Technology Adoption and Leapfrogging: Racing for Mobile Payments*

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Abstract

Paying with a mobile phone is a cutting-edge innovation transforming the global payments industry. However, some advanced economies like the U.S. are lagging behind in mobile payment adoption. We construct a dynamic model with sequential payment innovations to explain this puzzle, which uncovers how advanced economies' past success in adopting card-payment technology holds them back in the mobile-payment race. Our calibrated model matches the cross-country adoption patterns of card and mobile payments and also explains why advanced and developing countries favor different mobile payment solutions. Based on the model, we conduct several quantitative exercises for welfare and policy analyses.

Keywords: Technology Adoption, Sunk Cost, Payments System, FinTech

JEL Classification: E4, G2, O3

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1 Introduction

The payments system is a key financial technological 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 the leader of the card payment revolution in the world. After maintaining the global leadership in the payments industry for decades, however, the United States is falling behind in the recent mobile-phone-based payment innovation (henceforth, "mobile payment").

Kenya is an early success story 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). While the mobile payment technology in Kenya relies on short message service (SMS), China has introduced an innovation based on smart phones and QR (Quick Response) codes which experienced explosive growth of mobile payments 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]

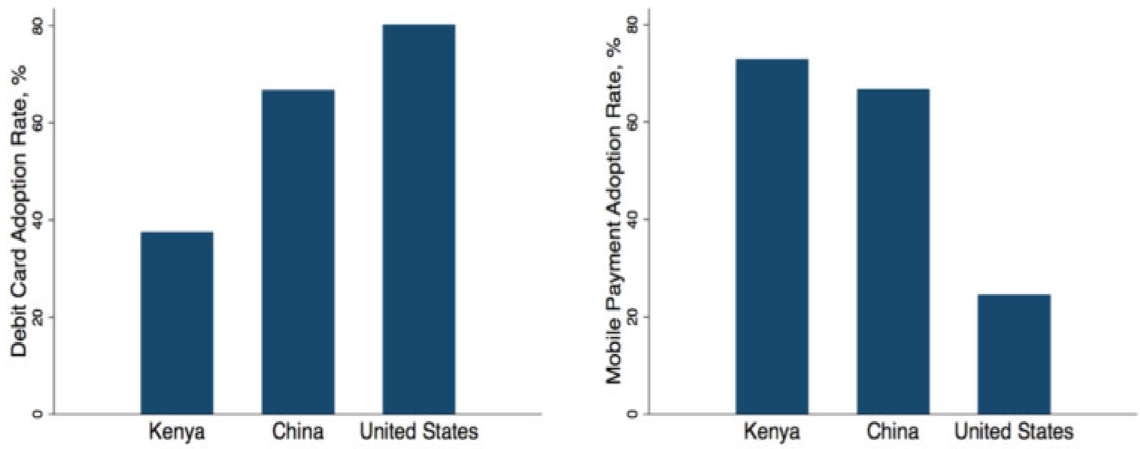
As a stark contrast, the United States appears to be lagging in mobile payment adoption. To illustrate, Figure 1 compares the adoption rates of card and mobile payments around 2017 in three countries: Kenya, China, and the United States. Figures 1A and 1B report the percentage of the adult population (age 15 and above) having a debit card and using a mobile payment service, respectively.[2] As depicted in Figure 1A, the card payment adoption rate of the United States is remarkably higher than Kenya and China, reflecting the global leadership of the United States in the card payment system. Figure 1B, however, shows that the mobile payment adoption rate of the United States is substantially lower than Kenya and China. Therefore, while the United States maintained the global leadership in the card payment era, it has been surpassed in the recent race of mobile payment adoption.

This has raised concerns about the efficiency and competitiveness of the U.S. payments system by the press, business leaders, and policymakers. With a headline of "China is out-mobilizing the United States," the Wall Street Journal (2018) was impressed by how

[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 Appendix I for the data details.

"Chinese consumers are adopting mobile payments in a way that is making U.S. tech companies green with envy."[3] Apple's CEO, Tim Cook, noted in a speech that China outdid the United States in the development of mobile payment technology.[4] Leaders of the Federal Reserve System recognized "that the U.S. retail payment infrastructure lags behind many other countries" and "the gap between the transaction capabilities in the digital economy and the underlying payment and settlement capabilities continues to grow."[5]



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

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

These observations and concerns lead to important questions: Why did developing countries like Kenya and China lag behind in adopting the card payment but leapfrog into the world frontier in the mobile payment stage? Has the United States lost the global leadership in the payment area? Should the U.S. government implement policies to boost mobile payment adoption?

This paper aims to address these questions. In doing so, we first compile a novel dataset to uncover the general adoption patterns of card and mobile payments across countries.

[3]See Wall Street Journal's report on "China's Great Leap to Wallet-Free Living," January 18, 2018.
[4]See Tim Cook's speech at the eighteenth China Development Forum in Beijing on March 18, 2017.
[5]See a speech by Lael Brainard, a Federal Reserve governor, on "Delivering Fast Payments for All" on August 5, 2019.

The data shows that the overtaking in mobile payment adoption is a systematic pattern between developing countries and advanced economies, beyond just Kenya, China, and the United States. Moreover, the adoption rate of mobile payment shows a non-monotonic relationship with per capita income: increasing in low-income countries, decreasing in middle-income countries, and increasing again in high-income countries. This is in contrast with the card payment, for which the adoption rate increases monotonically in per capita income across countries. Also, advanced economies and developing countries tend to adopt different mobile payment solutions: The former favor those complementary to card, while the latter favor those substituting card.

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 their adoption of mobile payment. In our model, three payment technologies, cash, card, and mobile, arrive sequentially. Newer payment technologies lower the variable costs of conducting payment transactions, but they require a fixed cost to adopt. As a result, when card arrives after cash, high-income consumers find it more attractive to adopt, which explains the high adoption rate in rich countries. However, when mobile arrives after card, the adoption incentives are remarkably different between existing card users and cash users. Since the fixed cost paid for adopting card is already sunk, card users have to face a higher income threshold to adopt mobile payment than cash users. Also, the same sunk cost makes it more attractive for card users to consider a mobile payment method complementary to card, while cash users would favor a card-substituting solution. This explains why most developing countries choose Mobile Money, a mobile payment method bypassing card services, while most advanced economies use card-complementing mobile solutions such as Apple Pay.

Our model calibration matches cross-country adoption patterns of both card and mobile payments well. Based on the calibrated model, we conduct quantitative analyses on several welfare and policy issues. We find that lagging behind in mobile payment adoption does not necessarily mean that advanced economies fall behind in overall payment efficiency, even though they benefit less from the mobile payment innovation compared with developing countries. Moreover, in our model economy, falling behind in adopting mobile payment is an optimal choice for advanced economies, and we provide a quantitative assessment of welfare loss of subsidizing mobile payment adoption. That said, our model also suggests that greater technological advances in mobile payment are needed for advanced economies to regain leading positions in the payment race, and governments may play positive roles in facilitating technological progress and market coordination.

Our paper contributes to several strands of literature. The first one is the studies on the payments system. Following the pioneering work of Rochet and Tirole (2002, 2003), a fast growing body of literature has been developed for studying market structure and pricing of retail payments system, especially card payments (see Rysman and Wright, 2014 for a literature review). However, most of those studies assume a static setting and ignore adoption decisions of payment methods. Among very few exceptions, Hayashi, Li, and Wang (2017) and Li, McAndrews, and Wang (2020) study payment system evolution in dynamic settings, but they do not consider cross-country patterns, which is the focus of this paper.

Our paper is also related to the literature that studies how electronic payments affect financial inclusion and social well-being using large micro datasets. For example, Jack and Suri (2014) find that M-PESA (a mobile payment service in Kenya) reduced transaction costs of remittances and facilitated the risk-sharing networks of households. Muralidharan, Niehaus, and Sukhtankar (2016) show that biometrically authenticated cards enabled faster, more predictable, and less corrupt payments process for beneficiaries of employment and pension programs in India. Our paper complements those work in the sense that we take a macro quantitative approach to study how cost savings brought by electronic payments affect payment efficiency and drive different adoption patterns across countries.

Finally, our paper contributes to the broad literature of technology diffusion. For a long time, researchers have been interested in the relationship between the adoption of new technologies and the heterogeneity of potential adopters (e.g., Griliches, 1957). While some argue that the observed adoption lags are evidence of information or coordination frictions, Manuelli and Seshadri (2014) among others have shown that the speed of adoption can be well explained by the moving equilibrium of frictionless models. Moreover, in the presence of sequential innovations, some firms could get stuck with old technologies due to their sunk investments in technology-specific learning (e.g., Parente, 1994; Jovanovic and Nyarko, 1996; and Klenow, 1998). Our paper extends this line of research to a new context where consumers make frictionless adoption decisions on sequential payment innovations. We show high-income consumers or countries could be overtaken by low-income counterparts in adopting mobile payments due to their sunk investments in precedent card payment technologies. Taking the theory to data, our quantitative model matches a non-monotonic relationship between mobile payment adoption and per capita income across countries, which is a novel empirical finding to the existing literature (e.g., Comin and Hobijn, 2004).

The remainder of this paper is structured as follows. Section 2 provides the background of mobile payment and summarizes stylized facts from a novel dataset regarding cross-country adoption patterns. Section 3 introduces the model and solves the equilibrium outcome. Section 4 calibrates the model and provides counterfactual exercises to illustrate the implications of the model. Section 5 conducts welfare and policy analyses. Section 6 provides further discussions. Finally, Section 7 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, whether or not 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. Around the same time, the oil company Mobil, also came out with an RFID (Radio Frequency Identification) 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 the SMS and the payments were made by a mobile account that was linked to the user's device.

