile payment adopters by date $t \geq T_m$ is

$$\begin{aligned} F_{m,t} &= F_{h\to m,t} + F_{d\to m,t} = \exp(-I_m/\lambda_t) - \exp(-I_d/\lambda_{T_m-1}) + \exp(-I_m^a/\lambda_t) \\ &= \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m-1}}) + \exp(-\frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)\lambda_t}) \end{aligned} \tag{20}$$

as long as $F_{d\to m,t} < F_{d,T_m-1}$. Otherwise, $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t})$. Note that in this case, the mobile payment adoption rate $F_{m,t}$ may again display a non-monotonic relationship with per capita income λ_t across countries. Once all the card adopters have adopted mobile, mobile payment adoption would become strictly increasing with per capita income across countries.

4 Model estimation and implications

In this section, we first estimate the model to fit the cross-country card and mobile payment adoption patterns. We then explore model implications using counterfactual exercises.

4.1 Model estimation

The unit of time is year and we set 2017 as the year T_m when mobile payment became widely available. We assume each country offers one mobile payment option, either the card-substituting one or the card-complementing one, whichever yields the higher mobile payment adoption (cf. Eqs. (16) and (19)).

Table 1. Parameter Values for the Benchmark Model

Panel A: Parameters based on a priori information			
Discount factor	Income growth rate	Cash variable cost	Card variable cost
β	g	τ_h	τ_d
0.95	2%	2.3%	1.4%
Panel B: Parameters based on estimation			
Card adoption cost	Mobile variable cost	Mobile adoption cost	Mobile add-on cost
k_d	τ_m	k_m	k_m^a
589.83	1.395%	175.76	78.17
(238.82)	(0.143%)	(94.33)	(39.09)

There are eight parameters in the benchmark model. Four parameters (i.e., β, g, τ_h, and τ_d) are calibrated by a priori information and they are reported in panel A of Table 1. Specifically, we follow the convention and set the discount factor $\beta = 0.95$ and the annual income growth rate $g = 2\%$. According to a study of the European Central Bank (Schmiedel et al., 2012) on retail payment costs in 13 participating countries, the average social cost of using cash is 2.3% of the transaction value, while that of using debit cards is 1.4%. Hence, we set $\tau_h = 2.3\%$ and $\tau_d = 1.4\%$ accordingly.

The other four parameters (i.e., k_d, τ_m, k_m, and k_m^a) cannot be pinned down by a priori information and we estimate them by matching the model predictions with six data targets: the mean and standard deviation of card payment adoption rates across countries, per capita income at both the peak and trough of mobile payment adoption, as well as the mean and standard deviation of mobile payment adoption rates across countries.[22] These six targeted

[22] The data moments on mobile payment are based on countries whose mobile payment adoption rate are above 10%. The data moments on card payment are based on the same set of countries. The data targets on per capita income at the peak and trough of mobile payment adoption are obtained by nonparametric estimations based on local polynomial smoothing.

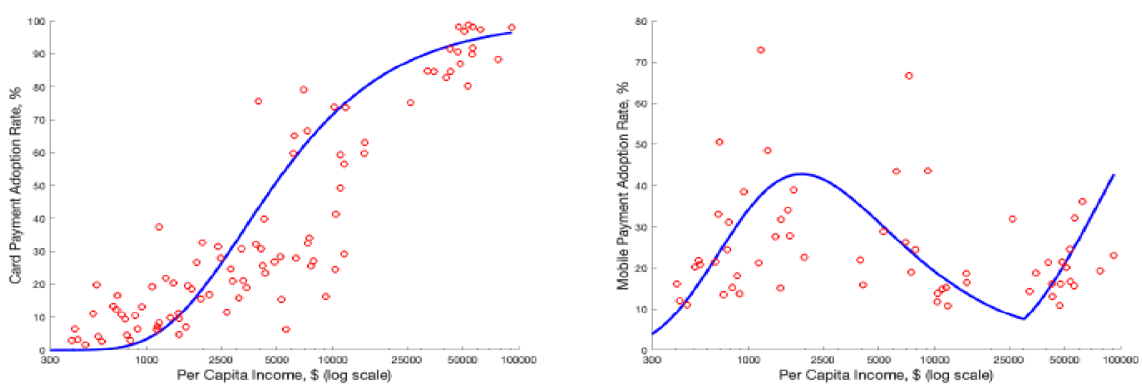
moments are chosen based on their sensitivity to changes in the payment cost parameters and we delineate our detailed identification strategy in Internet Appendix IV.

Panel B of Table 1 reports the four parameter estimates: $k_d = 589.83$, $\tau_m = 1.395\%$ $(< \tau_d)$, $k_m = 175.76$ $(< k_d)$ and $k_m^a = 78.17$ $(< k_m)$. Standard errors of the estimated parameters are reported in parentheses.

Table 2: Model Fit with Data, Targeted Moments

	Data	Model
Card payment adoption, mean	0.449	0.467
Card payment adoption, standard deviation	0.351	0.396
Per capita income at the peak of mobile payment adoption	1,918	1,918
Per capita income at the trough of mobile payment adoption	30,317	30,318
Mobile payment adoption, mean	0.245	0.251
Mobile payment adoption, standard deviation	0.129	0.101

Table 2 shows that our estimated model matches the targeted data moments well. As external validity checks, we plot the model predictions of card and mobile payment adoption rates at each level of per capita income in Figure 5. The figure shows that our estimated model fits the cross-country observations well. It matches the three stylized facts identified above: (1) *Positive relationship between per capita income and card adoption; (2) Non-monotonic relationship between per capita income and mobile payment adoption*; (3) *Overtaking in mobile payment adoption.*



(A) Card Payment Adoption (B) Mobile Payment Adoption

Figure 5. Model Fit with Data: Non-Targeted Observations

Figure 6 shows that our estimated model also matches the fourth stylized fact: (4) *Different technology choice across countries*. In the figure, the green solid line plots the model-implied mobile payment adoption rates assuming the card-substituting one is the only option offered in every country, and the blue solid line does the same for card-complementing mobile payment. The green solid line dominates the blue solid line until per capita income reaches \$30,318, which explains why low- and middle-income countries prefer card-substituting mobile payments while high-income countries favor card-complementing ones.

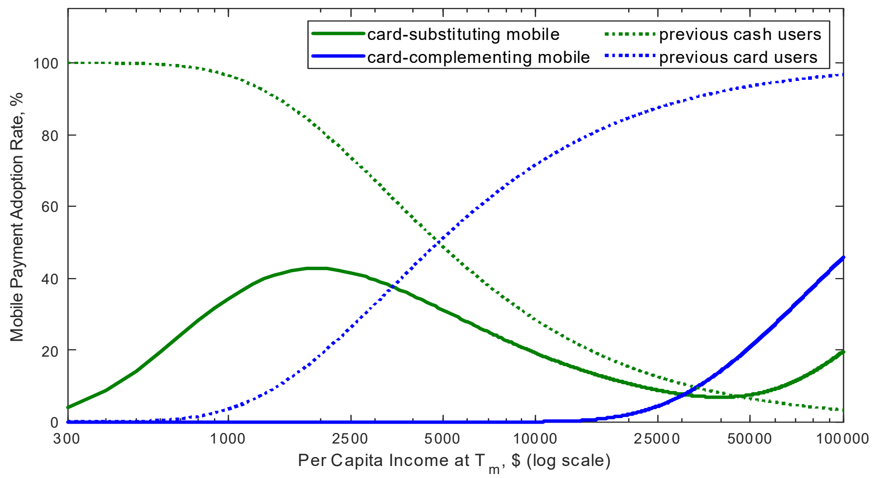


Figure 6. Mobile Payment Technoloy Choices

To better understand the non-monotonic relationship between mobile payment adoption and per capita income, Figure 6 also plots the fractions of existing cash users (green dotted line) and card users (blue dotted line) in each country at $T_m - 1$. Since most agents in low-income countries are cash users, the adoption of card-substituting mobile payments increases with per capita income. By contrast, middle-income countries feature a higher fraction of card users locked in by the card technology. As shown by the solid blue line, almost no card users in middle-income countries would adopt the card-complementing mobile payment option even if it is offered, which implies that they would not adopt card-substituting mobile payments, either (because of the higher adoption cost, i.e., $k_m > k_m^a$). As the fraction of such locked-in card users increases with per capita income, mobile payment adoption decreases with per capita income among middle-income countries. Finally, most agents in high-income countries are card users and some may adopt the card-complementing mobile payment technology if their incomes are sufficiently high. Consequently, the adoption of mobile payment increases with per capita income again.

4.2 Model implications

With the estimated model, we conduct several counterfactual exercises to illustrate the implications of the model.

4.2.1 Mobile payment options

We first investigate how the mobile payment options affect the cross-country adoption pattern. In Figure 7, the green dashed line and the blue dotted line each depict the mobile payment adoption pattern if the card-substituting technology or the card-complementing technology is the only option offered in each country (cf. Eqs. (16) and (19), respectively). The upper envelope of these two lines then tracks the adoption rate if each country chooses to offer one of the two mobile payment options whichever achieves the higher adoption rate. In comparison, the red solid line in the figure shows the adoption pattern if both mobile payment options are offered in each country (cf. Eq. (20)). This exercise provides the following insights.

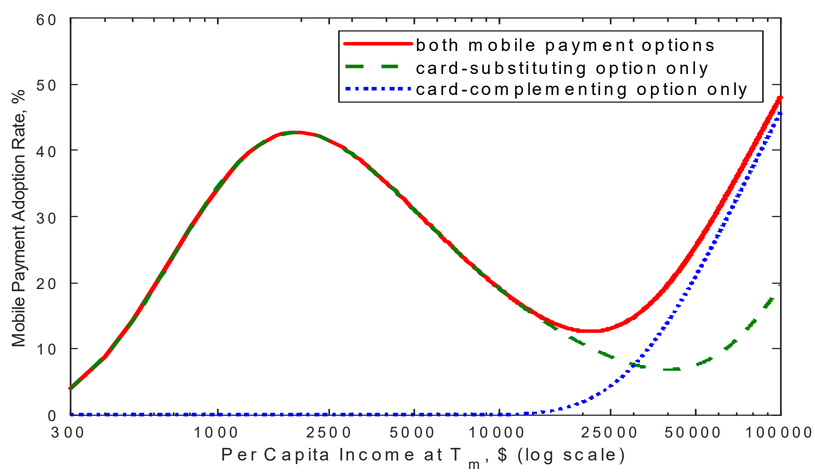


Figure 7. Mobile Payment Options

First, if each country chooses to offer one of the two mobile payment options that delivers the higher adoption rate (i.e., the upper envelope of the green dashed line and the blue dotted line), the result would be very similar to offering both options (i.e., the red line). The difference between the former and the latter is almost invisible in low- and middle-income countries. In high-income countries, there is a small difference because of a small number of cash-mobile switchers who would not exist if only card-complementing technology is offered. This comparison suggests that the parameter values we estimated (cf. Table 1) would allow the model to fit the cross-country mobile payment adoption pattern well even under the alternative assumption that both mobile payment options are offered in each country.

Second, if the card-substituting technology is the only mobile payment option for every country, there would be no drastic change to the cross-country adoption pattern. Under this scenario, mobile payment adoption in high-income countries would fall to some degree due to fewer card-mobile switchers, but the changes to low- and middle-income countries would be virtually negligible.

Finally, having the card-complementing technology as the only mobile payment option would overturn the cross-country adoption pattern. Essentially, this would kill mobile payment adoption in most low- and middle-income countries, and adoption would be increasing with per capita income across countries.

4.2.2 Income growth and technological progress

We now consider the effects of income growth and mobile payment technological progress. In the exercises, we assume both mobile payment technologies are offered in every country (cf. Eq. (20)). As discussed above, the results would be very similar if we instead assume low- and middle-income countries only offer card-substituting mobile payment while high-income countries only offer card-complementing mobile payment.

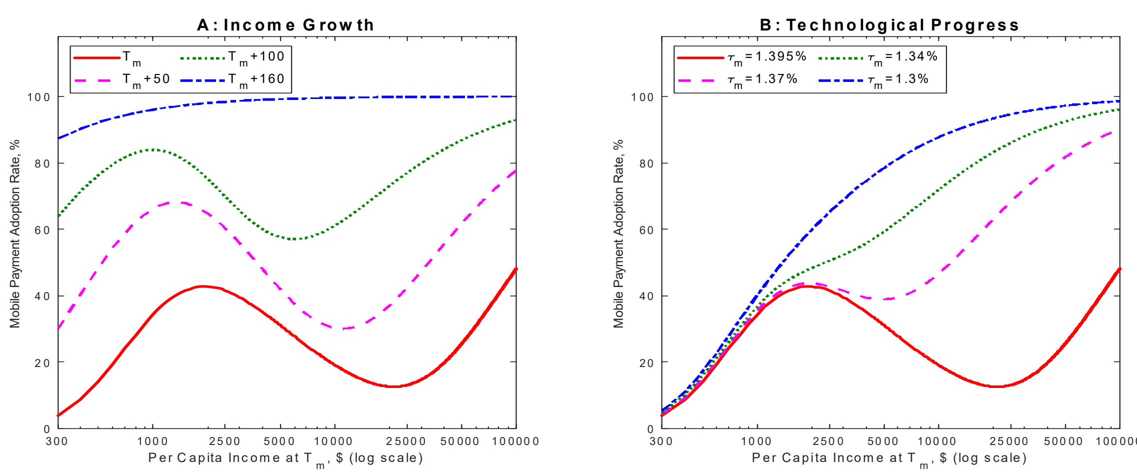


Figure 8. Income Growth and Technoloigical Progress

According to our theory, long-run income growth would eventually lift all the card adopters (who exist before date T_m) to cross the mobile payment adoption threshold. Once that happens, mobile payment adoption would be solely driven by cash-mobile switchers and the adoption rate would become monotonically increasing in per capita income. However, our quantitative exercise suggests that it would take very long for income growth to overturn the non-monotonic adoption pattern. Recall that we assume per capita income grows at 2% annually in each country. Figure 8A tracks each country by per capita income at T_m and plots mobile payment adoption rates at year T_m (red solid line), $T_m + 50$ (pink dashed line), $T_m + 100$ (green dotted line), and $T_m + 160$ (blue dash-dotted line). The figure shows that mobile payment adoption increases in every country as per capita income grows. Nevertheless, the adoption rate continues to be non-monotonic in per capita income. Ultimately, it takes about 160 years to converge to an adoption curve that strictly increases in per capita income.[23]

In contrast, the effect of mobile payment technological progress is more striking. According to our theory, advanced economies are stuck with card payment primarily because the value added of mobile payment is not substantial enough to induce some middle-income card adopters to switch. Therefore, greater technological progress of mobile payment would not only increase the adoption in every country, but could also restore advanced economies to the leading positions in the mobile payment race if the technological progression becomes sufficiently large. To evaluate the effect of technological progress on mobile payment, we reduce the variable mobile payment cost τ_m. As shown in Figure 8B, greater technological progress (i.e., smaller values of τ_m) promotes the mobile payment adoption rate in every country and advanced economies are especially benefitted. If the technological progress is sufficiently large, mobile payment adoption becomes strictly increasing with per capita income across countries.

5 Welfare and policy analyses

In this section, we use our estimated model to gauge payment efficiency and explore welfare and policy implications.

[23] In our quantitative exercise, with the 2% annual income growth rate, all the agents who have adopted card by $T_m - 1$ would have crossed the mobile payment adoption threshold in 160 years. Note that this calculation is only for illustration purpose, and the process would speed up if our model introduces birth and death of agents.

5.1 Payment efficiency

To assess the impact of sequential payment innovations, we conduct a welfare analysis. We first evaluate payment efficiency for individual agents and then for aggregate economies. To simplify notation, we denote each agent by her income level I (without the time subscript) in the analysis. For a symmetric comparison, we assume every country offers both mobile payment options. As we show in Section 5.2, the welfare comparison results are very similar if we instead assume that low- and middle-income countries only offer card-substituting mobile payment while high-income countries only offer card-complementing mobile payment.

5.1.1 Individual agents

We first consider individual agents in a cash economy. Denote $\bar{V}_h(I)$ as the value function of an agent I who would permanently use cash payment. By Eq. (1), we know

$$\bar{V}_h(I) = \frac{(1-\tau_h)\,I}{1-\beta(1+g)}. \tag{21}$$

Thus, the present-value welfare of agent I, denoted by $\omega_t(I)$, equals $\bar{V}_h(I)$ for any $t < T_d$.