The mobile payment systems based on SMS soon evolved into the world's first phone-based banking service launched by the Merita Bank of Finland in 1997. As time passed, the mobile payment technology progressed with more user applications, such as buying movie tickets, ordering pizza, and arranging travels. 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 macro and micro payments.[6] Vodafone launched this service in Kenya and Tanzania with the cooperation of the local telecom operators.

2011 was the year which saw major technology firms like Google and Apple entering the field of mobile payment. Google became the first major company to come up with its digital mobile wallet solution. The wallet was based on the NFC (Near Field Communication) technology and allowed the customers to make payments, redeem coupons, and earn loyalty points. In 2014, Apple launched its pay service in the United States called Apple Pay compatible with iPhone 6, which allowed the users to simply tap their phone against a contactless payment card terminal at the point of sale, paying instantaneously. Before long, competitors to Apple, such as Google and Samsung, released their respective mobile payment apps in the wake of Apple Pay's success.

As a cutting-edge payment innovation, mobile brings many additional benefits comparing with precedent card technologies, lowering both fixed and variable costs of making payments. First, given that mobile phone has been widely adopted in most countries, the fixed investment for adopting mobile payment is small 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 ID of an iPhone adds extra security to authenticate a purchase. Apple Pay also encrypts payment information by a tokenization technology, and, thus, enhance privacy and reduces the odds of fraud (Gupta et al., 2015). Third, as the mobile payment technology becomes more 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).[7]

[6] SMS (short message service) and USSD (Unstructured Supplementary Service Data) 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.

[7] Crowe et al. (2010) provides detailed discussions on the long-run benefits of mobile payments. For example, consumers could have their payments automatically logged in their financial planning software. Also, they could upload warranties and instructional videos at the time of purchase. Merchants could engage in sophisticated rewards programs, where consumers could access their status from their mobile device and receive alerts when they are close to rewards thresholds. Also, consumers could compare prices at nearby stores. If it is relatively easy to add new payment mechanisms to a mobile device and

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-related payment card systems. In this paper, we name them card-substituting and card-complementing mobile payments, respectively. The former is mainly used in developing countries like Kenya, and the latter is popular in advanced economies like the United States.

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 (i) deposit, withdraw, and transfer money, (ii) pay for goods and services, and (iii) redeem deposits for regular money. To deposit and withdraw money, M-PESA users rely on M-PESA agents (e.g., shops, gas stations, post offices). These agents in the M-PESA system are the analogs of the ATMs and bank branches in the banking system, allowing the M-PESA operation to bypass the banking system.

Achieving wild success in Kenya, M-PESA was emulated in many other developing countries. This category of mobile payment methods is defined as the "Mobile Money" payment by the Global System for Mobile Communications Association (GSMA) that meets the following conditions: First, the payment method must include transferring money as well as making and receiving payments using a mobile phone. Second, the payment method must be available to the unbanked (e.g., 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 payment in 2018 is illustrated in Figure 2.[8] The

to switch among options, one should see new entry and innovation in this arena.

[8]Source: GSMA (2018), "State of the Industry Report on Mobile Money."

percentage numbers in the figure refer to the shares of registered mobile money customers. The gray areas in the figure represent regions where the Mobile Money payment services are unavailable. Most users of Mobile Money payment are concentrating in developing countries, particularly sub-Saharan Africa (45.6%) and South Asia (33.2%). In contrast, Mobile Money payment services are barely relevant for developed countries.

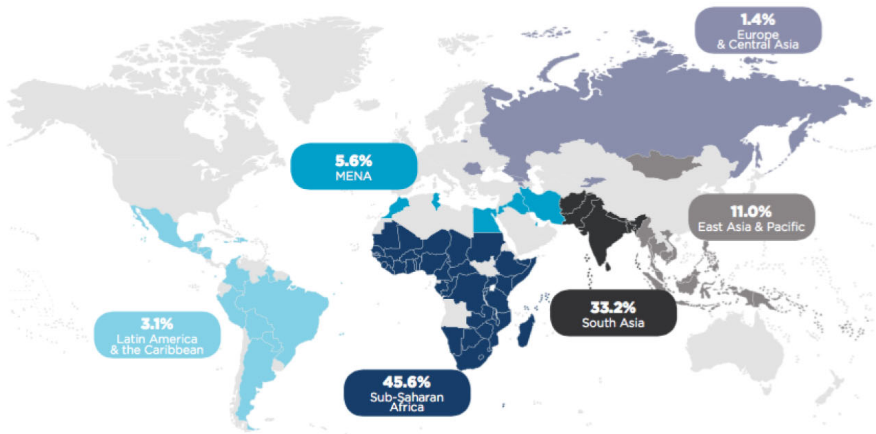


Figure 2. Global Adoption of Mobile Money Payment

2.1.2 Card-complementing mobile payment

In developed countries, the popular mobile payment methods, created by technology firms (e.g., Apple, Google, Samsung), rely heavily on banking and payment card networks. Because they typically use a proximity communication technology (e.g., NFC or QR codes), these methods are usually referred to as mobile proximity payment services.

Apple Pay is 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. Of the major mobile wallet services – Google Pay (formerly Android Pay), Samsung Pay and Apple Pay — the Apple service is the largest in terms of user adoption and market coverage.

Apple Pay represents a secure and sanitary payment option, since the app uses the NFC technology to transmit an encrypted virtual account number to the point-of-sale payment terminal. Originally launched in the United States, Apple Pay debuted in the United Kingdom, Australia, and Canada in 2015, and expanded to China, Switzerland, France, Singapore, and Japan in 2016. By 2020, Apple Pay has become available in dozens of countries (marked dark blue in Figure 3), most of which are developed countries.[9] Apple Pay supports both international payment card networks—such as American Express, Visa, Mastercard, and Discover—as well as country-specific domestic payment card services like China's UnionPay, Japan's JCB, France's Cartes Bancaires, and Canada's Interac.

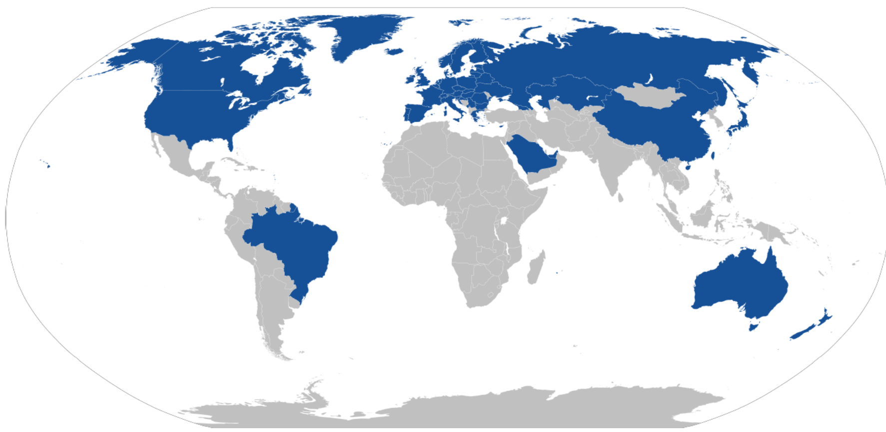


Figure 3. Global Availability of Apple Pay

2.2 Data and stylized facts

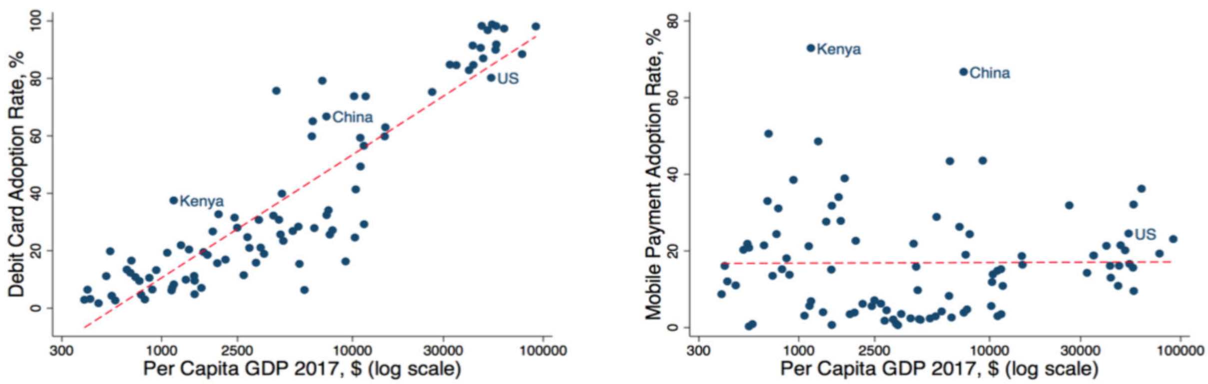
To study the global adoption pattern of mobile payments, we put together a novel dataset on debit card and mobile payment adoption in 94 countries.[10] The countries in our sample accounted for 91.4% of world GDP in 2017.

The dataset are drawn from the following sources (See Appendix I for more details). First, the data on the adoption rate 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 rate of card-complementing mobile payments

[9] Source: https://en.wikipedia.org/wiki/Apple Pay#Supported countries.

[10] Debit card ownership is a good measure of consumers who have access to card-payment technologies because credit card users almost surely own debit cards. For robustness checks, we also redid the analysis using an alternative measure from the World Bank dataset on the percentage of the adult population (age 15 and above) using a debit or credit card to make a purchase in the past year. The results are very similar.

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, among which five countries are covered in both data sources. We also collect the adoption rate 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 for each country in our sample from the World Bank.

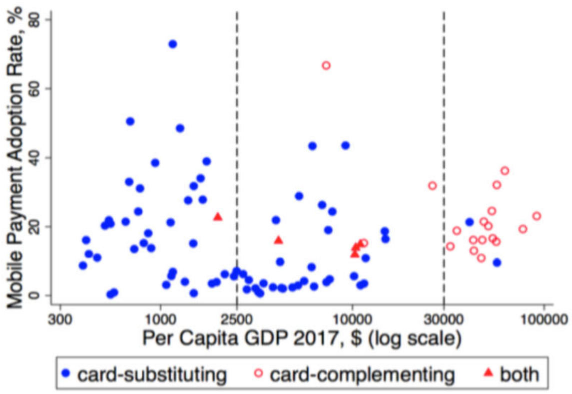


(A) Debit Card Adoption (B) Mobile Payment Adoption

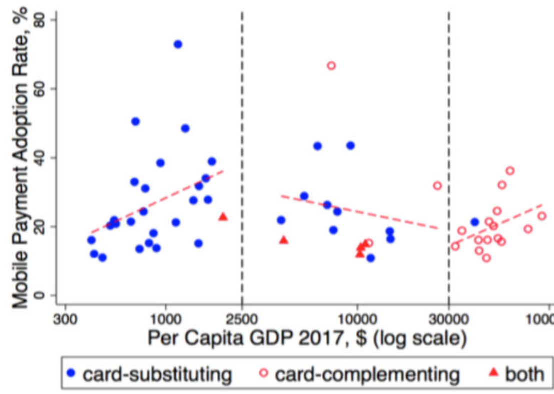
Figure 4. Card and Mobile Payment Adoption across Countries

Figure 4 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 rate strictly increases in per capita GDP across countries, while there appears no clear relationship between mobile payment adoption and per capita GDP.

However, as we delve further into the mobile payment adoption data, some pattern starts to emerge. First, we divide the sample into three income groups: low-income countries (i.e., per capita GDP $<$ \$2,500), middle-income countries (i.e., \$2,500 $\leq$ per capita GDP $\leq$ \$30,000), and high-income countries (i.e., per capita GDP $>$ \$30,000). We then distinguish different payment technologies used in each country in the sample. As shown in Figure 5A, there are clear differences in mobile payment technology choice: Most low- and middle-income countries choose card-substituting mobile payment, while most high-income countries choose card-complementing mobile payment.



(A) All Countries



(B) Excluding Low-Adoption Countries

Figure 5. Cross-Country Mobile Payment Adoption Pattern

Considering that mobile payment is a fairly recent technological innovation, it is possible that some countries (including those not covered by our dataset) may not have fully introduced it due to information or coordination frictions. We then remove the observations that have very low adoption rate (i.e., <10%) and add back linear regression lines by income-country group.[11] The results are shown in Figure 5B. It becomes visible that mobile payment adoption displays a non-monotonic relationship with per capita GDP: increasing in low-income countries, decreasing in middle-income countries, and increasing again in high-income countries. We report the regression results in Appendix II, and these patterns are robust for using a nonlinear regression model or an instrumental variable approach.

To sum up, we have the following stylized facts on cross-country adoption patterns of card and mobile payments:

1. *Positive income effect on card adoption.* – The adoption of card increases in per capita income across countries.

2. *Non-monotonic income effect on mobile payment adoption.* – The adoption of mobile payment increases in per capita income in low- and high-income countries, but

[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 implicitly applied a similar selection rule.

decreases in per capita income in middle-income countries.

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

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

In the rest of the paper, we will construct a theory to explain these stylized facts and conduct welfare and policy analyses. We will also provide discussions on the outlier countries with very low mobile payment adoption rates (i.e., <10%) in Section 6.

3 Model

In this section, we provide a model with sequential payment innovations to explain the stylized facts documented above. We outline the model environment in Section 3.1 and then characterize the model 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. 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 fixed costs may include time and resources spent on joining banking or mobile payment networks plus any installation and learning costs. The variable costs associated with using card and mobile are τ_d and τ_m per dollar of transactions, respectively. To capture the technology progress between cash, card, and mobile, we assume $\tau_h > \tau_d > \tau_m$ and $k_d > k_m$.

Time is discrete with an infinite horizon. We consider an endowment economy, where each agent receives an exogenous income I_t at time t. Without loss of generality, we assume that income I_t follows an exponential distribution across the population in the economy, with the cdf function $G_t(I_t) = 1 - \exp(-I_t/\lambda_t)$.[12] Note that the exponential distribution has a fixed Gini coefficient at 0.5 and the mean is λ_t. Over time, each agent's income I_t grows at a constant rate g, i.e., $I_{t+1} = I_t(1+g)$, so does the mean income of the economy, i.e., $\lambda_{t+1} = \lambda_t(1+g)$. We normalize the population size to unity.

An agent has a linear utility $u = c$, where c is her consumption. We assume no storage technology, so each agent consumes all her endowment net of payment costs each period. We also assume payment services and merchant services are provided by competitive markets, so that a consumer can always use her favorite payment technology to pay for her consumption at the social cost of the payment method she chooses to use.[13]

3.2 Equilibrium

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

The economy only has the cash technology before electronic payments are available. Cash is accessible to everyone, so the adoption rate is 100%. In such a cash economy, the value 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

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

[12] The exponential distribution fits income distributions well (e.g., see Dragulescu and Yakovenko, 2001).

[13] These simplifying assumptions allow us to focus on the technological side of payment innovations and provide a good benchmark for understanding the key cross-country differences. We provide more discussions in Section 6 on relaxing some of the assumptions.

3.2.2 Card payment

At time T_d, the payment card technology arrives as an exogenous shock. Each agent then compares card and cash technologies and makes the adoption decision.

At any point of time $t \geq T_d$, 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 time 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 each point of time $t \geq T_d$, 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, 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 time $t \geq T_d$ 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 payment card 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 in per capita income (i.e., $\partial F_{d,t}/\partial \lambda_t > 0$).

3.2.3 Mobile payment

Mobile payment arrives after card as another exogenous shock. In the following, we first study a scenario where only a card-substituting mobile payment technology (e.g., Mobile Money) is introduced, and we then study another scenario where a card-complementing mobile payment technology (e.g., Apple Pay) also becomes available.

A card-substituting mobile payment technology At a point of time $T_m > T_d$, 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 point $t \geq T_m$, the value function V_m of an agent who has income I_t and has adopted mobile can be written as

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

which yields

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

Because mobile is a better payment technology than card, (i.e., $\tau_m < \tau_d$ and $k_m < k_d$), an agent who has not adopted card by time $T_m - 1$ (i.e., $I_{T_m - 1} < I_d$) would no longer consider adopting card at time T_m and afterwards. Instead, they would adopt mobile payment at a point of time $t \geq T_m$ 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) show $I_m < I_d$, so the fraction of agents who have switched from cash to mobile by time $t \geq T_m$ 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 time $T_m - 1$ (i.e., $I_{T_m-1} \geq I_d$) would adopt mobile payment at a point of time $t \geq T_m$ 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:

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

Assuming $\frac{k_m}{\tau_d-\tau_m} > \frac{k_d}{\tau_h-\tau_d}$, we have $I_{m'} > I_d$, so the fraction of agents who have switched from card to mobile by time $t \geq T_m$ 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 time $t \geq T_m$ is

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

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: (i) taking the value of λ_{T_m-1} as given, Eq. (16) yields $\partial F_{m,t}/\lambda_t > 0$, which implies that a country's mobile payment adoption rate increases over time due to income growth; (ii) taking into account $\lambda_{T_m-1} = \lambda_t/(1+g)^{t-T_m+1}$, Eq. (16) shows that the sign of $\partial F_{m,t}/\lambda_t$ has to depend on parameter values. As a result, the mobile payment adoption rate may not show a monotonic relationship with per capita income across countries; and (iii) in the long run, once all the card adopters eventually adopt mobile (i.e., $F_{d\to m,t} = F_{d,T_m-1}$), we 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., $\partial F_{m,t}/\partial\lambda_t > 0$).

A card-complementing mobile payment technology We now extend the model to consider another scenario that at the same point of time T_m, a card-complementing mobile payment solution also becomes available in addition to the card-substituting one. This mobile payment technology is an add-on upgrade to the existing card technology, which allows an agent who has adopted card 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., $k_m^a < k_m$).

It is straightforward to see that in this scenario, 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 $k_m < k_d + k_m^a$.

Therefore, agents who have switched from cash to mobile by time $t \geq T_m$ should have chosen the card-substituting mobile payment technology. As shown in Eq. (11) above, the fraction of these agents is

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

On the other hand, agents who have chosen the card-complementing mobile payment by time $t \geq T_m$ are those whose income have crossed the threshold

$$I_t \geq I_{m'}^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}. \tag{17}$$

The fraction of these card-mobile switchers is

$$F_{d \to m,t} = 1 - G_t(I_{m'}^a) = \exp(-I_{m'}^a/\lambda_t) = \exp(-\frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)\lambda_t}), \tag{18}$$

as long as $F_{d \to m,t} \leq F_{d,T_m - 1}$, a result similar to what is derived in Eq. (15) except that k_m^a replaces k_m. Otherwise, $F_{d \to m,t} = F_{d,T_m - 1}$.

All together, the total fraction of agents who have adopted mobile payments by time $t \geq T_m$ is

$$\begin{aligned} F_{m,t} &= F_{h \to m,t} + F_{d \to m,t} = \exp(-I_m/\lambda_t) - \exp(-I_d/\lambda_{T_m - 1}) + \exp(-I_{m'}^a/\lambda_t) \quad (19) \\ &= \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t}) - \exp(-\frac{(1-\beta)k_d}{(\tau_h - \tau_d)\lambda_{T_m - 1}}) + \exp(-\frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)\lambda_t}) \end{aligned}$$

as long as $F_{d \to m,t} < F_{d,T_m - 1}$. Otherwise, $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t})$.

Again, Eq. (19) implies that depending on parameter values, the mobile payment adoption rate $F_{m,t}$ may not have a monotonic relationship with per capita income λ_t across countries. But once all the card adopters have adopted mobile so that $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h - \tau_m)\lambda_t})$, the mobile payment adoption rate becomes strictly increasing in per capita income across countries.