At date T_d, the card technology arrives. Denote $\bar{V}_d(I)$ as the value function of an agent I who would permanently use card payment. By Eq. (2), we know

$$\bar{V}_d(I) = \frac{(1-\tau_d)\,I}{1-\beta(1+g)}. \tag{22}$$

The present-value welfare of agent I at date T_d, denoted by $\omega_{T_d}(I)$, depends on the agent's income and the corresponding card adoption decisions:

$$\omega_{T_d}(I) = \begin{cases} \bar{V}_d(I) - k_d & \text{if } I \geq I_d; \\ \bar{V}_h(I) + \beta^s \begin{pmatrix} \bar{V}_d(I(1+g)^s) \\ -k_d - \bar{V}_h(I(1+g)^s) \end{pmatrix} & \begin{array}{l} \text{if } \frac{I_d}{(1+g)^s} \leq I < \frac{I_d}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}. \end{array} \end{cases} \tag{23}$$

Note that $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is given by Eq. (5). The top equation of (23) calculates the welfare of an agent whose income crosses the card adoption threshold at date T_d, and the bottom equation calculates the welfare of an agent who would adopt card at a future date.

At date T_m, the two mobile payment technologies arrive. Denote $\bar{V}_m(I)$ as the value function of an agent I who would permanently use mobile payment. By Eq. (7), we know

$$\bar{V}_m(I) = \frac{(1-\tau_m)\, I}{1-\beta(1+g)}. \tag{24}$$

The present-value welfare of agent I at date T_m, denoted by $\omega_{T_m}(I)$, depends on the agent's income and the corresponding mobile payment adoption decisions:

$$\omega_{T_m}(I) = \begin{cases} \bar{V}_m(I) - k_m^a & \text{if } I \geq I_m^a; \\ \bar{V}_d(I) + \beta^s \begin{pmatrix} \bar{V}_m(I(1+g)^s) \\ -k_m^a - \bar{V}_d(I(1+g)^s) \end{pmatrix} & \begin{array}{l} \text{if } \max(\frac{I_m^a}{(1+g)^s}, I_d(1+g)) \leq I < \frac{I_m^a}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}; \end{array} \\ \bar{V}_m(I) - k_m & \text{if } I_m \leq I < I_d(1+g); \\ \bar{V}_h(I) + \beta^s \begin{pmatrix} \bar{V}_m(I(1+g)^s) \\ -k_m - \bar{V}_h(I(1+g)^s) \end{pmatrix} & \begin{array}{l} \text{if } \frac{I_m}{(1+g)^s} \leq I < \frac{I_m}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}. \end{array} \end{cases} \tag{25}$$

Note that $I_m = \frac{(1-\beta)k_m}{(\tau_h - \tau_m)}$ is given by Eq. (10), and $I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}$ is given by Eq. (18). The top equation of (25) calculates the welfare of a card-mobile switcher whose income crosses the mobile adoption threshold at date T_m, and the second equation is the welfare of a card user who would adopt mobile at a future date. The third equation is the welfare of a cash-mobile switcher at date T_m, and the bottom equation is the welfare of a cash user who would adopt mobile at a future date.

Define the payment efficiency of an agent I, $x_t(I)$, as the ratio between the present value of welfare at date t with and without incurring the payment costs:

$$x_t(I) = \frac{\omega_t(I)}{\frac{I}{1-\beta(1+g)}}. \tag{26}$$

Note that the denominator, $\frac{I}{1-\beta(1+g)}$, is the maximal welfare in an economy without any payment costs, and thus $x_t(I)$ gauges the fraction of the maximal welfare level that can be achieved by agent I under available payment technologies at date t.

Using the parameter values in Table 1, we can compare payment efficiency for individual agents at different income levels under each payment innovation. As in the previous section, we assume that mobile payment technologies arrive at $T_m = 2017$. We then assume that the card payment arrives at $T_d = T_m - 30$.[24] Figure 9 plots the payment efficiency of each agent for $t < T_d$ (i.e., cash only), $t = T_d$ (i.e., card becomes available), $t = T_m$ (i.e., mobile becomes available), according to their individual income level at T_m. For a comparison, we also plot a counterfactual case for $t = T_m$ assuming mobile does not become available then, which we denoted as $\tilde{x}_{T_m}$.

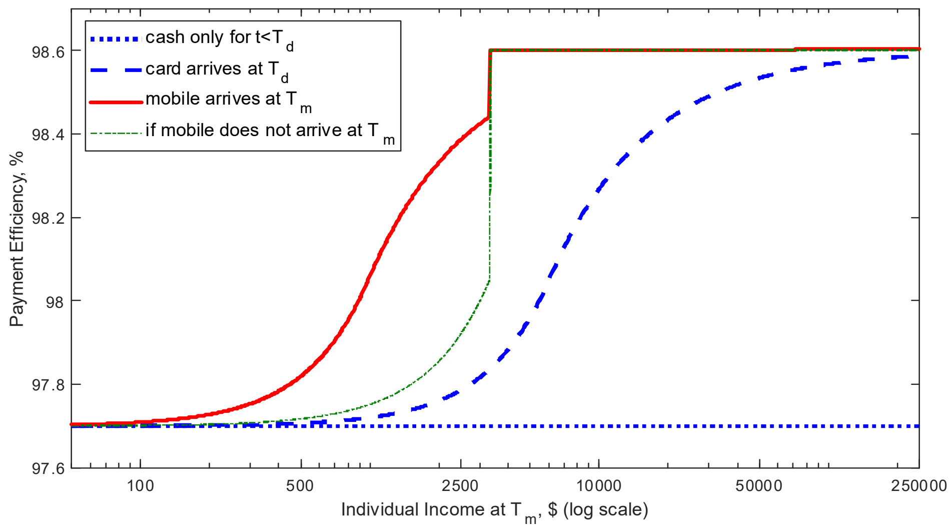


Figure 9. PAYMENT EFFICIENCY BY INDIVIDUAL INCOME

The blue dotted line in Figure 9 shows that every agent has the same payment efficiency when cash is the only payment means (i.e., $x_{t<T_d} = 1 - \tau_h$). Once the card technology arrives at T_d, the payment efficiency improves for every agent, and it increases in agents' income (as shown by the blue dashed curve). A similar pattern holds when the mobile payment arrives at T_m (as shown by the read solid curve). The intuition for why payment efficiency measures (i.e., x_{T_d} and x_{T_m}) increase in agents' income is as follows: It is always feasible for a higher-income agent to mimic a lower-income agent's adoption behavior. If that turns out to be the optimal decision, the higher-income agent enjoys higher payment efficiency than her lower-income counterpart because the adoption cost (i.e., k_d, k_m, or k_m^a) counts for a smaller share of her income. But if mimicking is not the optimal decision, the higher-income

[24] Since the large-scale introduction of debit cards in the U.S. started in the mid-1980s (see Hayashi, Li, and Wang, 2017), we set $T_d = T_m - 30$. Note that the quantitative findings are robust if we use an alternative year for T_d because choosing an earlier (or later) T_d would not change anything except adjusting down (or up) the level of the payment efficiency x_{T_d} given that the card adoption cost k_d counts for a larger (or smaller) share of agents' income in an earlier (or later) year.

agent must be able to achieve even higher payment efficiency by choosing a payment method different from her lower-income counterpart.

Figure 9 also illustrates how payment efficiency evolves across income levels over time. At date T_d, agents either pay or expect to pay in the future the fixed cost k_d to adopt card, and the agents whose incomes are at the card adoption threshold are indifferent between adopting card or not. Accordingly, the payment efficiency measure x_{T_d} is a continuous and increasing function of income. For any date $t \in (T_d, T_m)$, card users who have paid off k_d in the past no longer count the fixed cost in their payment efficiency measure, and thus $x_t = 1 - \tau_d$ for them. Meanwhile, since cash users who just meet or have not met the card adoption threshold need to pay the fixed cost, their payment efficiency x_t displays a jump at the card adoption threshold, as illustrated by the green dash-dotted curve $\tilde{x}_{T_m}$. For those cash users, their payment efficiency improves over time because the card adoption cost k_d accounts for a smaller share of their income levels as their incomes grow. Comparing the two curves x_{T_m} (the red solid one) and $\tilde{x}_{T_m}$ (the green dash-dotted one) shows that introducing mobile improves payment efficiency for every agent (though much more for cash users than for card users) and shrinks the jump at the card adoption threshold.[25]

5.1.2 Aggregate economies

We now evaluate overall payment efficiency across countries by solving the present-value welfare of the aggregate economies, denoted by $W_t(\lambda_t)$, for three periods: $t < T_d$ (i.e., cash only), $t = T_d$ (i.e., card becomes available), and $t = T_m$ (i.e., mobile becomes available).

Recall that $\bar{V}_h(I)$ is the value function of an agent I who would permanently use the cash technology, given by Eq. (21). Accordingly, the present-value welfare of a pure cash economy $W_{t<T_d}$ equals

$$W_{h,t} = \int_0^\infty \bar{V}_h(I)dG_t(I). \tag{27}$$

Recall that $\bar{V}_d(I)$ is the value function of an agent I who would permanently use the card

[25] For cash users, introducing mobile improves their payment efficiency substantially because of the much reduced adoption cost comparing with card (recall that $k_d = 589.83$ vs. $k_m = 175.76$). For card users, the red solid curve is indeed continuous and increasing in income, but the magnitude of the increase is small. As a result, it is not easily seen in the figure (recall that card users' payment efficiency only improves slightly somewhere between $1 - \tau_d$ and $1 - \tau_m$, where $\tau_d = 1.4\%$ and $\tau_m = 1.395\%$).

technology, given by Eq. (22). The present-value welfare of the economy at T_d is

$$W_{T_d} = W_{h,T_d} + \int_{I_d}^{\infty} \left(\bar{V}_d(I) - k_d - \bar{V}_h(I)\right) dG_{T_d}(I) + \sum_{s=1}^{\infty} \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_d(I(1+g)^s) - k_d - \bar{V}_h(I(1+g)^s)\right) dG_{T_d}(I), \tag{28}$$

where $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is from Eq. (5). Note that the first term of the right-hand side of Eq. (28) is the present value of welfare for all the agents if they continue using cash forever. The second term is the additional welfare gains for card adopters at date T_d, and the last term is the additional welfare gains for future card adopters.

Recall that $\bar{V}_m(I)$ is the value function of an agent I who would permanently use the mobile payment technology, given by Eq. (24). We can then derive the present value of welfare for the economy at T_m to be

$$\begin{aligned} W_{T_m} = & \int_0^{I_d(1+g)} \bar{V}_h(I) dG_{T_m}(I) + \int_{I_m}^{I_d(1+g)} \left(\bar{V}_m(I) - k_m - \bar{V}_h(I)\right) dG_{T_m}(I) \\ & + \sum_{s=1}^{\infty} \int_{\frac{I_m}{(1+g)^s}}^{\frac{I_m}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_m(I(1+g)^s) - k_m - \bar{V}_h(I(1+g)^s)\right) dG_{T_m}(I) \\ & + \int_{I_d(1+g)}^{\infty} \bar{V}_d(I) dG_{T_m}(I) + \int_{\max(I_m^a, I_d(1+g))}^{\infty} \left(\bar{V}_m(I) - k_m^a - \bar{V}_d(I)\right) dG_{T_m}(I) \\ & + \sum_{s=1}^{\infty} \int_{\max(\frac{I_m^a}{(1+g)^s}, I_d(1+g))}^{\max(\frac{I_m^a}{(1+g)^{s-1}}, I_d(1+g))} \beta^s \left(\bar{V}_m(I(1+g)^s) - k_m^a - \bar{V}_d(I(1+g)^s)\right) dG_{T_m}(I), \end{aligned} \tag{29}$$

where $I_m = \frac{(1-\beta)k_m}{(\tau_h - \tau_m)}$ is given by Eq. (10), and $I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}$ is given by Eq. (18). Note that the first term of the right-hand side of Eq. (29) is the present-value welfare for all the cash users at $T_m - 1$ if they continue using cash at date T_m and forever. The second term is the additional welfare gains of cash-mobile switchers at date T_m, and the third term is the additional welfare gains for future cash-mobile switchers. The fourth term is the present-value welfare for all the card adopters at $T_m - 1$ if they continue using card at date T_m and forever. The fifth term is the additional welfare gains of card-mobile switchers at date T_m, and the last term is the additional welfare gains for future card-mobile switchers.

With the exponential income distribution, one can solve Eqs. (27), (28), and (29) explicitly (see Internet Appendix V for the solution details). Analogous to the discussions above, we define the payment efficiency of an economy, $X_t(\lambda_t)$, as the ratio between the present value of aggregate welfare with and without incurring payment costs at date t:

$$X_t(\lambda_t) = \frac{W_t(\lambda_t)}{\frac{\lambda_t}{1-\beta(1+g)}}. \tag{30}$$

Using the parameter values in Table 1, we can now compare payment efficiency across countries under each payment technology. As in the previous section, we assume that mobile payment technologies arrive at $T_m = 2017$, and the card payment technology arrives at $T_d = T_m - 30$. Figure 10 plots the payment efficiency of each economy for $t < T_d$, $t = T_d$, and $t = T_m$, according to their per capita income level at T_m.

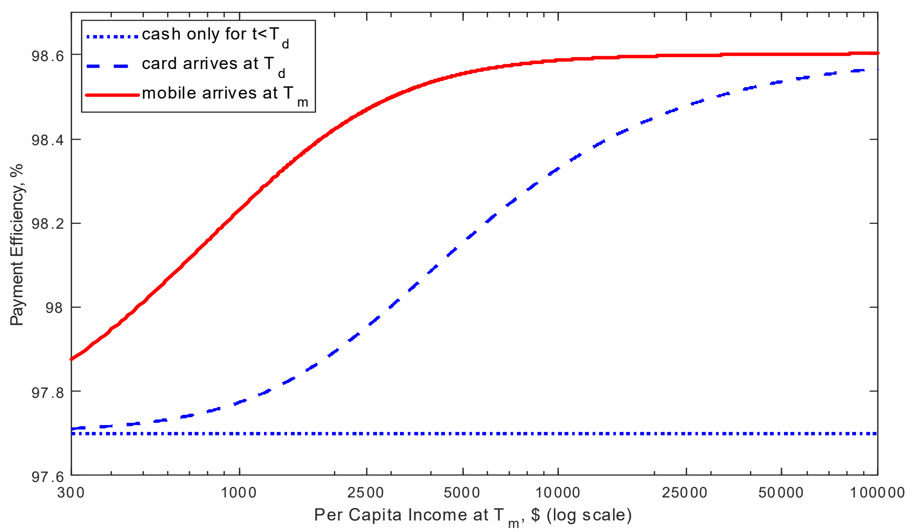


Figure 10. Payment Efficiency by Per Capita Income

As depicted in Figure 10, every country has the same payment efficiency when cash is the only payment means (i.e., $X_{t<T_d} = 1 - \tau_h$). Once the card technology arrives, the payment efficiency improves in every country, and the efficiency improvement increases in per capita income across countries. Hence, high-income countries gain the most from the card payment adoption. The arrival of mobile payments also benefits every country, though disproportionately. The relative welfare gain $(X_{T_m} - X_{T_d})/X_{T_d}$ peaks at the per capita income around \$1,900, but richest countries remain leaders in terms of overall payment efficiency. In contrast, the poorest countries do not gain much from either card or mobile payment innovations because most of their consumers are stuck with cash.

5.2 Policy implications

Our model sheds light on the welfare implications of public policies aimed at promoting mobile payment development. On the supply side, introducing mobile payments requires investment in the related infrastructures. Hence, it is important to evaluate the social return of such investment to guide policy decisions. Our model helps inform such decisions by quantifying the social benefit of introducing mobile payments given a country's per capita income level.[26]

In doing so, one could use the model to compare per capita welfare gain from introducing mobile payments and its counterfactual counterpart. In the counterfactual scenario, no mobile payment is introduced and card and cash continue to be the only payment options at date T_m. Per capita welfare of the counterfactual economy, denoted as $\tilde{W}_{T_m}$, is given by

$$\begin{aligned}\tilde{W}_{T_m} &= W_{h,T_m} + \int_{I_d(1+g)}^{\infty} \left(\bar{V}_d(I) - \bar{V}_h(I)\right) dG_{T_m}(I) + \int_{I_d}^{I_d(1+g)} \left(\bar{V}_d(I) - k_d - \bar{V}_h(I)\right) dG_{T_m}(I) \\ &\quad + \sum_{s=1}^{\infty} \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_d(I(1+g)^s) - k_d - \bar{V}_h(I(1+g)^s)\right) dG_{Tm}(I), \qquad (31)\end{aligned}$$

where $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is from Eq. (5). Note that Eq. (31) is similar to Eq. (28) except that the income distribution is measured at date T_m (instead of T_d) and agents who have already adopted card before T_m no longer need to pay the card adoption cost k_d. Given the exponential income distribution, one can solve $\tilde{W}_{T_m}$ explicitly.

With the parameter values in Table 1, we calculate $W_{T_m} - \tilde{W}_{T_m}$ using Eqs. (29) and (31) to quantify per capita welfare gain from introducing two mobile payment options (i.e., card-substituting and card-complementing ones) in each country at $T_m = 2017$ in dollar value. We also calculate per capita welfare gain from introducing just one mobile payment option, denoted as $W_{T_m}^{Subs} - \tilde{W}_{T_m}$ for the card-substituting one and $W_{T_m}^{Comp} - \tilde{W}_{T_m}$ for the card-complementing one.[27] The results, plotted in the left panel of Figure 11, are similar to the mobile payment options and adoption patterns shown in Figure 7.