4 Model calibration and implications

In this section, we calibrate the model to match the cross-country card and mobile payment adoption patterns. We then conduct counterfactual analyses to explore the model implications regarding different mobile payment options, income growth, and technological progress.

4.1 Model calibration

We first calibrate the model with two mobile payment options (i.e., the card-substituting and card-complementing ones) using the parameter values as shown in Table 1.

Table 1. Parameter Values for Model Calibration

Parameter	Value	Description	Source of Identification
β	0.95	Discount factor	Standard
g	2%	Income growth rate	Standard
τ_h	2.3%	Cash variable cost	ECB (2012)
τ_d	1.4%	Card variable cost	ECB (2012)
k_d	500	Card adoption cost	Cross-country card payment adoption pattern, Figure 6A
τ_m	1.395%	Mobile variable cost	Cross-country mobile payment adoption pattern, Figure 6B
k_m	150	Mobile adoption cost	Cross-country mobile payment adoption pattern, Figure 6B
k_m^a	100	Mobile add-on cost	Cross-country mobile payment adoption pattern, Figure 6B

The unit of time is year, and we set 2017 as the year T_m when mobile payment becomes available. Following convention, we set the discount factor $\beta = 0.95$ and the annual income growth rate $g = 2\%$. According to an ECB study (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%, so we set the values of τ_h and τ_d accordingly. We then calibrate $k_d = 500$ to fit the cross-country card adoption pattern in 2017. Finally, we calibrate the mobile payment variable cost $\tau_m = 1.395\%$ ($< \tau_d$) and the fixed costs $k_m = 150$ ($< k_d$) and $k_m^a = 100$ ($< k_m$) to fit the cross-country mobile payment adoption pattern in 2017.[14]

Note that in our model calibration, we treat per capita income/spending and per capita GDP interchangeable. In reality, per capita income/spending could be a fraction of per capita GDP. To account for that, we can simply rescale the payment adoption costs (i.e., k_d, k_m, and k_m^a) by the same fraction without affecting our analysis and findings.

Figure 6 shows that our calibration results fit the data well and match the first three stylized facts identified above: (1) *Positive income effect on card adoption; (2) Non-monotonic income effect on mobile payment adoption*; (3) *Overtaking in mobile payment adoption.*

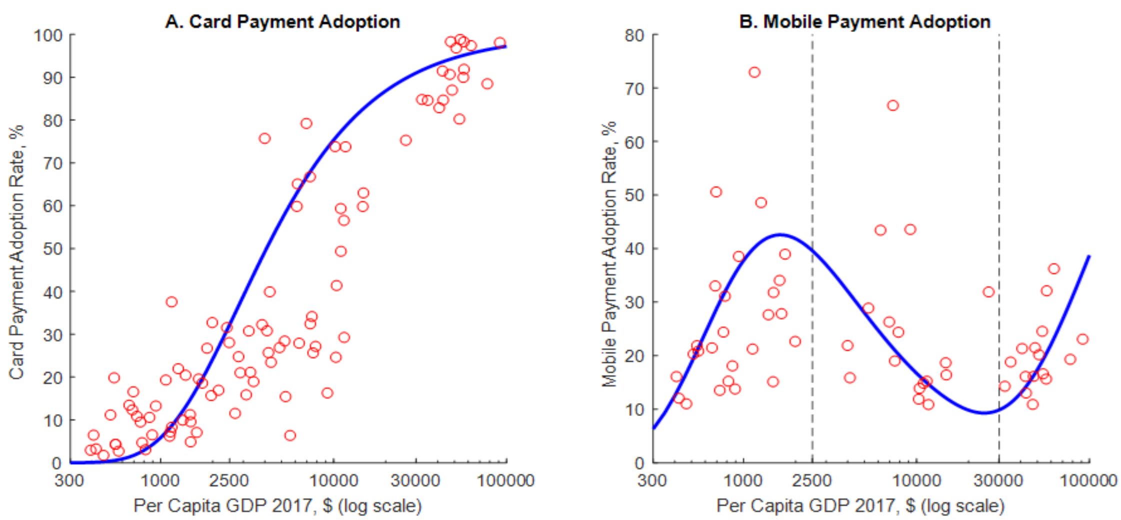


Figure 6. Model Fit with Data

Figure 7 below shows that our calibration also matches the fourth stylized fact: (4) *Different technology choice across countries.* In Figure 7, we decompose the fraction of total mobile payment adopters at $T_m = 2017$ (red dash line) into cash-mobile switchers (green solid line) and card-mobile switchers (blue solid line) by per capita income, and compare with the fractions of previous cash users (green dot line) and card users (blue dot line) at $T_m - 1$. In the low-income countries (i.e., $\lambda_{T_m} < \$2,500$) and most middle-income countries (i.e., $\$2,500 \leq \lambda_{T_m} \leq \$30,000$), mobile payment adoption almost entirely relies

[14]To discipline the calibration, we assume that the card-substituting and card-complementing mobile payment technologies share the same value of τ_m. Allowing different values of τ_m for the two technologies would provide an additional degree of freedom and let the model fit data even better.

on cash-mobile switchers who choose card-substituting technologies, while in most high-income countries (i.e., $\lambda_{T_m} > \$30,000$), mobile payment adoption relies on card-mobile switchers who choose card-complementing technologies.

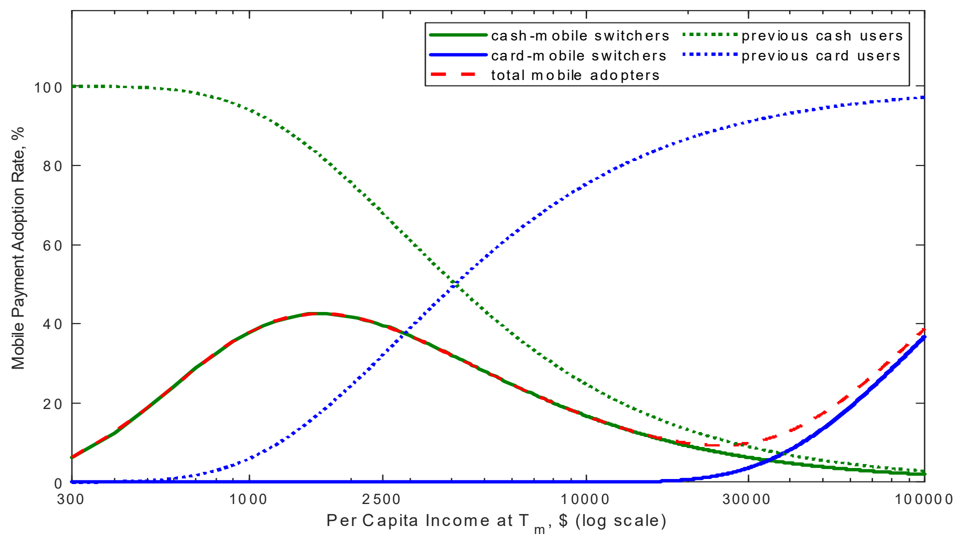


Figure 7. Composition of Mobile Payment Adopters

Moreover, Figure 7 helps explain the non-monotonic income effect on mobile payment adoption. In the low-income countries, because most agents are cash users, the adoption of mobile payments concentrates on card-substituting technologies and the adoption increases in per capita income. By contrast, in the middle-income countries, because more agents are card users who are locked in by the card technology (i.e., their income cannot justify switching to either card-substituting or card-complementing mobile payment technologies), the adoption of mobile payment decreases in per capita income. Finally, in the high-income countries, most agents are card users and their incomes are high enough to justify switching to the card-complementing mobile payment technology, so the adoption of mobile payment again increases in per capita income.

4.2 Model implications

Our calibrated model matches the average cross-country pattern of mobile payment adoption. Based on the model, we provide several counterfactual exercises to illustrate the implications of the model.

4.2.1 Mobile payment options

We first check how the availability of different mobile payment technology options affect the adoption pattern, as shown in Figure 8 below. The green dash line shows the mobile payment adoption pattern if only the card-substituting option is available in each country. The blue dot line shows the adoption pattern if only the card-complementing option is available in each country. The red solid line, as seen above, shows the adoption pattern when both mobile payment options are available in each country.

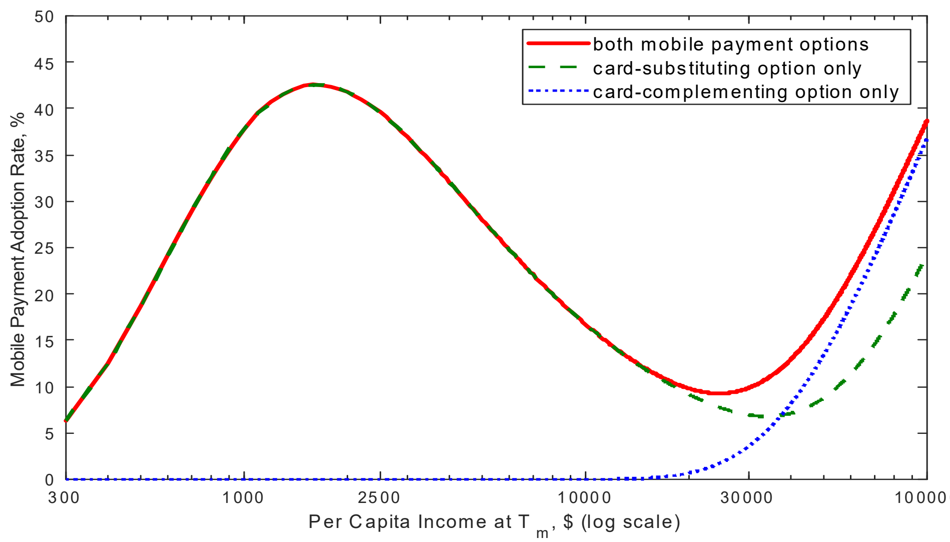


Figure 8. Mobile Payment Options and Adoption Patterns

The results in Figure 8 provide the following insights on the effects of mobile payment technology options:

First, the availability of both mobile payment options in each country increases adoption rate, especially for high-income countries. As shown in the figure, the red line is on top of both the green dash line and the blue dash line.