According to Figure 11A, the per capita welfare gain from introducing both mobile pay-

[26] Our analysis focuses on the direct social benefit from improving payment efficiency. To the extent that payment innovations may have indirect social benefits (e.g., financial inclusion) or feedback impact on the broad economy, our calculation can be viewed as a lower bound.

[27] Note that the calculation of $W_{T_m}^{Subs}$ is similar to W_{T_m} except that card-mobile switchers now need to pay a higher adoption cost k_m instead of k_m^a. The calculation of $W_{T_m}^{Comp}$, however, is different from W_{T_m} because any cash users now have to adopt card first before adopting mobile.

ment options is low for the poorest countries (e.g., welfare gain is \$14 per capita for countries with per capita income at \$300) as well as for some relatively high-income countries (e.g., welfare gain is \$35 per capita for countries with per capita income at \$28,000). In contrast, the welfare gain peaks at \$125 per capita for countries with per capita income at \$2,100. For a rich country at the U.S.-level of per capita income (\$53,356 in 2017), the welfare gain is \$51 per capita.

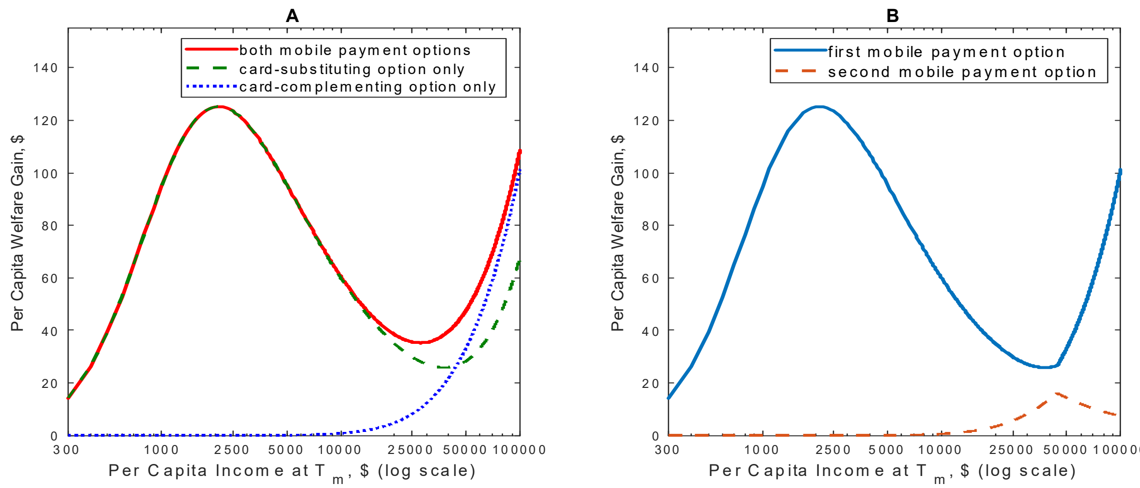


Figure 11. Welfare Gain from Mobile Payments

Figure 11A also suggests that the incremental welfare gain from introducing the second mobile payment option is relatively small and varies by per capita income. To make it clearer, we plot in Figure 11B each country's per capita welfare gain from its more desirable choice of the two mobile payment options (i.e., $\max(W_{T_m}^{Subs} - \tilde{W}_{T_m}, W_{T_m}^{Comp} - \tilde{W}_{T_m})$), and we then plot the per capita welfare gain from adding the second option (i.e., $W_{T_m} - \max(W_{T_m}^{Subs}, W_{T_m}^{Comp})$). The result shows that countries with per capita income below \$12,000 would derive little per capita welfare gain ($<$ \$0.99) from introducing card-complementing mobile payment as the second option. In contrast, a country with per capita income at \$44,300 could gain \$16.1 per capita by introducing card-substituting mobile payment as the second option, but that benefit would decline for countries with higher per capita income.

Based on the per capita welfare gain quantified in this exercise, one could calculate the total welfare gains for a country (i.e., per capita welfare gain $\times$ population) for introducing either one or two mobile payment options. Evaluating the welfare gains against the investment costs would then help determine the social return and the priority of making such investments.

On the demand side, without considering any market imperfection, our model implies that consumers always make payment adoption and usage decisions that are socially optimal. However, this simplified setting is intended to serve as a theoretic benchmark, and our model can be readily extended to incorporate market imperfections. In the next section, we develop a formal extension where externalities in the payment market distort consumers' payment decisions. We show most of our findings continue to hold even though market outcomes are no longer socially optimal, and we discuss how policy interventions may help improve welfare.

6 Two-sided market and payment externalities

In this section, we embed sequential payment innovations in a two-sided market setting. It is well known that the payment market is two-sided, in which consumers and merchants jointly use each payment technology in transactions but bear separate costs. A central friction of the two-sided payment market is price coherence: merchants typically charge consumers the same retail price no matter how they pay.[28] Consequently, consumers do not internalize the payment externalities they generate on merchants and through merchant pricing onto other consumers. In our model setting, such externalities would affect the adoption and usage of payment innovations and lead to welfare and policy consequences.

Formally, consider that each consumer receives an income I_t at date t, and I_t follows an exponential distribution across the population of consumers. Consumers spend their incomes on purchasing a numeraire good for consumption each period. The numeraire good is produced at a unit cost and distributed through competitive merchants. Conducting a transaction between a merchant and a consumer requires using a payment technology $i \in \{h$ (cash), d (card), m (mobile)$\}$, for which the merchant (seller) and the consumer (buyer) each incurs a variable cost $\tau_{s,i}$ or $\tau_{b,i}$ per dollar of transactions. As before, consumers incur a fixed cost k_d and k_m (or k_m^a) for adopting card and mobile payments, respectively. For simplicity, we assume that merchants each serve a large representative group of consumers, and the fixed cost for a merchant to adopt card or mobile payment technology is negligible on a per customer or per transaction basis.

[28] Price coherence is commonly seen in reality. It could be due to regulations or transaction costs that prohibit merchants from price discriminating based on payment means.

6.1 Price differentiation

In a price differentiation regime, a competitive merchant accepting payment means i would set price p_i for selling the numeraire good to break even:

$$p_i = \frac{1}{1 - \tau_{s,i}}.$$

Hence, a consumer using payment technology i at date t would purchase and consume the quantity $q_{i,t}$ of the good:

$$q_{i,t} = \frac{I_t(1 - \tau_{b,i})}{p_i} = I_t(1 - \tau_{b,i})(1 - \tau_{s,i}).$$

It transpires that under price differentiation, the new model setup is equivalent to our benchmark model by reinterpreting notations: For each payment technology $i \in \{h, d, m\}$, one simply needs to redefine the variable cost τ_i such that

$$1 - \tau_i = (1 - \tau_{b,i})(1 - \tau_{s,i}). \tag{32}$$

and all the analysis remains unchanged. Essentially, merchants pass on payment costs to consumers according to the payment technologies they use through retail prices.[29]

6.2 Price coherence

Alternatively, if merchants do not price differentiate based on payment means, consumers would pay the same retail price regardless of payment technologies they use. This is termed "price coherence" in the two-sided market literature, under which each consumer's adoption and usage of payment technologies would impose externalities on others. According to Rochet

[29] Besides the equivalent results, extending the model to a two-sided market setting brings additional insights. Because the payment market outcome depends on two sides' decisions, multiple equilibria can arise. The market outcome we analyzed previously remains a valid equilibrium, but it is no longer the unique one. For example, there could exist another equilibrium where no merchants or consumers adopt a new payment technology because they each expect no adoption from the other side. This so-called "chicken-and-egg" dynamic often arises in network industries or for technologies featuring strong adoption complementarity, and coordination becomes an important issue (see e.g., Buera et al., 2021). In terms of mobile payments, we observe in the data that some countries have an adoption rate far below their peers at similar per capita income levels, which might signal certain coordination failures among relevant parties. In those cases, appropriate policy interventions, such as coordinating standard setting or providing incentives to early adopters, may help align market expectations and enhance welfare.

and Tirole (2002, 2006) and the following two-sided market studies, price coherence is a key friction in the two-sided payment markets that causes efficiency losses.[30] In the following, we extend our model to incorporate this friction.

6.2.1 Card adoption

Since there is only one payment technology in a cash economy, the analysis does not change. Once the card technology arrives at date T_d, a price-coherent merchant would set a single price p_t regardless of payment means for any date $t \geq T_d$. This price is time varying because the composition of card and cash users as well as their spending evolve with income growth.

Denote $I_{d,t}$ the income threshold for adopting card at date t. The merchant receives total revenues

$$R_t = (1 - \tau_{b,h}) \int_0^{I_{d,t}} I dG_t(I) + (1 - \tau_{b,d}) \int_{I_{d,t}}^{\infty} I dG_t(I)$$

from cash and card customers, which equals buyers' total income net of their payment costs. These revenues, net of the seller's payments costs, would allow the merchant to provide a total quantity Q_t of numeraire goods (recall the cost of goods is 1 per unit):

$$Q_t = (1 - \tau_{s,h})(1 - \tau_{b,h}) \int_0^{I_{d,t}} I dG_t(I) + (1 - \tau_{s,d})(1 - \tau_{b,d}) \int_{I_{d,t}}^{\infty} I dG_t(I).$$

Therefore, the merchant sets the retail price $p_t = R_t/Q_t$ to break even. Given that consumer income is exponentially distributed, we derive

$$p_t = \frac{R_t}{Q_t} = \frac{(1 - \tau_{b,h})\lambda_t + (\tau_{b,h} - \tau_{b,d})\exp(-I_{d,t}/\lambda_t)(\lambda_t + I_{d,t})}{(1 - \tau_h)\lambda_t + (\tau_h - \tau_d)\exp(-I_{d,t}/\lambda_t)(\lambda_t + I_{d,t})}, \tag{33}$$

where we denote $\tau_i = 1 - (1 - \tau_{b,i})(1 - \tau_{s,i})$ for $i \in \{h, d\}$ in the equation.

Facing the coherent price p_t, a consumer using a payment technology $i \in \{h, d\}$ would

[30] Some studies, such as Edelman and Wright (2015) and Wang (2022), point out that due to price coherence, credit cards have become more costly payment means for merchants to accept compared with debit cards or cash, and excessive credit card rewards may reduce payment efficiency. In our analysis, by contrast, we choose to refrain from getting into detailed product differentiation of cards or country-specific market conditions. Instead, we focus on the general technological trends in the payment space that cash, card, and mobile each represents a new generation of more efficient payment means. This is consistent with cross-country social cost estimates of payment means (e.g., Schmiedel et al., 2012) as well as the revealed preference that almost all countries around the world are promoting financial inclusion and electronic payments.

purchase the quantity $q_{i,t}$:

$$q_{i,t} = \frac{I_t(1-\tau_{b,i})}{p_t}.$$

Accordingly, a consumer would adopt card if the flow benefit exceeds the flow cost, (i.e., $q_{d,t} - q_{h,t} \geq (1-\beta)k_d$), which implies an income threshold $I_{d,t}$ above which a consumer would adopt card at date t :

$$I_{d,t} = \frac{(1-\beta)k_d}{(\tau_{b,h} - \tau_{b,d})} p_t. \tag{34}$$

In contrast to our benchmark model, the income threshold $I_{d,t}$ for card adoption now depends on $(\tau_{b,h} - \tau_{b,d})$ instead of $(\tau_h - \tau_d)$ because under price coherence, consumers would only consider the buyer-side but not seller-side payment savings. The threshold $I_{d,t}$ also depends on the retail price p_t, which is time-varying. With the exponential income distribution, the card adoption rate $F_{d,t} = \exp(-I_{d,t}/\lambda_t)$, and we can rewrite Eq. (34) to pin down $F_{d,t}$ as a function of per capita income λ_t and other parameters:

$$-\lambda_t \ln(F_{d,t}) = \frac{(1-\beta)k_d}{(\tau_{b,h} - \tau_{b,d})} \frac{(1-\tau_{b,h}) + (\tau_{b,h} - \tau_{b,d})\, F_{d,t}(1-\ln(F_{d,t}))}{(1-\tau_h) + (\tau_h - \tau_d)\, F_{d,t}(1-\ln(F_{d,t}))}. \tag{35}$$

6.2.2 Mobile payment adoption

We assume two mobile payment technologies arrive at date T_m. A merchant would set the single retail price p_t for any $t \geq T_m$ based on the composition of cash, card, and mobile users. Denote $I_{m,t}$ and $I^a_{m,t}$ the date-t income thresholds for adopting card-substituting and card-complementing mobile payments, respectively. A merchant receives total revenues

$$R_t = \left\{ \begin{array}{c} (1-\tau_{b,h}) \int_0^{I_{m,t}} I dG_t(I) + (1-\tau_{b,m}) \int_{I_{m,t}}^{I_{d,T_m-1}(1+g)^{(t-T_m+1)}} I dG_t(I) \\ +(1-\tau_{b,d}) \int_{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}^{I^a_{m,t}} I dG_t(I) + (1-\tau_{b,m}) \int_{I^a_{m,t}}^{\infty} I dG_t(I) \end{array} \right\} \tag{36}$$

from customers, and provides the quantity of numeraire goods

$$Q_t = \left\{ \begin{array}{c} (1-\tau_h) \int_0^{I_{m,t}} I dG_t(I) + (1-\tau_m) \int_{I_{m,t}}^{I_{d,T_m-1}(1+g)^{(t-T_m+1)}} I dG_t(I) \\ +(1-\tau_d) \int_{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}^{I^a_{m,t}} I dG_t(I) + (1-\tau_m) \int_{I^a_{m,t}}^{\infty} I dG_t(I) \end{array} \right\}. \tag{37}$$

Accordingly, the merchant sets the retail price $p_t = R_t/Q_t$ to break even.

Taking the price p_t as given, a consumer using a payment means $i \in \{h, d, m\}$ would purchase the quantity $q_{i,t}$ of the good:

$$q_{i,t} = \frac{I_t(1-\tau_{b,i})}{p_t}.$$

Because mobile is more efficient than card (i.e., $\tau_{b,m} < \tau_{b,d}$ and $k_m < k_d$), an existing cash consumer who has not adopted card by date T_m would consider adopting the card-substituting mobile payment instead of card afterwards. Such cash users would adopt mobile if the flow benefit exceeds the flow cost, (i.e., $q_{m,t} - q_{h,t} \geq (1-\beta)k_m$), which implies an income threshold $I_{m,t}$:

$$I_{m,t} = \frac{(1-\beta)k_m}{(\tau_{b,h} - \tau_{b,m})} p_t. \tag{38}$$

Similarly, a consumer who has adopted card by date T_m would consider adopting card-complementing mobile if the flow benefit exceeds the flow cost, (i.e., $q_{m,t} - q_{d,t} \geq (1-\beta)k^a_m$). This implies an income threshold $I^a_{m,t}$:

$$I^a_{m,t} = \frac{(1-\beta)k^a_m}{(\tau_{b,d} - \tau_{b,m})} p_t. \tag{39}$$

Equations (38) and (39) suggest that $I_{m,t}$ and $I^a_{m,t}$ are connected so that

$$I^a_{m,t} = zI_{m,t}, \text{ where } z = \frac{k^a_m(\tau_{b,h} - \tau_{b,m})}{k_m(\tau_{b,d} - \tau_{b,m})}. \tag{40}$$

Denote $F_{e,t}$ the fraction of consumers who have adopted any electronic payments (card or mobile) by date t. The exponential income distribution implies that $F_{e,t} = \exp(-I_{m,t}/\lambda_t)$, and we can pin down $F_{e,t}$ via Eq. (38) together with Eqs. (36), (37) and (40) as follows:

$$-\lambda_t \ln(F_{e,t}) \frac{(\tau_{b,h} - \tau_{b,m})}{(1-\beta)k_m} = \tag{41}$$

$$\frac{\begin{array}{c} (1-\tau_{b,h}) + (\tau_{b,h} - \tau_{b,m})\, F_{e,t}(1-\ln(F_{e,t})) \\ +\, (\tau_{b,m} - \tau_{b,d}) \left[\begin{array}{c} \exp(-\frac{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}{\lambda_t})(1 + \frac{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}{\lambda_t}) \\ -\exp(z\ln(F_{e,t}))(1 - z\ln(F_{e,t})) \end{array} \right] \end{array}}{\begin{array}{c} (1-\tau_h) + (\tau_h - \tau_m)\, F_{e,t}(1-\ln(F_{e,t})) \\ +\, (\tau_m - \tau_d) \left[\begin{array}{c} \exp(-\frac{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}{\lambda_t})(1 + \frac{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}{\lambda_t}) \\ -\exp(z\ln(F_{e,t}))(1 - z\ln(F_{e,t})) \end{array} \right] \end{array}}.$$

With $F_{e,t}$, one can then solve all the endogenous variables including $I_{m,t}$, $I^a_{m,t}$ and p_t.

Note that as income grows, all the previous card consumers will eventually adopt mobile payments (i.e., $I^a_{m,t} = zI_{m,t} \leq I_{d,T_m-1}(1+g)^{(t-T_m+1)}$). Once that happens, there are just two payment means (i.e., cash and mobile) in use. Analogous to the analysis of the card economy discussed above, one can solve $F_{e,t}$ using the following equation

$$-\lambda_t \ln(F_{e,t}) = \frac{(1-\beta)k_m}{(\tau_{b,h}-\tau_{b,m})} \frac{(1-\tau_{b,h}) + (\tau_{b,h}-\tau_{b,m}) F_{e,t}(1-\ln(F_{e,t}))}{(1-\tau_h) + (\tau_h - \tau_m) F_{e,t}(1-\ln(F_{e,t}))}, \tag{42}$$

and then derive the other endogenous variables.

6.3 Quantitative analysis

To conduct quantitative analysis for the price-coherent model, we use parameter values consistent with the benchmark model, as shown in Table 3. We assume that cash, card and mobile each yield symmetric benefits to consumers and merchants: $\tau_{b,i} = \tau_{s,i}$ for $i \in \{h, d, m\}$. Under this assumption, Eq. (32) implies that $\tau_{b,i} = \tau_{s,i} = 1 - \sqrt{(1-\tau_i)}$, where $\tau_h = 2.3\%$, $\tau_d = 1.4\%$ and $\tau_m = 1.395\%$. We then show that for the price-coherent model to fit data as well as the benchmark model, one needs to reduce the adoption costs (i.e., k_d, k_m and k^a_m) by half from their previous values. For ease of notations, we round the values of k_d, k_m and k^a_m to the nearest integer in the following exercises.

Table 3. Parameter Values for Two-sided Market Model

Parameter	Value	Description	Comparing with benchmark model
β	0.95	Discount factor	same as the benchmark model
g	2%	Income growth rate	same as the benchmark model
$\tau_{b,h}$= $\tau_{s,h}$	1.157%	Cash variable cost	equals $1-\sqrt{1-\tau_h}$ where τ_h=2.3%
$\tau_{b,d}$= $\tau_{s,d}$	0.703%	Card variable cost	equals $1-\sqrt{1-\tau_d}$ where τ_d=1.4%
$\tau_{s,m}$= $\tau_{s,d}$	0.700%	Mobile variable cost	equals $1-\sqrt{1-\tau_m}$ where τ_m=1.395%
k_d	295	card adoption cost	half of the benchmark estimate where k_d=590
k_m	88	mobile adoption cost	half of the benchmark estimate where k_m=176
k^a_m	39	mobile add-on cost	half of the benchmark estimate where k^a_m=78

We plot model predictions of card and mobile payment adoption rates at each level of per capita income in Figure 12. The results show that with the same parameter values, the adoption of card and mobile payments would be lower under the price-coherent regime (drawn with red dotted lines) than under the price-differentiation regime (drawn with blue dashed lines) because under the former consumers would only consider savings of payment costs on the buyer side but not on the seller side. In comparison, once we reduce the adoption costs (i.e., k_d, k_m and k_m^a) by half, the price-coherent model replicates almost the same adoption patterns generated by the price-differentiation model (which is equivalent to our benchmark model), as shown by the yellow solid lines in the figure.

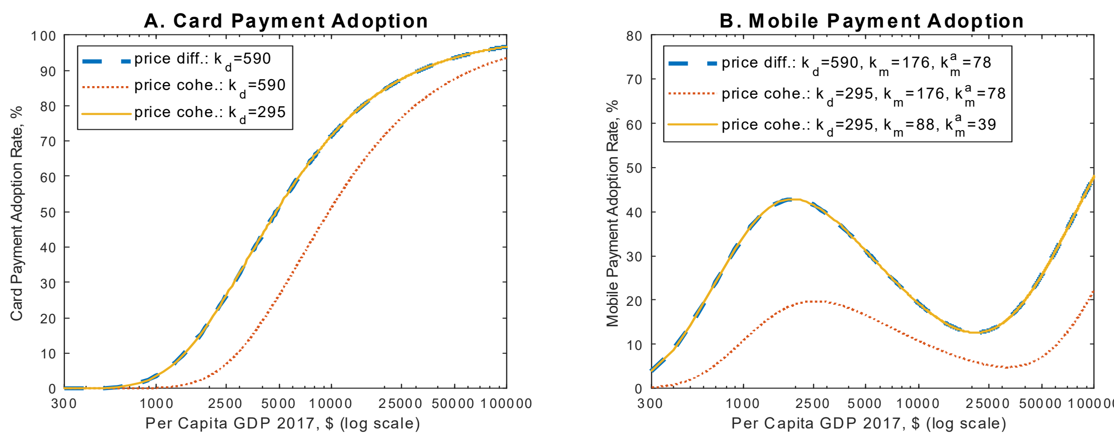


Figure 12. Payment Adoption under Price Coherence

To understand this, we can compare the card adoption thresholds, $I_{d,t}^{disc}$ in the price-differentiation regime versus $I_{d,t}^{cohe}$ in the price-coherent regime,

$$I_{d,t}^{disc} = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)} \quad \text{vs.} \quad I_{d,t}^{cohe} = \frac{(1-\beta)k_d}{(\tau_{b,h} - \tau_{b,d})} p_t. \tag{43}$$

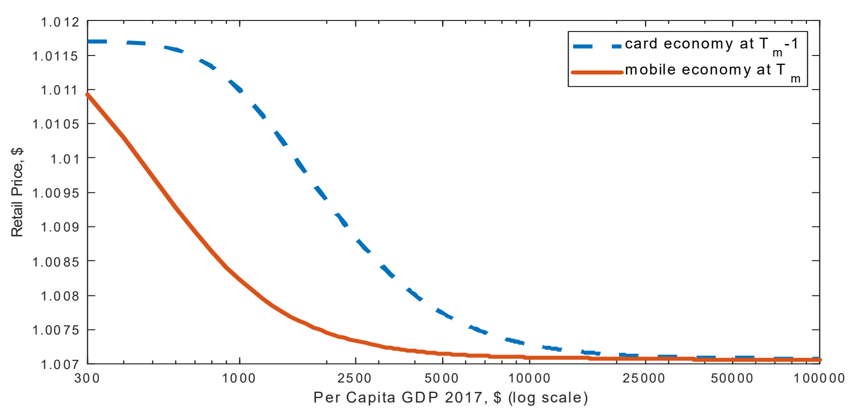


Figure 13. Retail Price under Price Coherence

Note that p_t is time varying but its effects on the adoption threshold is small. Between a full cash economy and a full card economy, p_t only changes from $p_t = \frac{1-\tau_{b,h}}{1-\tau_h} = 1.0117$ to

$p_t = \frac{1-\tau_{b,d}}{1-\tau_d} = 1.0071$ (see Figure 13). Because $(\tau_{b,h} - \tau_{b,d}) \approx (\tau_h - \tau_d)/2$, halving k_d under the price-coherent regime would then generate an adoption threshold $I^{cohe}_{d,t}$ very close to the one $I^{disc}_{d,t}$ under the price differentiation regime. A similar analysis applies to comparing mobile payment adoption between the two regimes.

6.4 Welfare and policy analysis

6.4.1 Payment Efficiency

The above analysis suggests that halving the adoption costs would allow the price-coherent model to match data equally well as our benchmark model. Assuming the price-coherent model is the true model, we then redo the welfare analysis. With the new values of adoption costs ($k_d = 295$, $k_m = 88$ and $k^a_m = 39$), we compute under the price-coherent regime, the welfare $W_{h,t}$ for a cash-only economy ($t < T_d$), the welfare W_{T_d} when card arrives at $t = T_d$, and the welfare W_{T_m} when mobile payments arrive at $t = T_m$. We also compute the welfare $\tilde{W}_{T_m}$ for the counterfactual scenario where mobile payments do not arrive at $t = T_m$.

Figure 14A plots payment efficiency for an economy, defined by Eq. (30). The patterns are similar to our findings from the benchmark model (cf. Figure 10). Figure 14B computes the welfare gain from introducing mobile payments at date T_m (i.e., $W_{T_m} - \tilde{W}_{T_m}$). Again, the cross-country pattern is similar to our finding from the benchmark model, but the magnitude of welfare gains from introducing mobile payments becomes higher due to the lower values of adoption costs.

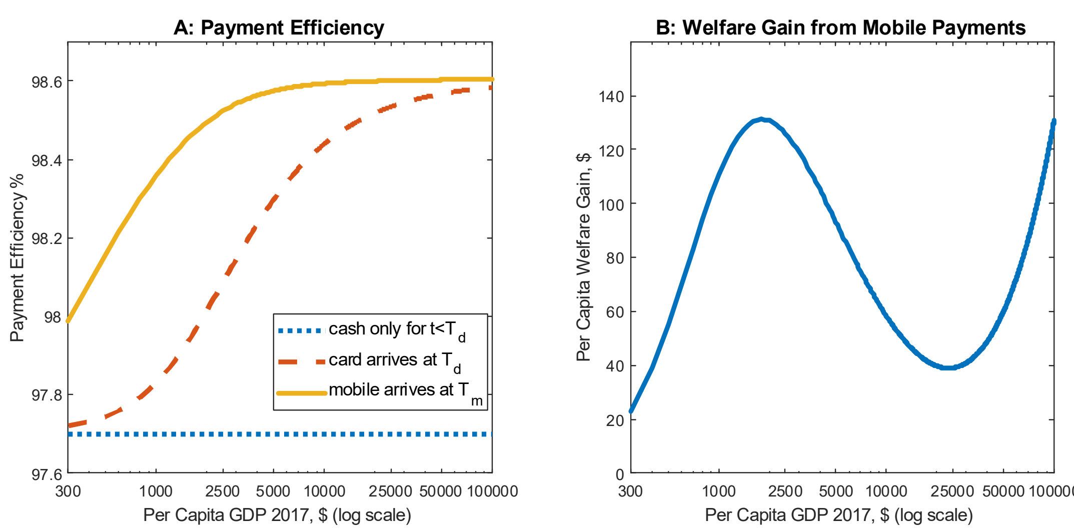


Figure 14. Welfare Results under Price Coherence

6.4.2 Policy interventions

Since our benchmark model is equivalent to the price-differentiation two-sided market model, it achieves the social optimum and there is no need for policy intervention. In contrast, in a price-coherent model where consumers do not internalize the externalities of adopting and using more efficient electronic payments, policies can play welfare enhancing roles.

We conduct the following counterfactual analysis to assess the implications of policy intervention. We assume that economies remain price coherent until date T_m when mobile payments arrive. We then consider three scenarios: (1) price coherence with $k_m = 88$, $k_m^a = 39$, (2) price differentiation with $k_m = 88$, $k_m^a = 39$, and (3) price coherence with a 50% mobile payment adoption subsidy financed by a non-distortionary tax (i.e., $k_m = 44$, $k_m^a = 19.5$).

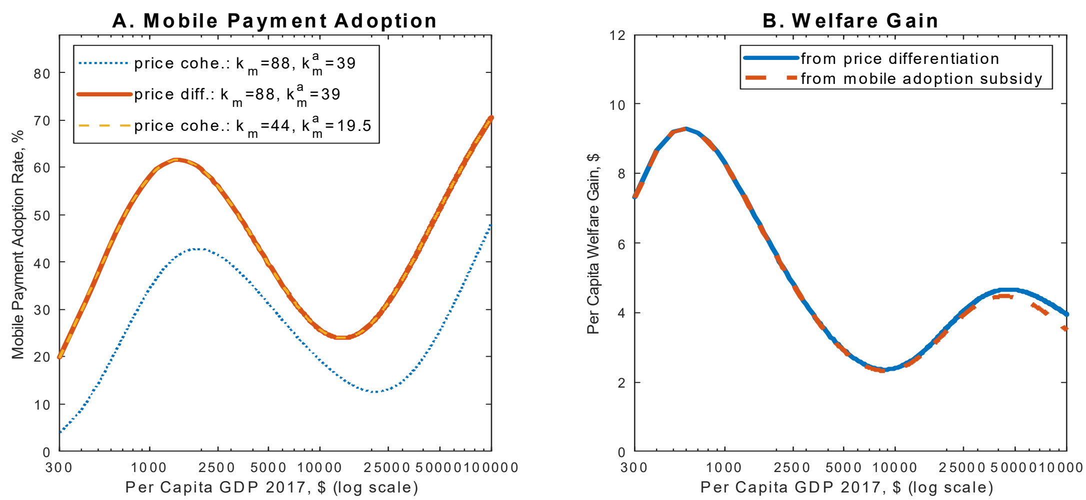


Figure 15. Effects of Policy Interventions

The results, plotted in Figure 15, show that switching from price coherence to price differentiation increases mobile payment adoption and social welfare. This suggests that price differentiation policies, such as surcharging cash use or rewarding mobile payment use at the point of sale can be welfare enhancing. However, in practice, it can be difficult for merchants to price differentiate based on payment means. Alternatively, policymakers could subsidize mobile payment adoption costs k_m and k_m^a financed by a non-distortionary tax. The subsidy would induce consumers to adopt mobile payments close to the socially optimal level. In our numerical example, subsidizing half of k_m and k_m^a would achieve nearly the social optimum. Moreover, Figure 15B shows that low-income countries would benefit more from these policies than middle- and high-income countries. This is because for the low-income countries, internalizing payment externalities would convert more consumers from cash users to mobile payment users and lead to a larger decline in retail prices for all consumers. Such a policy would also benefit middle- and high-income countries but to a lesser extent because the incremental benefit of switching from card to mobile payment is limited.

Finally, we compare the counterfactuals where government subsidizes one or two mobile payment technologies. The results, plotted in Figure 16, suggest that low-income countries would benefit primarily from subsidizing card-substituting mobile payments while high-income countries would benefit most from subsidizing card-complementing ones.

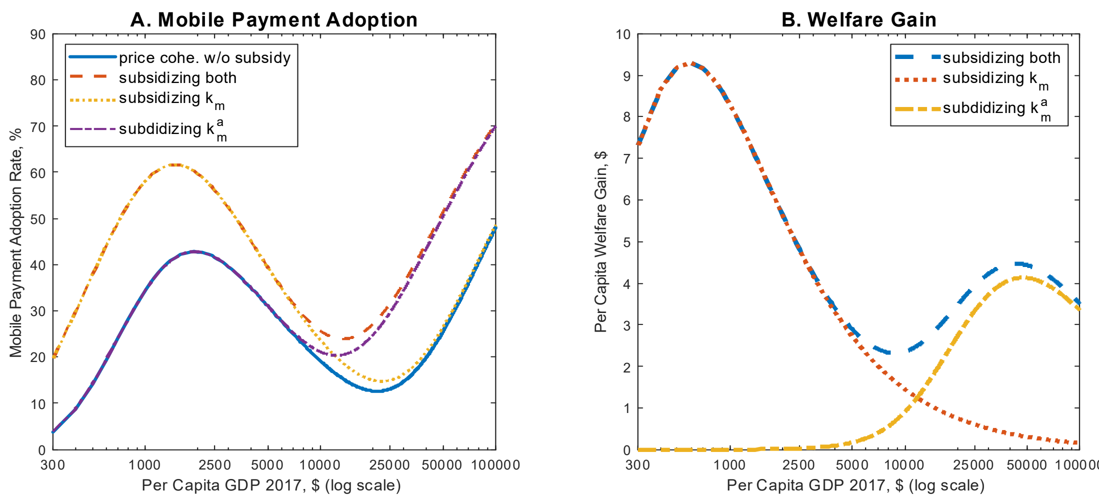


Figure 16. Subsidizing Mobile Payment Adoption

7 Additional robustness checks

We have shown that the main findings of our benchmark model continue to hold in the two-sided market extension. In this section, we conduct additional robustness checks for the benchmark model and provide some further discussions.

7.1 Anticipation for mobile payments

We first relax the assumption that mobile payments arrive as an unanticipated shock. It is possible that at some stage in the 2000s or 2010s mobile payments were anticipated in some countries, which may have affected the incentives to adopt card. Extending our model to consider this scenario, we find that agents may hold off their card adoption in the hope of adopting mobile payments later, but that effect is quantitatively small.

Formally, we assume that at date $T_m - n$, agents receive news that two mobile payments options (i.e., card-substituting and card-complementing ones) may arrive at a Poisson rate ρ starting from next period in each country.[31] We then characterize how this information affects the income threshold of card adoption and the card and mobile adoption rates as follows.