Second, only having the card-substituting mobile payment option in each country would not change much of the cross-country adoption pattern. Its effects on low- and middle-income countries are almost entirely negligible, though it pushes down mobile payment adoption in high-income countries almost by half.

Third, only having the card-complementing mobile payment option, however, would overturn the cross-country adoption pattern, making adoption increasing in per capita income. Essentially, it would kill mobile payment adoption in most low- and middle-income countries, and it pushes down only slightly mobile payment adoption in high-income countries.

Finally, with both mobile payment technologies being available, it is possible that each country, depending on its per capita income, may only choose to supply one type of mobile payment technology (e.g., due to network effects or a minimum scale requirement). If that is the case, the adoption pattern would be given by the upper envelope of the green dash line and the blue dot line. In this case, the cross-country adoption pattern does not change much comparing with our calibrated model.[15]

4.2.2 Income growth

We now consider the effect of income growth. According to our theory, long-run income growth would eventually take all the card adopters who exist before time T_m to cross the mobile payment adoption threshold. Once that happens, the mobile payment adoption would solely depend on cash-mobile switchers, and the adoption rate would become increasing monotonically in per capita income. However, our quantitative exercise suggests that it would just take too long for income growth to overturn the non-monotonic mobile payment adoption pattern.

Recall that we assume per capita income grows at 2% annually in each country. Figure 9 tracks each country by per capita income at time T_m and plots mobile payment adoption rates at year T_m (red solid line), $T_m + 50$ (pink dash line), $T_m + 100$ (green dot line), and $T_m + 180$ (blue dash-dot line). It shows that as per capita income grows, mobile payment adoption increases in every country. Meanwhile, the adoption rate continues to be non-monotonic in per capita income. Ultimately, it takes 180 years to converge to an adoption curve that strictly increases in per capita income.[16]

[15] An alternative way to calibrate our model is to assume that a country only supplies one type of mobile payment technology, either the card-substituting one or the card-complementing one, whichever would yield the higher adoption rate. However, Figure 8 suggests that this alternative calibration would not change much of the data fitting, and the counterfactual analyses would be very similar.

[16] In our model simulation, 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 180 years. Once that happens, the mobile payment adoption rate only depends on the fraction of cash-mobile switchers and it increases in per capita income λ_t. Note that this process could speed up if our model introduces birth and death of agents.

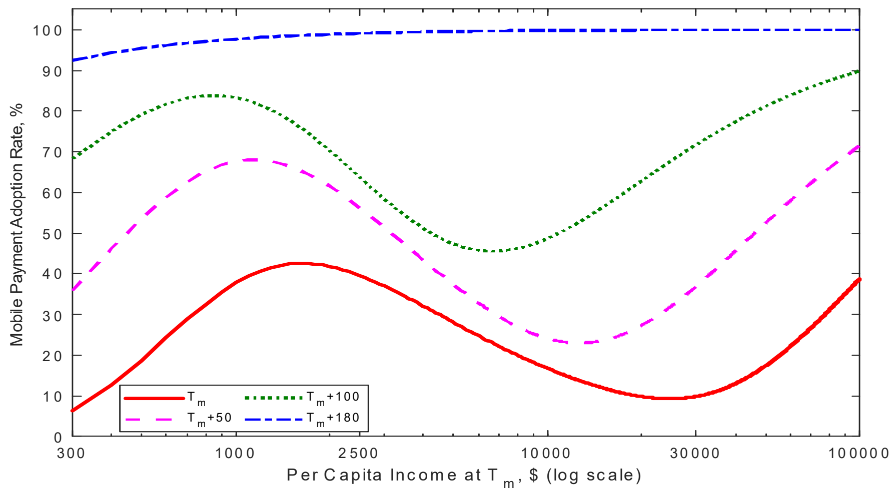


Figure 9. Income Growth and Mobile Payment Adoption

Figure 10 decomposes mobile payment adopters into cash-mobile switchers and card-mobile switchers. It shows that as per capita income grows over time, both cash-mobile switchers and card-mobile switchers increase in every country. Eventually, after all the previous card users have adopted mobile payment at year $T_m + 180$ in every country, the adoption rate of mobile payment is determined solely by cash-mobile switchers and it strictly increases in per capita income.

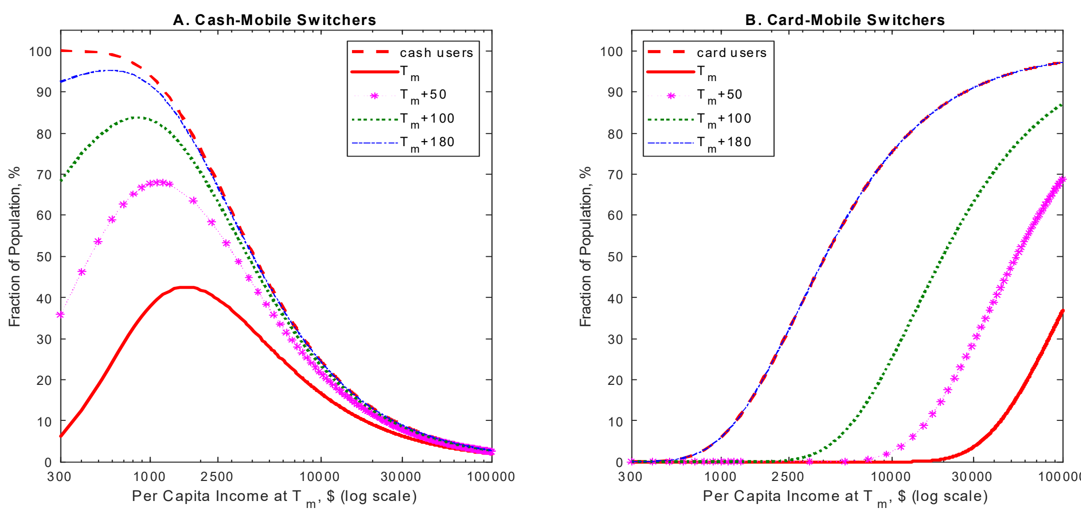


Figure 10. Income Growth and Mobile Payment Adopters

4.2.3 Technological progress

Comparing with income growth, the effect of technological progress on mobile payment adoption can be more striking. According to our theory, the main reason that advanced economies are stuck with card payment is because the value added of mobile payment is not substantial enough. Therefore, greater technological progress of mobile payment not only would increase the adoption in every country, but also could restore advanced economies to the leading positions in the mobile payment race if the technological progression is sufficiently large.

To see this, we conduct a counterfactual exercise with different values of τ_m. Figure 11 plots the result. It shows that with larger technological progress (i.e., smaller values of τ_m), the mobile payment adoption rate gets higher in every country and advanced economies are especially benefitted. If the technological progress is sufficiently large, mobile payment adoption becomes strictly increasing in per capita income across countries.

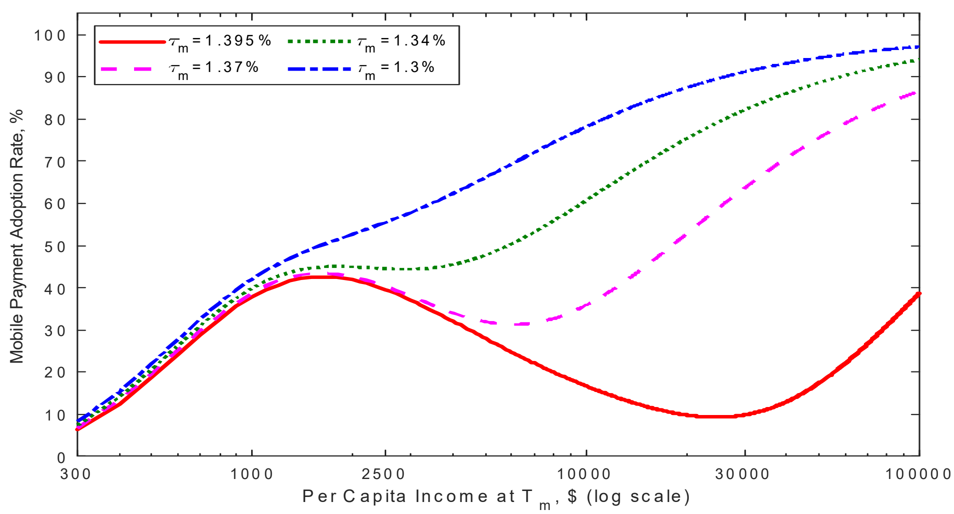


Figure 11. Technological Progress and Mobile Payment Adoption

Taking a step furture, Figure 12 decomposes mobile payment adopters into cash-mobile switchers and card-mobile switchers. One can see technological progress mainly boosts mobile payment adoption among previous card users who enjoy more cost savings than cash users through a lower τ_m due to their higher income and spending. This explains why high-income countries benefit more. Therefore, should some major technological progress occur down the road, advanced economies might see their mobile payment adoption jump up and they may even regain leading positions in the mobile payment race.