Recall that the value of being a mobile payment user, $V_m(I_t)$, is given by Eq. (7). Once mobile payments have arrived, the value of being a cash user $V_h(I_t)$ is given by Eq. (9) and the value of being a card user $V_d(I_t)$ is given by Eq. (17). Starting from date $T_m - n$ until date $T_m - 1$ before mobile payments actually arrive, the value of being a cash user, denoted by $\tilde{V}_h(I_t)$, is given by

$$\tilde{V}_h(I_t) = (1-\tau_h)I_t + \beta \left\{ \begin{array}{c} \rho \max\left[V_h(I_{t+1}), V_m(I_{t+1}) - k_m\right] \\ +(1-\rho)\max\left[\tilde{V}_h(I_{t+1}), \tilde{V}_d(I_{t+1}) - k_d\right] \end{array} \right\}, \tag{44}$$

where $\tilde{V}_d(I_t)$ is the value of being a card user during this period, which is given by

$$\tilde{V}_d(I_t) = (1-\tau_d)I_t + \beta \left\{ \begin{array}{c} \rho \max\left[V_d(I_{t+1}), V_m(I_{t+1}) - k_m^a\right] \\ +(1-\rho)\tilde{V}_d(I_{t+1}) \end{array} \right\}. \tag{45}$$

Denote I_d^ρ the income threshold at which an agent is indifferent between adopting card and continuing with cash at any date between $T_m - n$ and $T_m - 1$. Given the mobile payment news, the income threshold of adopting card becomes higher (i.e., $I_d^\rho > I_d > I_m$) and satisfies the condition that

$$\tilde{V}_d(I_d^\rho) - \tilde{V}_h(I_d^\rho) = k_d. \tag{46}$$

Evaluating Eqs. (44) and (45) at I_d^ρ and inserting them into Eq. (46) then pins down I_d^ρ (see Internet Appendix VI for the solution details).

Given the solution of I_d^ρ, we can then derive the adoption of card and mobile payment for any $t \geq T_m$. Note that agents would stop adopting card once mobile payments arrive at date T_m, and thus the card adoption rate is fixed at F_{d,T_m-1} for any date $t \geq T_m - 1$. To be specific, F_{d,T_m-1} is the fraction of agents whose incomes have crossed the old card adoption

[31] Alternatively, one may assume that agents in low- and middle-income countries expect the card-substituting mobile payment while agents in high-income countries expect the card-complementing mobile payment. The analysis and results are very similar.

threshold I_d at date $T_m - n - 1$ or the fraction of agents whose incomes have crossed the new card adoption threshold I_d^ρ at date $T_m - 1$, whichever is larger. With the card adoption rate F_{d,T_m-1}, the adoption of mobile payments for any $t \geq T_m$ can then be derived.

Using the set of parameter values in Table 1, we compute I_d^ρ and conduct the following counterfactual analysis. We consider two scenarios: Agents anticipate mobile payments 5 years (i.e., $n = 5$ and $\rho = 1/n = 0.2$) or 10 years (i.e., $n = 10$ and $\rho = 1/n = 0.1$) ahead of the actual arrival at $T_m = 2017$. The resulting card and mobile adoption patterns are plotted in Figure 17. In either scenario, an increased card adoption threshold satisfies $I_d^\rho > I_d(1+g)^n$, which induces agents who otherwise would have adopted card between $T_m - n$ and $T_m - 1$ to postpone their card adoption. Once mobile payments arrive at date T_m, those delayed card adopters become additional mobile payment adopters. The earlier the anticipation, the more the delayed card adopters, and the higher the mobile payment adoption. However, as Figure 17 shows, comparing with our benchmark model where mobile payments arrive unexpectedly, the effect of anticipation is quantitatively small.[32]

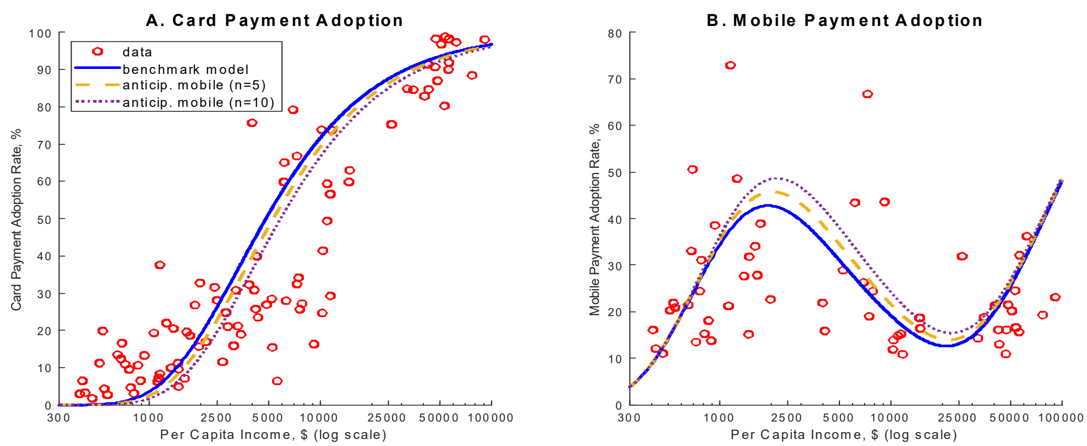


Figure 17. Anticipated Mobile Payments

7.2 Income distribution and Gini coefficient

We so far have assumed an exponential income distribution in the analysis. While this is a simplifying assumption and fits the data well, one may wonder if our findings are robust

[32]Note that our findings are robust to any alternative values of $\rho \in [0, 1]$. When $\rho = 0$, we are back to the benchmark model where mobile payments are not anticipated. When ρ is sufficiently large, as in the two examples we considered (i.e., $\rho = 0.1$, $n = 10$ or $\rho = 0.2$, $n = 5$), the new income threshold for card adoption satisfies $I_d^\rho > I_d(1+g)^n$. As a result, all the agents who otherwise would have adopted card between $T_m - n$ and $T_m - 1$ hold off their card adoption until mobile payments actually arrive at date T_m. The same result would hold for any larger value of ρ. Therefore, for $n = 10$ or $n = 5$, the benchmark model and the extended model provide the upper and lower bounds for card and mobile adoption rates for any $\rho \in [0, 1]$.

under alternative distributional assumptions. Moreover, the property that the exponential distribution has a fixed Gini coefficient at 0.5 raises the question of how much of the cross-country payment technology adoption pattern is affected by country-specific Gini coefficients outside the model.

To address these questions, we extend the model by assuming a log-logistic income distribution, which has also been popularly used in empirical studies (e.g., see Fisk, 1961). Figure 18 presents an example of fitting the U.S. household income distribution in 2017 with a log-logistic distribution. The log-logistic distribution has two parameters that capture the mean and the Gini coefficient separately.

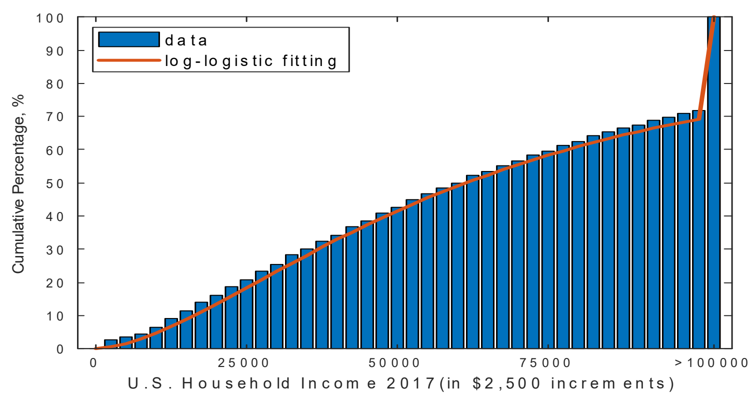


Figure 18. Log-logistic Income Distribution

Keeping all other assumptions the same as our benchmark model, we now assume income I_t follows a log-logistic distribution in each economy, with the cumulative distribution function (cdf)

$$G_t(I_t) = 1 - \frac{1}{1 + \left(\frac{I_t}{\lambda_t}\right)^{\frac{1}{\eta}} \Phi},$$

where λ_t is the mean of income, η is the Gini coefficient, and $\Phi = \left(\frac{\pi\eta}{\sin(\pi\eta)}\right)^{\frac{1}{\eta}}$. Over time, each agent's income grows at a constant rate g, i.e., $I_{t+1} = I_t(1+g)$, as does the mean income of the economy (i.e., $\lambda_{t+1} = \lambda_t(1+g)$).

We assume that each country offers both mobile payment technologies.[33] The analysis is the same as the benchmark model except that we now replace the card adoption equation (6) with Eq. (47) and replace the mobile adoption equation (20) with Eq. (48) as follows:

[33] Alternatively, one may assume that low- and middle-income countries only offer the card-substituting mobile payment while high-income countries only offer the card-complementing mobile payment. The analysis and results are very similar.

$$F_{d,t} = \frac{1}{1 + \left(\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_t}\right)^{\frac{1}{\eta}} \Phi}, \tag{47}$$

$$F_{m,t} = \frac{1}{1 + \left(\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}\right)^{\frac{1}{\eta}} \Phi} - \frac{1}{1 + \left(\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m - 1}}\right)^{\frac{1}{\eta}} \Phi} + \frac{1}{1 + \left(\frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)\lambda_t}\right)^{\frac{1}{\eta}} \Phi}. \tag{48}$$

Under the log-logistic distribution assumption, all the theoretical results of the benchmark model continue to hold. Nevertheless, we are interested in assessing how much the log-logistic distribution would affect the quantitative findings, and what role the country-specific Gini coefficients could play in explaining cross-country payment technology adoption patterns.

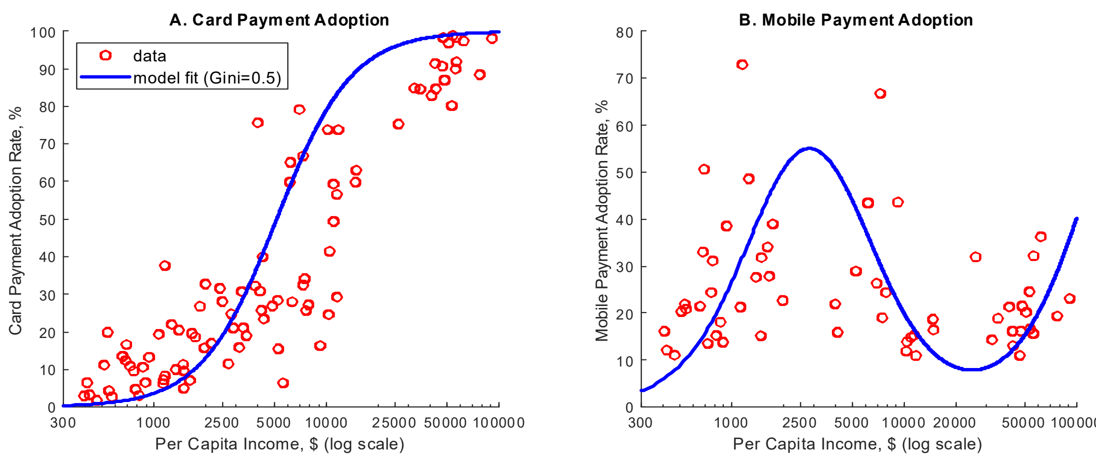


Figure 19. Log-logistic Model Fit (Gini =0.5).

To compare directly with our previous findings, we first assume a log-logistic income distribution with $\eta = 0.5$, the same value of the Gini coefficient under the exponential distribution, for every country in the sample. Using the same set of parameter values in Table 1, we plot the card and mobile payment adoption rates at each level of per capita income in Figure 19. The results are similar to the benchmark model shown in Figure 7.[34]

We then compute the mobile payment adoption rates while allowing each country to have the actual country-specific Gini coefficient as observed in the data.[35] In Figure 20, we plot the results and contrast them with those assuming a uniform Gini coefficient = 0.5. The comparison suggests that the cross-country card and mobile adoption patterns are mainly

[34]Note that we use the same parameter values in Table 1 in this exercise. If one re-estimates the model parameter values under the log-logistic distribution assumption, the model could fit the data even better.

[35]In the exercise, we use the average value of the Gini coefficient during the one decade before the sample period (i.e., 2007-2016) for each country. The resulting Gini coefficients range from 0.27 to 0.61 among our sample countries.

governed by the level of per capita income, and the difference in Gini coefficient only plays a small role quantitatively. This finding is consistent with the regression results reported in Tables A3 and A4 of Internet Appendix III, which show that the cross-country mobile payment adoption pattern is significantly correlated with per capita income but not the Gini index.

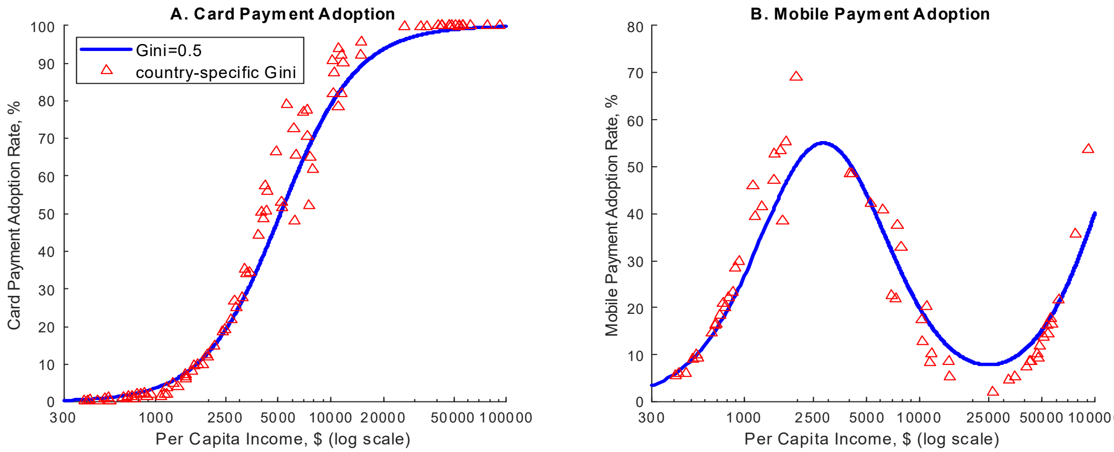


Figure 20. Log-logistic Models (Country-specific Gini vs. Gini =0.5).

7.3 Payment user cost

In our benchmark model, it is assumed that consumers face the payment user cost equal to the social cost of providing payment services. Nevertheless, there can be factors that create wedges between the user cost and social cost. Such user cost wedges may originate from the markups charged by payment firms, taxes or regulations imposed by government agencies, or certain inefficiency in the payment sector.

To incorporate the user cost wedges in our analysis, we consider the following exercise. We assume that card uses face a user cost $\hat{\tau}_d$ higher than the social cost τ_d of card services. Specifically,

$$\hat{\tau}_d = \tau_d + s(\tau_h - \tau_d) \quad \text{where} \quad 1 \geq s > 0.$$

The factor s measures the size of the wedges. As s increases, cards become more expensive to users and the user benefit (compared with using cash) eventually vanishes as $s \to 1$.

Our benchmark model captures the case where $s = 0$. In terms of robustness checks, we find that a different value of s would not affect our model's fit with the data of cross-country card and mobile payment adoption. In fact, one can restore our benchmark estimation results by simply adjusting the values of model parameters as follows:

$$\hat{k}_d = \frac{(\tau_h - \hat{\tau}_d)I_d}{1-\beta}, \qquad \hat{\tau}_m = \frac{I'_m \hat{\tau}_d - I_m \tau_h}{I'_m - I_m},$$
$$\hat{k}_m = \frac{(\hat{\tau}_d - \hat{\tau}_m)I'_m}{1-\beta}, \qquad \hat{k}^a_m = \frac{(\hat{\tau}_d - \hat{\tau}_m)I^a_m}{1-\beta}.$$

This implies that the estimate of $\hat{\tau}_m$ is higher than that of τ_m in the benchmark model while the estimates of adoption costs ($\hat{k}_d$, $\hat{k}_m$ and $\hat{k}^a_m$) are a fraction s lower than their benchmark counterparts. As a result, the four key adoption thresholds (i.e., I_d, I_m, I'_m and I^a_m) remain the same as that in the benchmark model, and thus the model fitting does not change.

As an example, Table 4 reports the parameter values for the case $s = 0.25$. These parameter values can replicate the same card and mobile adoption estimation results as the benchmark model (where $s = 0$).

Table 4. Model Parameterization with User Cost Wedges

	$\hat{\tau}_d$	$\hat{k}_d$	$\hat{k}_m$	$\hat{k}^a_m$	$\hat{\tau}_m$
Benchmark: s=0	1.40%	589.83	175.76	78.17	1.395%
Alternative: s=0.25	1.63%	442.37	131.82	58.63	1.621%

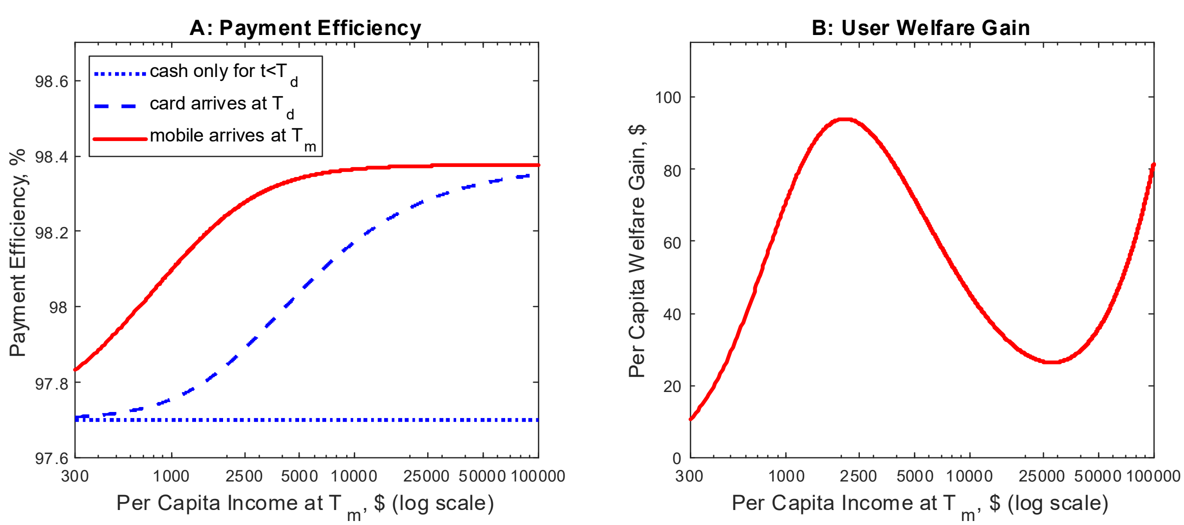


Figure 21. Welfare Results with User Cost Wedges

Figure 21 plots the welfare results with $s = 0.25$. Comparing the figure with Figures 10 and 11A, we find that the results of the welfare analysis (in terms of payment efficiency and user welfare from introducing mobile payments) are very similar to the benchmark case where $s = 0$, though the levels become lower due to the payment user cost wedges.[36]

7.4 Other factors

While we have considered multiple robustness checks of the benchmark model, our analysis may still abstract from certain factors that could also affect payment technology adoption. For example, the extraordinary mobile payment adoption in Kenya and China (cf. Figure 2B) cannot be fully explained by our theory, and they should be regarded as outliers due to country-specific factors. Jack and Suri (2014) highlight the importance of M-PESA in urban-rural remittances in Kenya, which provides a crucial risk-sharing function. In China, the two tech giants, Alibaba and Tencent, have developed their mobile payment services, Alipay and WeChat Pay, to strategically extend their business models to cross-sell consumer and business loan services based on payments data (Hau et al., 2019).

Nevertheless, by focusing on income heterogeneity, our theory provides a parsimonious model to explain cross-country payment technology adoption patterns without being bogged down by idiosyncratic details. It is known from consumer surveys that income is a key factor explaining card adoption at household level (e.g., see Greene and Shy, 2022), which is consistent with our finding that per capita GDP positively correlates with card adoption across countries. It is striking that such a positive relation is absent for mobile payments, and our model offers a coherent explanation in the context of sequential payment innovations.[37] Our estimated model fits the cross-country mobile payment adoption pattern well and provides a convenient framework for welfare and policy analysis. Incorporating additional factors into the analysis may further enhance our understanding of payment technology adoption across countries, especially the variations in the data that are not accounted for by our theory, and those will be valuable venues for future research.[38]

[36] Note that user welfare measures welfare to payment end users and it does not include profits of payment service providers. In our model context, user welfare equals social welfare when $s = 0$.

[37] Through the lens of our model, the non-monotonic relationship between mobile payment adoption and per capita income reflects that the incremental benefits of mobile payment are not substantial comparing with card. This is consistent with common users' perception in the U.S. For instance, according to the mobile payment survey conducted by the Pew Charitable Trusts, "many Americans have been hesitant to adopt mobile payments because traditional methods simply work well enough to meet consumers' needs while offering robust consumer protections." More details can be found in the survey report of the Pew Charitable Trusts on "Are Americans Embracing Mobile Payments?", October 3, 2019.

[38] In Internet Appendix VII, we provide an extension of the benchmark model to consider possible effects of the informal sector on mobile payment adoption in developing vs. developed countries.

8 Conclusion

This paper provides a framework to explain the adoption of card and mobile payments within and across countries. With a novel dataset, we find that the adoption of mobile payment exhibits a non-monotonic relationship with per capita income. This is in contrast with card payment, for which the adoption increases monotonically in per capita income across countries. Also, countries choose different mobile payment solutions: Advanced economies favor those complementary to the existing card payments, while developing countries prefer those substituting cards.

Our theory provides a consistent explanation for these patterns. In our model, three payment technologies, cash, card, and mobile, arrive sequentially. Newer payment technologies lower the variable costs of conducting payments, but they require a fixed cost to adopt. Rich countries enjoy advantages in adopting card payments for replacing cash early on, but this success later hinders their adoption of the mobile payment innovation. Also, the fixed-cost considerations provide strong incentives for card-intensive countries to adopt mobile payment methods complementary to cards, while cash-intensive countries favor card-substituting mobile solutions.

Our estimated model matches the cross-country payment technology adoption patterns well. We find that lagging behind in mobile payment adoption does not necessarily mean that advanced economies fall behind in overall payment efficiency. Rather, slower adoption may simply reflect that the incremental benefit of switching from card to the current mobile payment technology is not large enough. Based on the model, we conduct quantitative analysis to assess welfare and policy implications.

While our paper focuses on consumers' choices of making payments, mobile payments may have broader impact. For example, it may affect financial inclusion and credit markets. Moreover, the rise of nonbank payment service providers, particularly FinTech firms, may pose new challenges to financial stability and regulations. Those would be interesting topics for continuing research (see Goldstein et al. (2019) for a general discussion). Last but not least, our analysis is related to other financial or non-financial innovations. By deriving conditions for leapfrogging in the payment context, our findings shed light on the broad issue on rank-preserving versus leapfrogging in the adoption of new technologies.

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Internet Appendix to
"Technology Adoption and Leapfrogging: Racing for Mobile Payments"

I. Global pattern of mobile payments

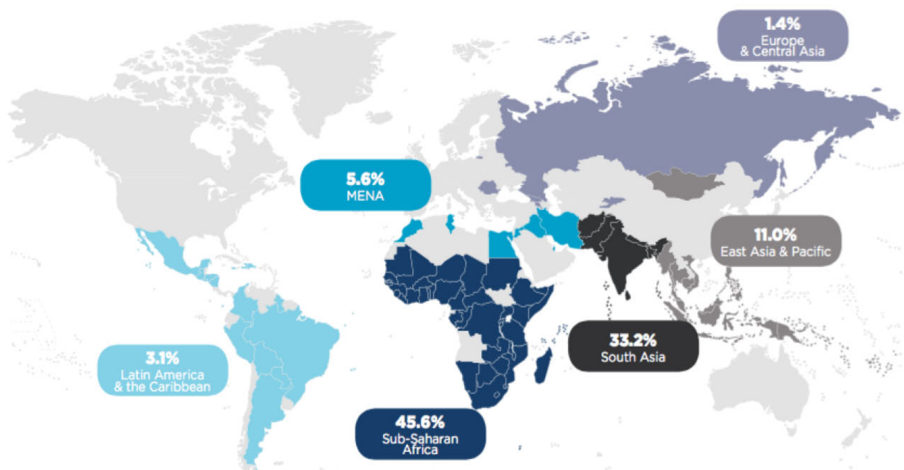


Figure A1. Global Adoption of Mobile Money

Data source: GSMA (2018), "State of the Industry Report on Mobile Money."

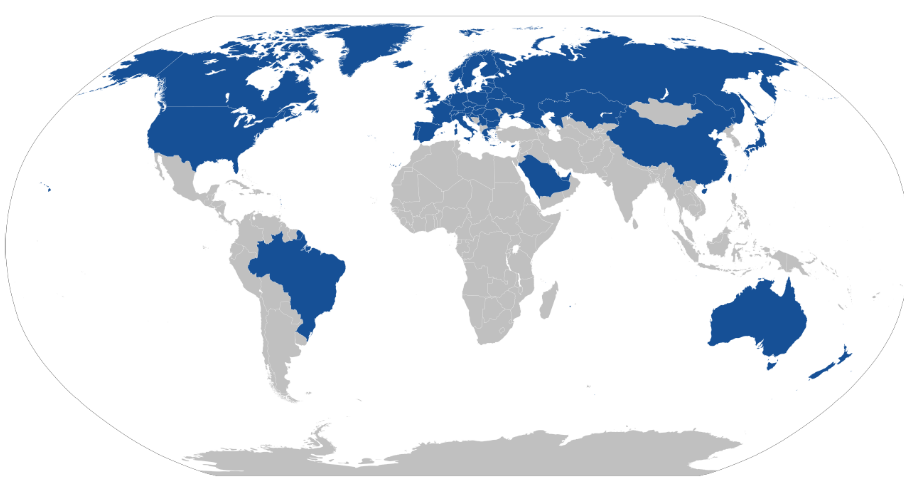


Figure A2. Global Deployment of Apple Pay

Data source: https://en.wikipedia.org/wiki/Apple Pay#Supported countries.

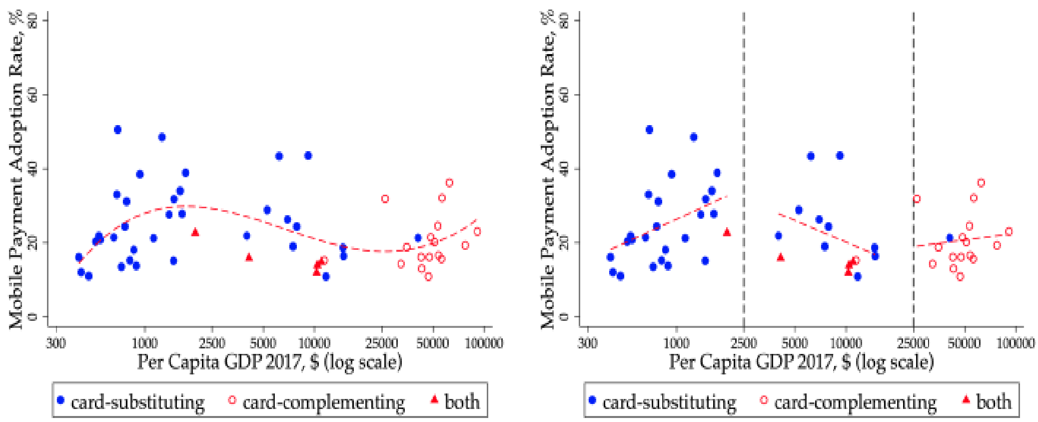
II. Data sources

The mobile payment data introduced in Section 2.2 are drawn from two sources. First, the data of the adoption rates for card-substituting mobile payment services in 2017 are based on the Global Financial Inclusion (Global Findex) Database of the World Bank, which surveyed 76 countries with a visible presence of Mobile Money payment services. The Global Findex database was launched in 2011 and has been published every three years since then. The 2017 version of the database is based on nationally representative surveys of more than 150,000 adults (age 15 and above) in 144 economies. Among the 144 economies, 76 economies where mobile money accounts were available at the time were surveyed for mobile money adoption. Specifically, "To identify people with a mobile money account, the 2017 Global Findex survey asked respondents about their use of specific services available in their economy — such as M-PESA, MTN Mobile Money, Airtel Money, or Orange Money — and included in the GSM Association's Mobile Money for the Unbanked (GSMA MMU) database. The definition of a mobile money account is limited to services that can be used without an account at a financial institution."

Second, the data of the adoption rates for card-complementing mobile payments around 2017 is gathered from eMarketer's public website. eMarketer is a market research company headquartered in New York City. Its report on "Proximity Mobile Payment Users Worldwide, 2019" estimates adult mobile proximity payment users (age 14+) in 23 countries where mobile proximity payments have a visible presence. According to the European Payments Council, "mobile proximity payments are mobile payments in which the payer and the payee are in the same location and where the communication between their devices takes place through a proximity technology (such as Near Field Communication (NFC), Quick Response (QR) codes, Bluetooth technology, etc.)." To be more specific, the adoption rate of mobile proximity payments in the eMarketer data is the adoption rate among mobile phone users, and we multiply that by the mobile phone ownership rate of each country (obtained from GSMA) to obtain the mobile proximity payment adoption rate in the population. As a sanity check, our estimate of the mobile payment adoption rate in the eMarketer data is 24.6% for the U.S., comparable to the mobile payment adoption rate of 28.7% estimated from the U.S. Survey of Consumer Payment Choice conducted by the Federal Reserve in 2017.

III. Regression results

Figure 3 in Section 2.2 shows that mobile payment adoption displays a non-monotonic relationship with per capita GDP: increasing among countries with per capita GDP less than \$2,500, decreasing among countries with per capita GDP between \$2,500 and \$25,000, and increasing again among countries with per capita GDP greater than \$25,000. Figure A3 demonstrates that this pattern continues to hold if we exclude from the estimation two outlier countries (Kenya and China) that have exceptionally high mobile payment adoption rates (>60%).



(A) Nonparametric fit (B) Linear fit

Figure A3. Mobile Payment Adoption (exclu. Kenya & China)

Table A1 reports the OLS regression results for card and mobile payment adoption related to Figures 2, 3B and A3B. Across the 94 countries in the sample, column (1) indicates that the card adoption rate is significantly and positively related to per capita GDP. In contrast, column (2) suggests that the mobile payment adoption bears no significant relationship with per capita GDP for the same sample. In fact, the adjusted R^2 shows a negative value, which implies that the fit would be better if we simply run the regression with only a constant.

Table A1. Cross-Country Payment Adoption: OLS Regressions

	Card	Mobile		
	(1)	(2)	(3)	(4)
ln(GDP per capita)	0.186***	0.001	0.113**	0.091**
	(0.009)	(0.010)	(0.053)	(0.040)
ln(GDP per capita) $\times 1\{$Middle Income$\}$			-0.220**	-0.175**
			(0.096)	(0.072)
ln(GDP per capita) $\times 1\{$High Income$\}$			-0.087	-0.065
			(0.116)	(0.087)
1{Middle Income}			1.708**	1.344**
			(0.804)	(0.609)
1{High Income}			0.425	0.295
			(1.169)	(0.882)
Constant	-1.179***	0.163*	-0.497	-0.366
	(0.079)	(0.083)	(0.362)	(0.274)
Observations	94	94	59	57
Adjusted R^2	0.81	-0.01	0.07	0.08

Regressions in this table are based on OLS models. The dependent variable in column (1) is debit card adoption rate in 2017. The dependent variables in columns (2), (3) and (4) are mobile payment adoption rate in 2017. The independent variables include the GDP per capita of 2017 and a constant in columns (1) and (2), plus two dummy variables (i.e., Middle Income and High Income) and their interaction terms with the GDP per capita in columns (3) and (4). In column (4), we exclude two outliers that have mobile payment adoption rates greater than 60% (i.e., Kenya and China). Standard errors are reported in the parentheses. *** denotes statistical significance at 1% level, ** at 5% level, and * at 10% level.

However, a subtle pattern of mobile payment adoption emerges once we remove countries with exceptionally low adoption rates of mobile payments (adoption rate $<$ 10%) and group the remaining ones by income. Column (3) shows that mobile payment adoption increases in per capita GDP for low-income countries (per capita GDP $<$ \$2,500) and high-income countries (per capita GDP $>$ \$25,000), but decreases in per capita GDP for middle-income countries (\$2,500 $\leq$ per capita GDP $\leq$ \$25,000). Specifically, the coefficient estimate of ln(GDP per capita) for the low-income countries is 0.113 and statistically significant. This suggests that doubling per capita GDP is associated with an 11.3% increase in mobile payment adoption among the low-income countries. The coefficient estimate of ln(GDP per capita) $\times 1\{$High Income$\}$ is small and not statistically significant, suggesting that the relationship between per capita GDP and mobile payment adoption among high-income countries is not significantly different from that among low-income countries. On the other hand, the coefficient estimate of ln(GDP per capita) $\times 1\{$Middle Income$\}$ is -0.220 and statistically significant. This implies that the relationship between per capita GDP and mobile payment adoption among middle-income countries is significantly different from that among low-income (and high-income) countries. The coefficient difference, (0.113-0.220), suggests that doubling per capita GDP is associated with a 10.7% reduction in mobile payment adoption rate among middle-income countries.

As a robustness check, we exclude two outlier countries (Kenya and China) with exceptionally high mobile payment adoption rates ($> 60\%$) in column (4). The results are similar to column (3) though the estimates are smaller in absolute values.

For additional robustness checks, we use the fractional logit (FL) model instead of the OLS model to address the fractional nature of the dependent variables (i.e., card and mobile adoption rates), which are bounded by 0 and 1. The estimated marginal effects, shown in Table A2, are very similar to the OLS results in Table A1.