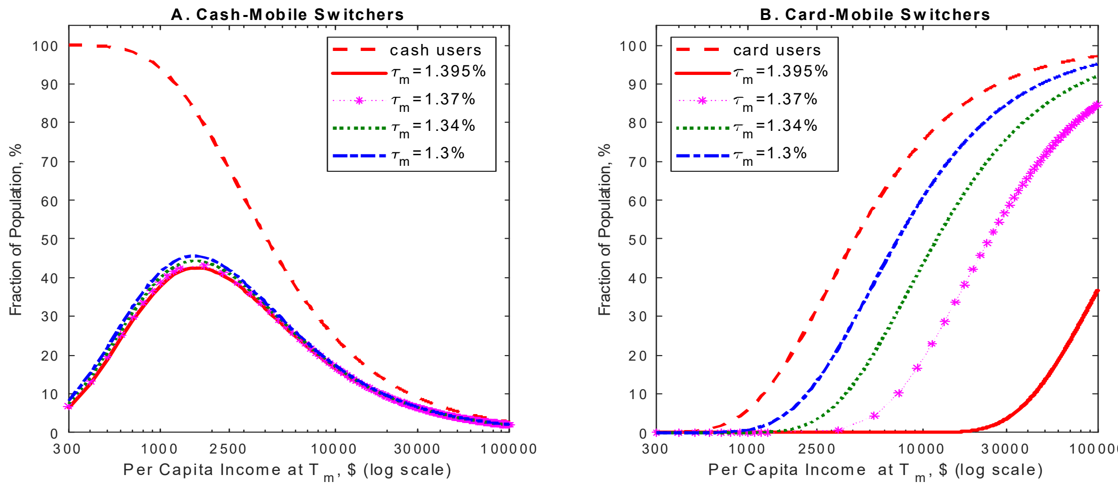


Figure 12. Technological Progress and Mobile Payment Adopters

5 Welfare and policy analyses

In this section, we use our calibrated model to conduct welfare and policy analyses.

5.1 Payment efficiency

Given our model framework, an intriguing question is to identify the winners and losers in adopting new payment technologies. To address this question, we conduct a welfare analysis. We first evaluate payment efficiency for individual agents and then for aggregate economies. For ease of notation, we denote each agent by her income level I (without the time subscript) in the analysis.

5.1.1 Individual agents

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

$$\bar{V}_h(I) = \frac{(1-\tau_h)\, I}{1-\beta(1+g)}, \tag{20}$$

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

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

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

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

$$\omega_{T_d}(I) = \begin{cases} \bar{V}_d(I) - k_d & \text{if } I \geq I_d; \\ \bar{V}_h(I) + \beta^s \begin{bmatrix} \bar{V}_d(I(1+g)^s) \\ -k_d - \bar{V}_h(I(1+g)^s) \end{bmatrix} & \begin{array}{l} \text{if } \frac{I_d}{(1+g)^s} \leq I < \frac{I_d}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}. \end{array} \end{cases} \tag{22}$$

Note that $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is given by Eq. (5). The top equation of (22) calculates the welfare of an agent whose income crosses the card adoption threshold at time T_d, and the bottom equation calculates the welfare of an agent who would adopt card at a future time.

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

$$\bar{V}_m(I) = \frac{(1-\tau_m)\, I}{1-\beta(1+g)}. \tag{23}$$

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

$$\omega_{T_m}(I) = \begin{cases} \bar{V}_m(I) - k_m^a & \text{if } I \geq I_{m'}^a; \\ \bar{V}_d(I) + \beta^s \begin{bmatrix} \bar{V}_m(I(1+g)^s) \\ -k_m^a - \bar{V}_d(I(1+g)^s) \end{bmatrix} & \begin{array}{l} \text{if } \max(\frac{I_{m'}^a}{(1+g)^s}, I_d(1+g)) \leq I < \frac{I_{m'}^a}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}; \end{array} \\ \bar{V}_m(I) - k_m & \text{if } I_m \leq I < I_d(1+g); \\ \bar{V}_h(I) + \beta^s \begin{bmatrix} \bar{V}_m(I(1+g)^s) \\ -k_m - \bar{V}_h(I(1+g)^s) \end{bmatrix} & \begin{array}{l} \text{if } \frac{I_m}{(1+g)^s} \leq I < \frac{I_m}{(1+g)^{s-1}}, \\ \text{for } s \in \{1,2,3,...\}. \end{array} \end{cases} \tag{24}$$

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. (17). The top equation of (24) calculates the welfare of a card-mobile switcher whose income crosses the mobile adoption threshold at time T_m, the second equation is the welfare of a card user who would adopt mobile at a future time, the third equation is the welfare of a cash-mobile switcher at time T_m, and the bottom equation is the welfare of a cash user who would adopt mobile at a future time.

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

$$x_t(I) = \frac{\omega_t(I)}{\frac{I}{1-\beta(1+g)}}. \tag{25}$$

Note that $\frac{I}{1-\beta(1+g)}$ is the first-best welfare in a frictionless economy without any payment costs, so $x_t(I)$ gauges the fraction of the first-best welfare level that can be achieved by agent I under available payment technologies at time 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 before, we assume that the mobile payment technology arrives at $T_m = 2017$. We then assume that the card payment arrives at $T_d = T_m - 30$.[17] Figure 13 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 13 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 everyone and it increases in agents' income. A similar pattern holds when the mobile payment arrives at T_m. The intuition 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

[17] The large-scale introduction of debit cards in the U.S. started in the mid-1980s (see Hayashi, Li, and Wang, 2017), so we set $T_d = T_m - 30$. Note that the simulation results 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.

k_m^a) counts for a smaller share of her income. But if mimicking is not the optimal decision, the higher-income agent must be able to achieve even higher payment efficiency by choosing a payment method different from her lower-income counterpart.

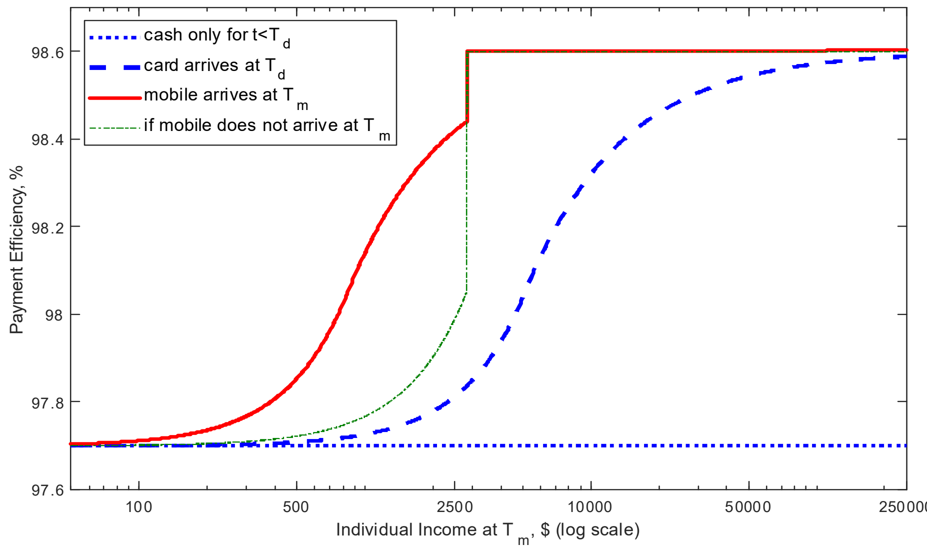


Figure 13. Payment Efficiency by Individual Income

Figure 13 also illustrates how payment efficiency evolves across income levels over time. At time T_d, agents either pay or expect to pay in the future the fixed cost k_d to adopt card, and the payment efficiency measure x_{T_d} is a continuous and increasing function of income. Then for any time $t \in (T_d, T_m)$, card users who have paid off k_d in the past no longer count the fixed cost in their payment efficiency measure so $x_t = 1 - \tau_d$ for them. Meanwhile, cash users who just meet or have not met the card adoption threshold need to pay the fixed cost, so their payment efficiency x_t displays a jump at the card adoption threshold, as shown by the curve $\tilde{x}_{T_m}$. For those cash users, their payment efficiency does improve over time due to income growth and thus a declining share of k_d relative to their income. Comparing the two curves x_{T_m} and $\tilde{x}_{T_m}$ shows that the introduction of mobile improves payment efficiency for everyone (especially for cash users) and makes the jump at the card adoption threshold smaller.[18]

[18] For cash users, introducing mobile improves their payment efficiency substantially because of the much reduced adoption cost comparing with card (recall that $k_d = 500$ vs. $k_m = 150$). For card users, their payment efficiency only improves slightly somewhere between $1 - \tau_d$ and $1 - \tau_m$ (recall that $\tau_d = 1.4\%$ vs. $\tau_m = 1.395\%$).

5.1.2 Aggregate economies

We now take a step further to compare the overall payment efficiency across countries by aggregating over each country's income distribution. With the exponential income distribution, we can solve explicitly the present-value welfare of aggregate economies, denoted by $W_t(\lambda_t)$, for $t < T_d$ (i.e., cash only), $t = T_d$ (i.e., card becomes available), and $t = T_m$ (i.e., mobile becomes available). Appendix III provides the solution details.

Similar 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 time t:

$$X_t(\lambda_t) = \frac{W_t(\lambda_t)}{\frac{\lambda_t}{1-\beta(1+g)}}. \tag{26}$$

Using the parameter values in Table 1, we can now compare payment efficiency across countries under each payment innovation. As before, we assume that the mobile payment technology arrives at $T_m = 2017$ and the card payment arrives at $T_d = T_m - 30$. Figure 14 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.