Table A2. Cross-Country Payment Adoption: FL Regressions

	Card		Mobile	
	(1)	(2)	(3)	(4)
ln(GDP per capita)	0.229***	0.001	0.106***	0.085***
	(0.012)	(0.008)	(0.039)	(0.032)
ln(GDP per capita) ×1{Middle Income}			-0.211***	-0.171***
			(0.076)	(0.059)
ln(GDP per capita) ×1{High Income}			-0.077	-0.058
			(0.083)	(0.077)
1{Middle Income}			1.644**	1.317***
			(0.651)	(0.505)
1{High Income}			0.347	0.237
			(0.831)	(0.787)
Observations	94	94	59	57

Regressions in Table A2 are based on the fractional logit (FL) models. The dependent and independent variables in the regressions are the same as those in Table A1. The coefficient estimates are expressed in terms of marginal effects evaluated at the means of the independent variables. Standard errors are reported in the parentheses. *** denotes statistical significance at 1% level, ** at 5% level, and * at 10% level.

Finally, we incorporate additional control variables into the mobile payment adoption regression. The regressions in Table A3 exclude countries with adoption rates less than 10% and the regressions in Table A4 also exclude Kenya and China. The results in both tables support the findings in Tables A1 and A2 that mobile payment adoption features a non-monotonic relationship with per capita income.

Table A3. Mobile Payment Adoption: OLS Regressions with More Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(GDP per capita)	0.113**	0.116**	0.132**	0.146*	0.164**	0.164**	0.160**	0.153**
	(0.053)	(0.056)	(0.065)	(0.074)	(0.072)	(0.072)	(0.073)	(0.075)
ln(GDP per capita) × 1{Middle income}	-0.220**	-0.220**	-0.238**	-0.250**	-0.246**	-0.243**	-0.263**	-0.278**
	(0.096)	(0.097)	(0.103)	(0.111)	(0.107)	(0.109)	(0.117)	(0.118)
ln(GDP per capita) × 1{High income}	-0.087	-0.086	-0.107	-0.108	-0.126	-0.125	-0.133	-0.134
	(0.116)	(0.117)	(0.125)	(0.139)	(0.134)	(0.136)	(0.138)	(0.145)
1{Middle income}	1.708**	1.710**	1.863**	1.976**	1.924**	1.902**	2.048**	2.161**
	(0.804)	(0.812)	(0.869)	(0.924)	(0.892)	(0.910)	(0.961)	(0.971)
1{High income}	0.425	0.420	0.613	0.621	0.841	0.836	0.872	0.861
	(1.169)	(1.181)	(1.246)	(1.359)	(1.315)	(1.330)	(1.343)	(1.393)
Education		-0.037	-0.063	-0.190	-0.245	-0.234	-0.278	-0.239
		(0.242)	(0.249)	(0.281)	(0.272)	(0.281)	(0.296)	(0.298)
Mobile phones			-0.041	-0.076	-0.081	-0.085	-0.098	-0.108
			(0.078)	(0.086)	(0.083)	(0.087)	(0.091)	(0.096)
Banking concentration				-0.044	-0.046	-0.053	-0.048	-0.075
				(0.127)	(0.123)	(0.130)	(0.131)	(0.135)
Bank ROA					4.491**	4.357*	3.862	3.679
					(2.144)	(2.286)	(2.500)	(2.486)
Share of population above 65						-0.116	-0.110	-0.092
						(0.629)	(0.634)	(0.642)
Share of self-employed							-0.130	-0.166
							(0.253)	(0.267)
Gini index								-0.084
								(0.347)
Constant	-0.497	-0.498	-0.565	-0.530	-0.705	-0.693	-0.533	-0.405
	(0.362)	(0.365)	(0.390)	(0.500)	(0.490)	(0.499)	(0.593)	(0.605)
Observations	59	59	59	55	55	55	55	54
R^2	0.146	0.146	0.151	0.170	0.243	0.244	0.249	0.265
Adjusted R^2	0.065	0.048	0.034	0.025	0.092	0.072	0.056	0.050

The dependent variable in each regression is mobile payment adoption rate in 2017. The independent variables include those in Table A1 plus the additional ones: Education (World Bank education index), Mobile phones (number of mobile phones per capita), Banking concentration (assets of five largest banks as a share of total commercial banking assets), Bank ROA (bank return on assets), Share of population above 65 (share of population with age 65 and above), Share of self-employed (share of total employment that is self-employed), and Gini index. Most independent variables are dated by year 2017 except that Banking concentration, Bank ROA and Gini index are the averages between 2007-2016. *** denotes statistical significance at 1% level, ** at 5% level, and * at 10% level.

Table A4. Mobile Payment Adoption: OLS Regressions with More Control Variables (Excluding Kenya and China)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(GDP per capita)	0.091**	0.097**	0.100**	0.120**	0.134**	0.133**	0.128**	0.109*
	(0.040)	(0.042)	(0.049)	(0.056)	(0.054)	(0.054)	(0.055)	(0.054)
ln(GDP per capita) × 1{Middle income}	-0.175**	-0.175**	-0.178**	-0.188**	-0.184**	-0.175**	-0.199**	-0.199**
	(0.072)	(0.073)	(0.079)	(0.084)	(0.081)	(0.083)	(0.088)	(0.086)
ln(GDP per capita) × 1{High income}	-0.065	-0.062	-0.066	-0.088	-0.103	-0.098	-0.109	-0.079
	(0.087)	(0.088)	(0.094)	(0.105)	(0.101)	(0.102)	(0.103)	(0.104)
1{Middle income}	1.344**	1.347**	1.376**	1.443**	1.390**	1.317*	1.484**	1.477**
	(0.609)	(0.613)	(0.662)	(0.704)	(0.678)	(0.690)	(0.721)	(0.703)
1{High income}	0.295	0.278	0.313	0.510	0.676	0.660	0.704	0.433
	(0.882)	(0.889)	(0.941)	(1.023)	(0.988)	(0.994)	(1.000)	(0.998)
Education		-0.094	-0.099	-0.184	-0.205	-0.171	-0.218	-0.149
		(0.185)	(0.191)	(0.216)	(0.208)	(0.215)	(0.223)	(0.215)
Mobile phones			-0.007	-0.026	-0.027	-0.038	-0.052	-0.040
			(0.060)	(0.066)	(0.064)	(0.066)	(0.068)	(0.070)
Banking concentration				0.038	0.032	0.013	0.018	-0.031
				(0.097)	(0.093)	(0.098)	(0.098)	(0.097)
Bank ROA					3.557**	3.199*	2.655	2.492
					(1.680)	(1.766)	(1.891)	(1.807)
Share of population above 65						-0.332	-0.332	-0.248
						(0.474)	(0.476)	(0.462)
Share of self-employed							-0.158	-0.146
							(0.192)	(0.194)
Gini index								0.135
								(0.250)
Constant	-0.366	-0.366	-0.378	-0.485	-0.627*	-0.593	-0.399	-0.333
	(0.274)	(0.276)	(0.296)	(0.377)	(0.369)	(0.374)	(0.442)	(0.433)
Observations	57	57	57	53	53	53	53	52
R^2	0.162	0.167	0.167	0.186	0.263	0.272	0.284	0.323
Adjusted R^2	0.080	0.066	0.048	0.039	0.109	0.098	0.092	0.115

The dependent variable in each regression is mobile payment adoption rate in 2017. The independent variables include those in Table A1 plus the additional ones: Education (World Bank education index), Mobile phones (number of mobile phones per capita), Banking concentration (assets of five largest banks as a share of total commercial banking assets), Bank ROA (bank return on assets), Share of population above 65 (share of population with age 65 and above), Share of self-employed (share of total employment that is self-employed), and Gini index. Most independent variables are dated by year 2017 except that Banking concentration, Bank ROA and Gini index are the averages between 2007-2016. *** denotes statistical significance at 1% level, ** at 5% level, and * at 10% level.

IV. Benchmark model estimation: Identification strategy

In our benchmark model, four parameters (i.e., k_d, τ_m, k_m, and k_m^a) cannot be pinned down by a priori information and we estimate them by matching the model predictions with the following six data targets: the mean and standard deviation of card payment adoption rates across countries, per capita income at both the peak and trough of mobile payment adoption, as well as the mean and standard deviation of mobile payment adoption rates across countries. All these six moments are chosen based on their sensitivity to changes in the payment cost parameters and we delineate our identification strategy as follows.

While our theory predicts a positive relationship between card payment adoption and per capita income, the specific levels of adoption rate hinge on three parameters: τ_h (cash variable cost), τ_d (card variable cost), and k_d (card adoption cost). Since τ_h and τ_d are calibrated by a priori information (i.e., Schmiedel et al., 2012), the model prediction of card payment adoption rate associated with each per capita income depends on k_d. In order to identify k_d, we include the mean and standard deviation of card payment adoption rates across countries as the first two data targets.

Though our model can potentially give rise to a non-monotonic adoption pattern of mobile payment, such non-monotonicity is not guaranteed. Instead, the actual relationship between mobile payment adoption rate and per capita income hinges on the payment cost parameters, especially τ_m (mobile variable cost). For instance, the comparative static analysis in Section 4.2.2 indicates that the model predictions of mobile payment adoption rate would be strictly increasing in per capita income when τ_m is sufficiently smaller than τ_d (i.e., when the benefits of switching from card to mobile payment are sufficiently large). In light of this, we seek to match the per capita income at both the peak and trough of mobile payment adoption in the data (as obtained by nonparametric estimations based on local polynomial smoothing). By matching these peak and trough data targets, this estimation strategy ensures the model predictions of mobile payment adoption rate would be increasing in per capita income among low-income countries, decreasing among middle-income countries, and increasing again among high-income countries, with the same per capita income turning points as observed in the data. While these peak and trough data targets of mobile payment adoption are inevitably affected by all payment cost parameters, they are particularly sensitive to changes in τ_m (as demonstrated by the comparative static analysis in Section 4.2.2). Thus, these two peak and trough data targets of mobile payment adoption are particularly informative about τ_m.

While matching the peak and trough data targets mimics the per capita income turning points of the non-monotonic adoption pattern, the specific levels of mobile payment adoption rate depends on k_m (mobile adoption cost) and k_m^a (mobile add-on cost). Specifically, an increase (decrease) in k_m and k_m^a contributes to lower (higher) mobile payment adoption rate in each country, and, thus, leads to a downward (upward) shift in the mobile payment adoption curve. In order to mimic both the per capita income turning points and the levels of the mobile payment adoption curve, we also attempt to match the mean and standard deviation of mobile payment adoption rate across countries, and these data targets are instrumental in pinpointing k_m and k_m^a.

V. Present-value welfare of aggregate economies

Given the exponential distribution $G_t(I)$, Eq. (27) yields that the present-value welfare of a cash economy at date t ($< T_d$) is

$$W_{t<T_d} = \int_0^\infty \bar{V}_h(I) dG_t(I) = \frac{(1-\tau_h)\,\lambda_t}{1-\beta(1+g)}.$$

Given the exponential distribution $G_{T_d}(I)$, Eq. (28) yields that

$$\begin{aligned}
W_{T_d} &= \frac{(1-\tau_h)\,\lambda_{T_d}}{1-\beta(1+g)} + \left(\frac{\tau_h-\tau_d}{1-\beta(1+g)}\right)\int_{I_d}^\infty I dG_{T_d}(I) - k_d \int_{I_d}^\infty dG_{T_d}(I) \\
&\quad + \sum_{s=1}^\infty \beta^s \left(\frac{(\tau_h-\tau_d)\,(1+g)^s}{1-\beta(1+g)}\right) \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} I dG_{T_d}(I) - k_d \sum_{s=1}^\infty \beta^s \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} dG_{T_d}(I) \\
&= \frac{(1-\tau_h)\,\lambda_{T_d}}{1-\beta(1+g)} + \left(\frac{\tau_h-\tau_d}{1-\beta(1+g)}\right)\exp(-\frac{I_d}{\lambda_{T_d}})(\lambda_{T_d}+I_d) - k_d \exp(-\frac{I_d}{\lambda_{T_d}}) \\
&\quad + \sum_{s=1}^\infty \beta^s \left(\frac{(\tau_h-\tau_d)\,(1+g)^s}{1-\beta(1+g)}\right) \left(\begin{array}{c} \exp(-\frac{I_d}{(1+g)^s\lambda_{T_d}})(\lambda_{T_d}+\frac{I_d}{(1+g)^s}) \\ -\exp(-\frac{I_d}{(1+g)^{s-1}\lambda_{T_d}})(\lambda_{T_d}+\frac{I_d}{(1+g)^{s-1}}) \end{array}\right) \\
&\quad - \sum_{s=1}^\infty \beta^s \left(\exp(-\frac{I_d}{(1+g)^s\lambda_{T_d}}) - \exp(-\frac{I_d}{(1+g)^{s-1}\lambda_{T_d}})\right) k_d.
\end{aligned}$$

Denote that ϕ satisfies $\frac{I_m^a}{(1+g)^\phi} > I_d(1+g)$ and $\frac{I_m^a}{(1+g)^{\phi+1}} \leq I_d(1+g)$. Eq. (29) implies

$$\begin{aligned}
W_{T_m} &= \frac{(1-\tau_h)}{1-\beta(1+g)} \int_0^{I_d(1+g)} I dG_{T_m}(I) + \frac{(\tau_h-\tau_m)}{1-\beta(1+g)} \int_{I_m}^{I_d(1+g)} I dG_{T_m}(I) - k_m \int_{I_m}^{I_d(1+g)} dG_{T_m}(I) \\
&+ \sum_{s=1}^{\infty} \beta^s \left(\frac{(\tau_h-\tau_m)(1+g)^s}{1-\beta(1+g)} \right) \int_{\frac{I_m}{(1+g)^s}}^{\frac{I_m}{(1+g)^{s-1}}} I dG_{T_m}(I) - k_m \sum_{s=1}^{\infty} \beta^s \int_{\frac{I_m}{(1+g)^s}}^{\frac{I_m}{(1+g)^{s-1}}} dG_{T_m}(I) \\
&+ \frac{(1-\tau_d)}{1-\beta(1+g)} \int_{I_d(1+g)}^{\infty} I dG_{T_m}(I) + \left(\frac{(\tau_d-\tau_m)}{1-\beta(1+g)} \right) \int_{I_m^a}^{\infty} I dG_{T_m}(I) - k_m^a \int_{I_m^a}^{\infty} dG_{T_m}(I) \\
&+ \sum_{s=1}^{\phi} \beta^s \frac{(\tau_d-\tau_m)(1+g)^s}{1-\beta(1+g)} \int_{\frac{I_m^a}{(1+g)^s}}^{\frac{I_m^a}{(1+g)^{s-1}}} I dG_{T_m}(I) - k_m^a \sum_{s=1}^{\phi} \beta^s \int_{\frac{I_m^a}{(1+g)^s}}^{\frac{I_m^a}{(1+g)^{s-1}}} dG_{T_m}(I) \\
&+ \beta^{\phi+1} \frac{(\tau_d-\tau_m)(1+g)^{\phi+1}}{1-\beta(1+g)} \int_{I_d(1+g)}^{\frac{I_m^a}{(1+g)^\phi}} I dG_{T_m}(I) - k_m^a \beta^{\phi+1} \int_{I_d(1+g)}^{\frac{I_m^a}{(1+g)^\phi}} dG_{T_m}(I).
\end{aligned}$$

Given the exponential distribution $G_{T_m}(I)$, this yields

$$\begin{aligned}
W_{T_m} &= \frac{(1-\tau_h)}{1-\beta(1+g)} \left(\lambda_{T_m} - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g)) \right) \\
&+ \frac{(\tau_h-\tau_m)}{1-\beta(1+g)} \left(\exp(-\frac{I_m}{\lambda_{T_m}})(\lambda_{T_m} + I_m) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g)) \right) \\
&- k_m \left(\exp(-\frac{I_m}{\lambda_{T_m}}) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}}) \right) \\
&+ \sum_{s=1}^{\infty} \beta^s \left(\frac{(\tau_h-\tau_m)(1+g)^s}{1-\beta(1+g)} \right) \left(\begin{array}{c} \exp(-\frac{I_m}{(1+g)^s \lambda_{T_m}})(\lambda_{T_m} + \frac{I_m}{(1+g)^s}) \\ - \exp(-\frac{I_m}{(1+g)^{s-1} \lambda_{T_m}})(\lambda_{T_m} + \frac{I_m}{(1+g)^{s-1}}) \end{array} \right) \\
&- k_m \sum_{s=1}^{\infty} \beta^s \left(\exp(-\frac{I_m}{(1+g)^s \lambda_{T_m}}) - \exp(-\frac{I_m}{(1+g)^{s-1} \lambda_{T_m}}) \right) \\
&+ \frac{(1-\tau_d)}{1-\beta(1+g)} \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g)) \\
&+ \left(\frac{(\tau_d-\tau_m)}{1-\beta(1+g)} \right) \exp(-\frac{I_m^a}{\lambda_{T_m}})(\lambda_{T_m} + I_m^a) - k_m^a \exp(-\frac{I_m^a}{\lambda_{T_m}}) \\
&+ \sum_{s=1}^{\phi} \beta^s \frac{(\tau_d-\tau_m)(1+g)^s}{1-\beta(1+g)} \left(\begin{array}{c} \exp(-\frac{I_m^a}{(1+g)^s \lambda_{T_m}})(\lambda_{T_m} + \frac{I_m^a}{(1+g)^s}) \\ - \exp(-\frac{I_m^a}{(1+g)^{s-1} \lambda_{T_m}})(\lambda_{T_m} + \frac{I_m^a}{(1+g)^{s-1}}) \end{array} \right) \\
&- k_m^a \sum_{s=1}^{\phi} \beta^s \left(\exp(-\frac{I_m^a}{(1+g)^s \lambda_{T_m}}) - \exp(-\frac{I_m^a}{(1+g)^{s-1} \lambda_{T_m}}) \right)
\end{aligned}$$

$$
+\beta^{\phi+1}\frac{(\tau_d-\tau_m)(1+g)^{\phi+1}}{1-\beta(1+g)})\left(\begin{array}{c}\exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m}+I_d(1+g))\\ -\exp(-\frac{I_m^a}{(1+g)^{\phi}\lambda_{T_m}})(\lambda_{T_m}+\frac{I_m^a}{(1+g)^{\phi}})\end{array}\right)
$$

$$
-k_m^a\beta^{\phi+1}\left(\exp(-\frac{I_d(1+g)}{\lambda_{T_m}})-\exp(-\frac{I_m^a}{(1+g)^{\phi}\lambda_{T_m}})\right).
$$

VI. Anticipation for mobile payments: Solution details

Denote I_d^{ρ} as the income threshold at which an agent is indifferent between adopting card and continuing with cash at any dates between T_m-n and T_m-1. Given the mobile payment news, the income threshold of adopting card becomes higher, which means $I_d^{\rho}>I_d>I_m$. At income I_d^{ρ}, Eqs. (44) and (45) imply that

$$
\tilde{V}_h(I_d^{\rho})=(1-\tau_h)I_d^{\rho}+\beta\left\{\begin{array}{c}\rho\left[V_m(I_d^{\rho}(1+g))-k_m\right]\\ +(1-\rho)\left[\tilde{V}_d(I_d^{\rho}(1+g))-k_d\right]\end{array}\right\}, \tag{49}
$$

and

$$
\tilde{V}_d(I_d^{\rho})=(1-\tau_d)I_d^{\rho}+\beta\left\{\begin{array}{c}\rho\max\left[V_d(I_d^{\rho}(1+g)),V_m((I_d^{\rho}(1+g))-k_m^a\right]\\ +(1-\rho)\tilde{V}_d(I_d^{\rho}(1+g))\end{array}\right\}. \tag{50}
$$

Inserting Eqs. (49) and (50) into Eq. (46) yields

$$
\begin{aligned}
k_d-\beta(1-\rho)k_d &= (\tau_h-\tau_d)I_d^{\rho}+\beta\rho\max\left[V_d(I_d^{\rho}(1+g)),V_m((I_d^{\rho}(1+g))-k_m^a\right] \qquad (51)\\
&\quad -\beta\rho\left[V_m(I_d^{\rho}(1+g))-k_m\right].
\end{aligned}
$$

To solve I_d^{ρ}, we can use Eq. (51) with a guess-and-verify method. We first guess that $I_d^{\rho}(1+g)\geq I_m^a=\frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$. Equation (51) then yields

$$
k_d-\beta(1-\rho)k_d=(\tau_h-\tau_d)I_d^{\rho}+\beta\rho\left(k_m-k_m^a\right),
$$

which pins down

$$
I_d^{\rho}=\frac{k_d-\beta(1-\rho)k_d-\beta\rho\left(k_m-k_m^a\right)}{(\tau_h-\tau_d)}.
$$

We then check if the guess $I_d^{\rho}(1+g)\geq I_m^a$ indeed holds. With the model parameter values given in Table 1 and for any $\rho\in[0,1]$, we find that the guess does not hold.

We then guess $I_d^\rho(1+g) < I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}$. Equation (51) now yields

$$\begin{aligned} & k_d - \beta(1-\rho)k_d = (\tau_h - \tau_d)I_d^\rho + \beta\rho V_d(I_d^\rho(1+g)) - \beta\rho\left[V_m(I_d^\rho(1+g)) - k_m\right] \\ \Longrightarrow \quad & (1-\beta)k_d + \beta\rho(k_d - k_m) = (\tau_h - \tau_d)I_d^\rho + \beta\rho\left[V_d(I_d^\rho(1+g)) - V_m(I_d^\rho(1+g))\right]. \end{aligned}$$

From Eq. (7), we know

$$V_m(I_d^\rho(1+g)) = \frac{(1-\tau_m)(1+g)I_d^\rho}{1-\beta(1+g)}.$$

From Eq. (17), we have

$$\begin{aligned} & V_d(I_t) = (1-\tau_d)I_t + \beta \max\left[V_d(I_{t+1}), V_m(I_{t+1}) - k_m^a\right] \\ \Longrightarrow \quad & V_d(I_t) = \sum_{x=0}^{J} \beta^x(1-\tau_d)I_t(1+g)^x + \beta^{J+1}\tfrac{(1-\tau_m)I_t(1+g)^{J+1}}{1-\beta(1+g)} \\ \Longrightarrow \quad & V_d(I_d^\rho(1+g)) = \sum_{x=0}^{J}\left[\beta^x(1-\tau_d)I_d^\rho(1+g)^{x+1}\right] + \beta^{J+1}\tfrac{(1-\tau_m)I_d^\rho(1+g)^{J+2}}{1-\beta(1+g)}, \end{aligned}$$

where J satisfies $I_d^\rho(1+g)^{J+1} < I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$ and $I_d^\rho(1+g)^{J+2} \geq I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$. Therefore, I_d^ρ can be solved by

$$(1-\beta)k_d + \beta\rho(k_d - k_m) = (\tau_h - \tau_d)I_d^\rho + \beta\rho\begin{bmatrix} \sum_{x=0}^{J}\left[\beta^x(1-\tau_d)I_d^\rho(1+g)^{x+1}\right] \\ +\beta^{J+1}\frac{(1-\tau_m)I_d^\rho(1+g)^{J+2}}{1-\beta(1+g)} - \frac{(1-\tau_m)(1+g)I_d^\rho}{1-\beta(1+g)} \end{bmatrix},$$

and we verify that $I_d^\rho(1+g) < I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$ indeed holds.

Given the solution of I_d^ρ, the model yields the adoption of card and mobile payment for any $t \geq T_m$ as follows. Note that agents would stop adopting card once mobile payments arrive at date T_m, so the card adoption rate is fixed at F_{d,T_m-1} for any date $t \geq T_m - 1$. To be specific, F_{d,T_m-1} is the fraction of agents whose incomes have crossed the card adoption threshold I_d at date $T_m - n - 1$ or the fraction of agents whose incomes have crossed the new card adoption threshold I_d^ρ at date $T_m - 1$, whichever is larger:

$$\begin{aligned} F_{d,t} &= F_{d,T_m-1} = \max\left(1 - G_{T_m-n-1}(I_d), 1 - G_{T_m-1}(I_d^\rho)\right) \\ &= \max\left(\exp(-\frac{I_d}{\lambda_{T_m-n-1}}), \exp(-\frac{I_d^\rho}{\lambda_{T_m-1}})\right), \end{aligned}$$

where $\lambda_{T_m-1} = \lambda_{T_m-n-1}(1+g)^n$.

The mobile payment adoption rate at any date $t \geq T_m$ comes from two sources. The first one is the cash-mobile switchers (i.e., the fraction of agents who have switched from cash to mobile by date t):

$$\begin{aligned} F_{h\to m,t} &= 1 - F_{d,T_m-1} - G_t(I_m) \\ &= \exp\left(-\frac{I_m}{\lambda_t}\right) - \max\left(\exp(-\frac{I_d}{\lambda_{T_m-n-1}}), \exp(-\frac{I_d^{\rho}}{\lambda_{T_m-1}})\right). \end{aligned} \tag{52}$$

The second one comprises of the card-mobile switchers (i.e., the fraction of agents who have switched from card to mobile by date t):

$$F_{d\to m,t} = 1 - G_t(I_m^a) = \exp\left(-\frac{I_m^a}{\lambda_t}\right) \tag{53}$$

as long as some card adopters have not adopted mobile (i.e., $F_{d\to m,t} < F_{d,T_m-1}$). Otherwise, $F_{d\to m,t} = F_{d,T_m-1}$. Combining cash-mobile switchers (i.e., $F_{h\to m,t}$) and card-mobile switchers ($F_{d\to m,t}$) together then yields the overall mobile payment adopters.

VII. Informal sector

In developing countries, a challenge for deepening financial inclusion is the informal sector, where a fraction of population remains outside the formal economy, either to avoid taxes and regulations or due to lack of information or resources to access the formal sector. Many people working in the informal sector are not banked and heavily rely on using cash. Low income, as considered by our benchmark model, may explain part of the reason for being unbanked. Other factors, including distrust of banks or concerns about government monitoring, may also play roles. In those circumstances, introducing mobile payments might help address some of the issues and provide the unbanked population an alternative access to electronic payments.

To incorporate informal sector into our analysis, we assume a fraction η of the population considers adopting banking and cards in the way described by our benchmark model. The remaining fraction (i.e., $1-\eta$) of the population does not consider adopting banking and cards due to reasons related to working in the informal sector. Suppose η takes the value of η^l in developing countries (i.e., the low- and middle-income countries in our sample) and η^h

in developed countries (i.e., the high-income countries in our sample). To the extent that mobile payments may address some of the concerns that informal workers have on banking and cards, we assume some of them would consider adopting mobile payments when they become available.

With this model extension, card payment adoption in a country becomes

$$F_{d,t} = \eta \times \exp\left(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_t}\right),$$

where η takes the value of η^l in developing countries and η^h in developed countries.

We then assume one half of the $(1-\eta)$ population in the informal sector is locked in by cash, and the other one half can potentially switch to mobile payments.[39] Hence, if card-substituting mobile payment is offered in a country, its mobile payment adoption rate would be

$$\begin{aligned} F^s_{m,t} &= \eta \times \left\{\exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m - 1}}) + \exp(-\frac{(1-\beta)k_m}{(\tau_d - \tau_m)\lambda_t})\right\} \\ &\quad + \frac{1-\eta}{2} \times \left\{\exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t})\right\}, \end{aligned}$$

where η takes the value of η^l and η^h in developing countries and developed countries, respectively.

If card-complementing mobile payment is offered in a country, its mobile payment adoption rate would be

$$F^c_{m,t} = \eta \times \exp(-\frac{(1-\beta)k^a_m}{(\tau_d - \tau_m)\lambda_t}).$$

Again, η takes the value of η^l and η^h in developing countries and developed countries, respectively. Note that introducing card-complementing mobile payments would not benefit the $(1-\eta)$ informal workers who do not consider getting banked.

We assume that the actual mobile payment adoption rate in a country takes the greater value of $F^s_{m,t}$ and $F^c_{m,t}$ and estimate the extended model to fit data. Table A5 reports the estimates of the parameters: $k_d = 437.64$, $\tau_m = 1.395\%$, $k_m = 174.01$, $k^a_m = 82.86$, $\eta^l = 0.748$ and $\eta^h = 0.971$, and standard errors are reported in the parentheses.

[39] Note that this "one-half" assumption serves as a benchmark, and one can consider alternative assumptions for robustness checks.

Table A5. Parameter Values for the Informal Sector Extension

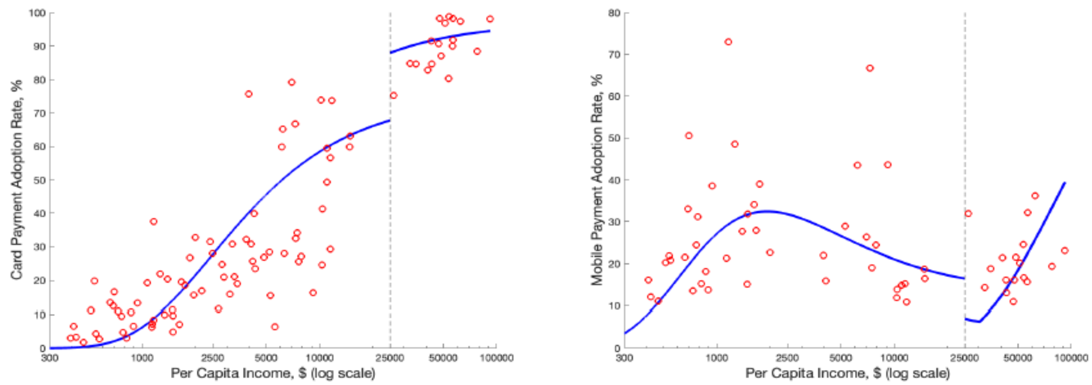
Panel A: Parameters based on a priori information			
Discount factor	Income growth rate	Cash variable cost	Card variable cost
β	g	τ_h	τ_d
0.95	2%	2.3%	1.4%
Panel B: Parameters based on estimation			
Card adoption cost	Mobile variable cost	Mobile adoption cost	Mobile add-on cost
k_d	τ_m	k_m	k_m^a
437.64	1.395%	174.01	82.86
(163.25)	(0.138%)	(49.06)	(21.50)
Share of formal sector			
Developing countries	Developed countries		
η_l	η_h		
0.748	0.971		
(0.129)	(0.212)		

Table A6 shows how the estimated model fits the targeted moments. Our identification strategy in this informal sector model extension is essentially the same as that in the benchmark model, except that we need to account for the differences in η (the population share of the formal sector) between developing and developed countries. In accordance with such differences in η, we distinguish different average payment adoption rate (for both card and mobile payment) between developing and developed countries, and we incorporate them as separate data targets in Table A6.

Table A6: Model Fit with Data, Informal Sector, Targeted Observation

	Data	Model
Card payment adoption, mean, developing countries	0.278	0.265
Card payment adoption, mean, developed countries	0.908	0.923
Card payment adoption, standard deviation	0.351	0.369
Per capita income at the peak of mobile payment adoption	1,918	1,918
Per capita income at the trough of mobile payment adoption	30,317	30,316
Mobile payment adoption, mean, developing countries	0.262	0.226
Mobile payment adoption, mean, developed countries	0.200	0.195
Mobile payment adoption, standard deviation	0.129	0.073

Figure A7 shows how the extended model fits the cross-country observations. The results convey a similar message as our benchmark model: The low card adoption in developing countries accounts for their leapfrogging in adopting mobile payment. Comparing with the benchmark model, the informal sector provides an additional explanation for why developing countries adopt less card payment but more mobile payment than their developed counterparts.



(A) Card Payment Adoption

(B) Mobile Payment Adoption

Figure A7. Model Fit: Informal Sector, Non-Targeted Obs.

Figure A8 plots aggregate payment efficiency. Accounting for the informal sector reduces the level of payment efficiency for both card and mobile in every country comparing with our benchmark model (cf. Figure 10). It also widens the payment efficiency gap between developing and developed economies following card payment adoption. Nevertheless, the informal sector creates an additional channel for developing economies to benefit from mobile payment and thus narrows the payment efficiency gap between developing and developed economies following mobile payment adoption.

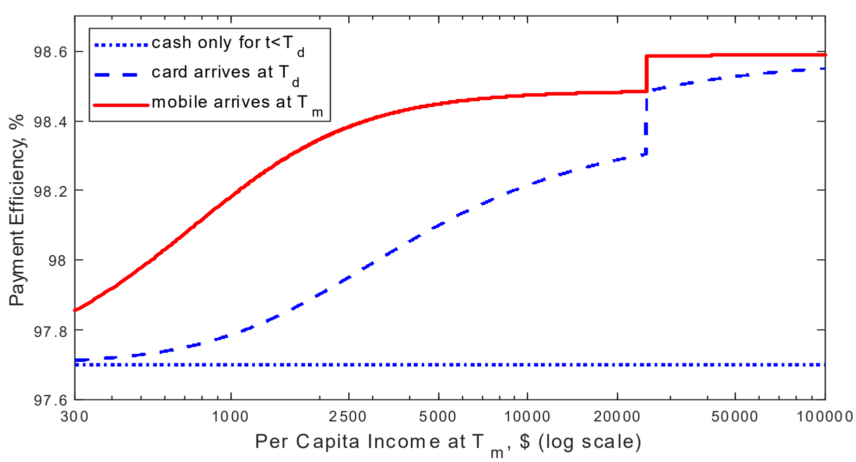


Figure A8. Payment Efficiency with Informal Sector