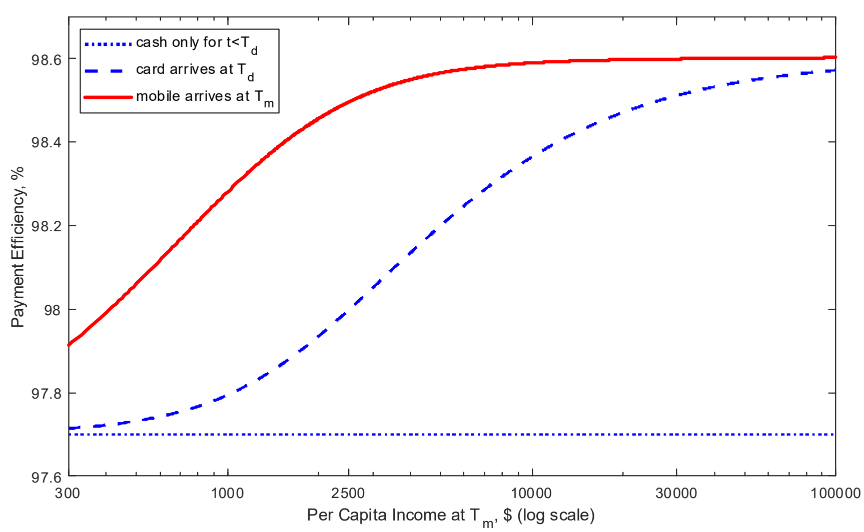


Figure 14. Payment Efficiency by Per Capita Income

Figure 14 shows that 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 welfare improvement increases in per capita income across countries. Hence, high-income countries gain the most from the card payment adoption. The arrival of mobile payment also benefits every country though disproportionately. As shown in Figure 15, the relative welfare gain $(X_{T_m} - X_{T_d})/X_{T_d}$ peaks for countries with per capita income around $1,600. Figures 14 and 15 suggest that while the richest countries appear to gain relatively little from their mobile payment adoption, they remain leaders in terms of overall payment efficiency. In contrast, the poorest countries do not gain much from either card or mobile payment innovation, and they lag far behind in overall payment efficiency. Therefore, despite the promise of mobile payment for financial inclusion, its benefits to poorest countries are limited at this stage. In light of this, global financial inclusion may entail further innovations to reduce the payment costs, especially the adoption costs.

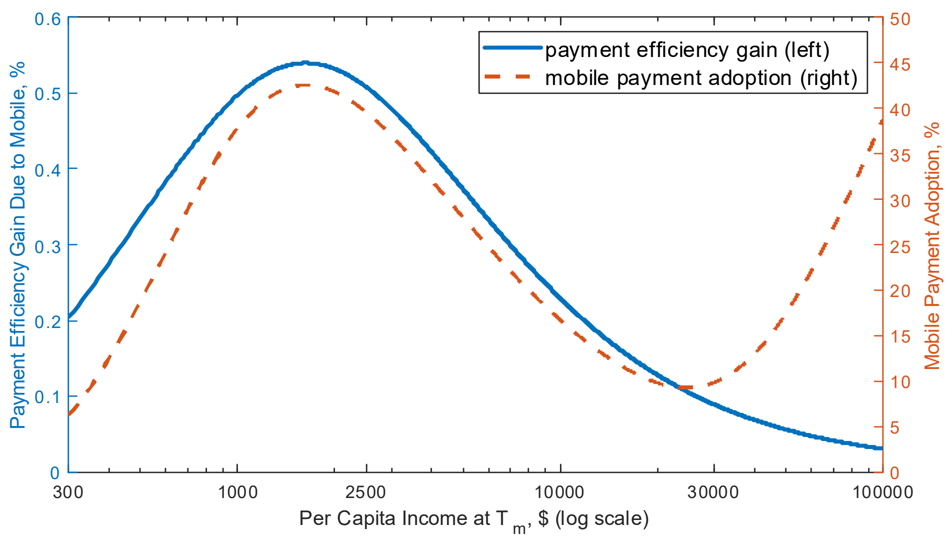


Figure 15. Payment Efficiency Gain by Per Capita Income

5.2 Subsidizing mobile payment adoption

In our model economy, with mobile payment technologies being given, the market outcome is socially efficient. Falling behind in the race for mobile payments could be an optimal choice for advanced economies. However, policymakers in those countries have been concerned about losing the race. Many argue that governments should play a more active role in promoting mobile payment adoption.

As shown in Section 4.2.3, encouraging technological progress of mobile payment might be an effective way for advanced economies to restore leading positions in the mobile payment race. To the extent that private firms may not internalize all the social welfare gains in their R&D decisions, government intervention could be welfare improving.

On the other hand, given a fixed mobile payment technology, pushing up mobile payment adoption by providing subsidies would cause a welfare loss. To quantify this, we conduct the following exercise. Based on our calibrated model, a country at the U.S. per capita income level in 2017 ($53,356) would on average have a 94.8% card adoption rate and a 19.0% mobile payment adoption rate. Assume that upon the arrival of mobile payment at time $T_m = 2017$, the government offers each mobile payment adopter a subsidy S to reduce the adoption cost, and the subsidy is financed by lump-sum income taxation. Presumably, the subsidy would change the mobile payment adoption thresholds (i.e., I_m and $I^a_{m'}$) for cash users and card users, but without changing the social costs (i.e., k_m and k^a_m) of adoption. Therefore, we can calculate the present value of social welfare at time T_m under the subsidy by using the new adoption thresholds (cf. Eq. (29) in Appendix III):

$$I_m = \frac{(1-\beta)(k_m - S)}{(\tau_h - \tau_m)} \quad \text{and} \quad I^a_{m'} = \frac{(1-\beta)(k^a_m - S)}{(\tau_d - \tau_m)}.$$

Figures 16 and 17 show the effects of such a subsidy. In each figure, we normalize the present value of social welfare under no subsidy to zero. We then plot the change of welfare relative to the no-subsidy benchmark at different subsidy levels, ranging from $0 to $150 per adopter. Recall that in our calibration, it costs $100 for a card user to adopt the card-complementing mobile payment technology, and it costs $150 for a cash user to adopt the card-substituting one.

Figure 16 reports the overall effects. As the amount of subsidy per adopter rises, mobile payment adoption increases, but welfare falls at an increasing rate. However, the welfare loss slows down and turns almost flat when the subsidy reaches $98 per adopter. Eventually, as the subsidy increases to $150 per adopter, the mobile payment adoption rate reaches 100%, and the welfare loss maximizes at $88.17 per capita. The reason that the maximal welfare loss per capita is smaller than the subsidy per adopter is that a part of the tax used to finance the subsidy is offset by the increased transaction efficiency from using mobile payments.

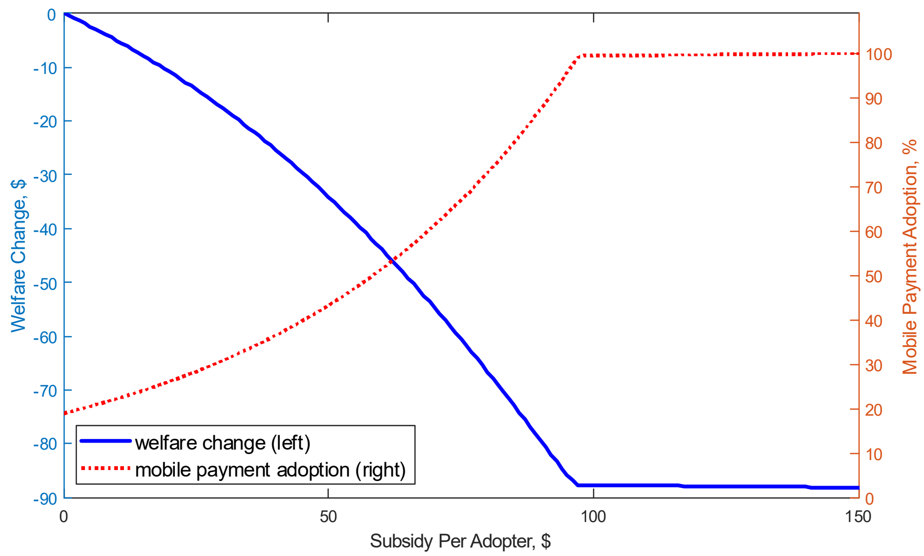


Figure 16. Effects of Mobile Payment Adoption Subsidy

Figure 17 decomposes the overall subsidy effects between card users and cash users. It becomes clear that most of the subsidy effects come from the card users. In this economy, right before time T_m, 94.8% of agents are card users and 5.2% are cash users. Without any subsidy, the mobile payment adoption rate at time T_m would be 19.0%, among which 15.3% are card users and 3.6% are cash users. Should the subsidy per adopter increase and reach \$98 per adopter, all the 94.8% card users would have adopted mobile payments, which would lead to a welfare drop of \$87.32 per capita. In the meantime, another 4.6% of adopters would come from cash users, resulting in a welfare loss of \$0.36 per capita. If the subsidy goes above \$98, no further changes would occur from card users, but mobile payment adoption and welfare loss would continue to rise from cash users though the magnitude would be small. Eventually, when the subsidy reaches \$150 per adopter, all the 5.2% cash users would adopt mobile payment, leading to a welfare loss of \$0.85 per capita.

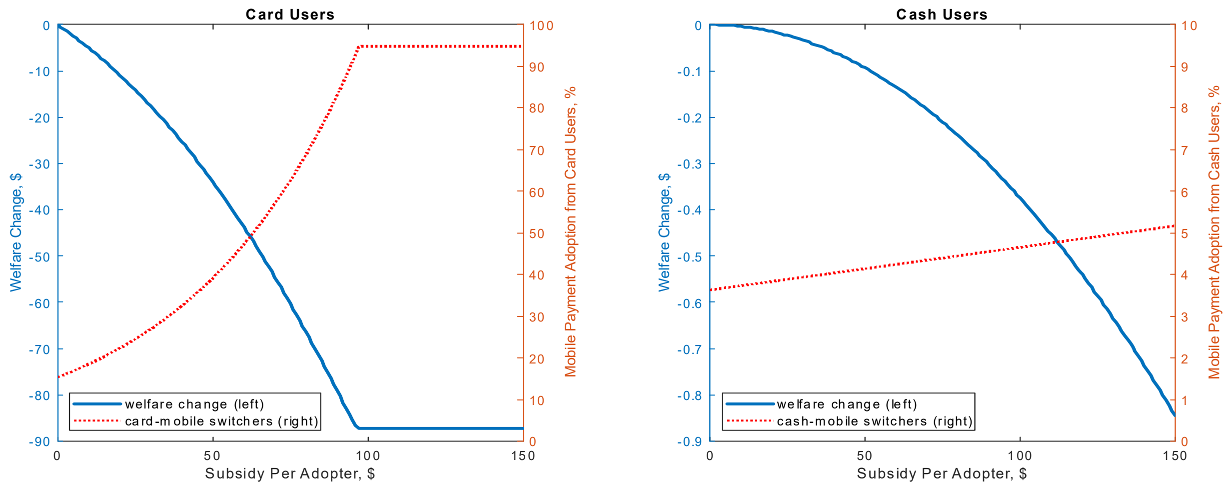


Figure 17. Effects of Mobile Payment Subsidy on Card and Cash Users

The above exercise is based on the assumption that both mobile payment options, the card-complementing one and the card-substituting one, are offered in the country. In an alternative scenario where only the card-complementing option is available, we may just need to exclude the small fraction of the cash-mobile switchers from the calculation. In the end, the quantitative findings, because they are mainly driven by card-mobile switchers, are very similar.

6 Further discussions

While our model fits well the average cross-country pattern of mobile payment adoption, it does not cover all the factors affecting payment adoption decisions. In this section, we extend our model and provide some further discussions.

6.1 Two-sided market considerations

It is well known in the literature that the payment market is two-sided. A payment technology needs to be adopted by both buyers and sellers for being widely used in the economy. Our model so far has been explicit about consumers' (buyers') side of the market but not much about the merchants' (sellers') side. We now extend our model to the two-sided market setting and discuss the implications.

First, our model can be easily extended to a setting where merchants incur a zero fixed cost for adopting a new payment technology. Consider that each consumer receives an income of I_t of the numeraire good at time t, and I_t follows an exponential distribution across the population of consumers. The numeraire good needs to be processed and distributed through competitive merchants, where merchants' processing and distributing costs are normalized to zero. Conducting a transaction between a merchant and a consumer requires using a payment technology $i \in \{h \text{ (cash)}, d \text{ (card)}, m \text{ (mobile)}\}$, for which the merchant (seller) and the consumer (buyer) each incurs a variable cost $\tau_{s,i}$ and $\tau_{b,i}$ per dollar of transactions, respectively. Assume merchants require customers to use a particular payment technology or they charge different prices based on payment means. Therefore, a competitive merchant accepting payment technology i would set price p_i for selling the good to break even:

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

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

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

Assume that merchants incur no fixed cost for adopting a new payment technology, while consumers need to pay k_d and k_m as the one-time fixed adoption costs associated with adopting card and mobile payment technology, respectively. It is straightforward to see the new model setting is equivalent to our original model by changing notations: For each payment technology $i \in \{h, d, m\}$, we simply need to redefine the variable cost τ_i such that

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

As before, to capture the technology progress between cash, card, and mobile, we assume $\tau_h > \tau_d > \tau_m$ and $k_d > k_m$.

More generally, our model can be extended to scenarios where merchants do incur a fixed cost for adopting a new payment technology. In fact, as long as merchants can price discriminate based on payment methods, they may find ways to transfer the adoption costs to their customers, for example, by charging a one-time setup fee for customers to use a new payment technology. However, in the case where merchants are heterogenous and do not price discriminate based on payment methods, things become more complicated and our model may serve as a first-order approximation (See Li, McAndrews, and Wang, 2020 for a detailed analysis).

Extending our model interpretation to the two-sided market setting does bring additional insights. For one thing, the discussion makes it clear that one should take into account payment costs of both merchants and consumers in the analysis. That is the reason why we choose to calibrate our model using measures of social costs of payment means instead of just consumers' costs. Also, pending future data availability, it would be useful to model merchant heterogeneity and their payment adoption decisions and match those with data.

Moreover, given that the payment market outcome depends on two sides' decisions, multiple equilibria can arise. The market outcome we discussed previously remains a valid equilibrium, but it is no longer the unique one. For example, there could exist another equilibrium where no merchant or consumer adopts 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, which might result from certain coordination failures among relevant parties.[19] In those cases, appropriate government interventions may have positive welfare effects.

6.2 Kenya, China, and the U.S.

Kenya and China currently are world front-runners in mobile payment adoption. Figure 18 suggests that their extraordinary performance may have idiosyncratic components beyond the theory that we offer to explain the average cross-country pattern.

[19] For example, Aker, Prina and Welch (2020) show that mobile money has failed to take off in Niger because of a chicken-and-egg problem: Agents need to be widespread for the service to be useful, but putting agents everywhere isn't viable until the service is widespread.

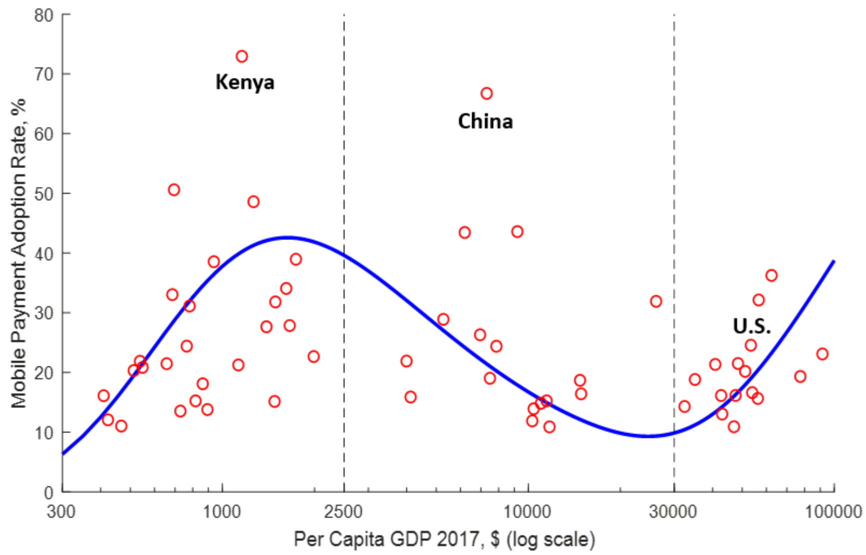


Figure 18. Model Fit: Kenya, China and the U.S.

Note that in our model calibration, we assume that all the countries in the sample share the same set of parameter values, which provides useful model discipline. However, this assumption is not intended to fit outlier cases, and our model provides some clues on how things would differ when relaxing the assumption. According to our model (cf. Eq. (19)), mobile payment adoption would be higher if mobile payment technology is more efficient (i.e., a lower τ_m) or less costly (i.e., a lower k_m), or the card technology is less efficient (i.e., a higher τ_d) or more costly (i.e., a higher k_d). These factors could be relevant for the Kenya and China discussions. In both countries, it is well known that the banking sectors have been quite inefficient, which suggests a higher k_d or τ_d. In contrast, the mobile payment service providers in each country, Safaricom and Vodafone in Kenya as well as Alibaba and Tencent in China, are very innovative and successful players, which may suggest a lower k_m or τ_m.

Some factors outside our model may also play important roles. For example, our benchmark model does not consider the variation of market structure and government intervention across countries, which may also have driven some of the adoption pattern. Also, our model focuses on the payment aspect of the mobile payment technology, while in reality the new technology may serve multiple functions. For example, Jack and Suri (2014) highlight the role of M-PESA in urban-rural remittances in Kenya, which provides an important risk-sharing function.[20] In China, the two giant tech firms, Tencent and Alibaba, have developed their mobile payment services, WeChat Pay and Alipay, strategically to extend their business models, for instance, to cross-sell consumer and business loan services based on payments data (Hau et al., 2019). It would be very valuable for future research to explore these additional factors.

In comparison, the United States has been lagging in mobile payment adoption. Its performance, however, is not out of line with the cross-country average pattern explained by our theory. Therefore, our model provides a useful framework for policy discussions in the U.S. context. Our analysis shows that countries like the United States, the previous card payment leaders, naturally tend to fall behind in the mobile payment race. Falling behind is an optimal choice for such countries because the incremental improvement introduced by the current mobile payment technology does not provide a sufficient incentive for them to switch. Given this finding, directly subsidizing mobile payment adoption would be socially inefficient in those countries.[21] Instead, policymakers may consider promoting mobile payments in more productive ways, for example, by encouraging greater mobile payment technology progress or reducing market frictions of coordination.

7 Conclusion

In this paper, we construct a quantitative theoretical framework to explain the cross-country pattern of mobile payment adoption. With a novel dataset, we find that the adoption rate of mobile payment has a non-monotonic relationship with per capita income. This is in contrast with the card payment, for which the adoption increases monotonically in per capita income across countries. Also, countries favor different mobile payment solutions: advanced economies favor those complementary to the existing card payments,

[20] Recent studies suggest that the unique urban-rural remittance pattern in Kenya may help explain its exceptionally wide adoption of M-PESA. Therefore, Kenya's success in adopting mobile payment should be regarded as an outlier rather than normative (see Piper, Kelsey (September 11, 2020). *What Kenya can teach its neighbors — and the US — about improving the lives of the "unbanked."* Vox). This is consistent with our model's prediction, which underestimates the mobile payment adoption rate of Kenya but fits well the adoption rates of Kenya's neighboring countries.

[21] As a theoretical benchmark, our model assumes that payment services are provided by competitive firms, while in reality some payment service providers may have market power that distorts payment pricing and adoption. In the latter case, certain government interventions might be warranted.

while developing countries favor 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. As a result, rich countries enjoyed advantages in adopting card payments for replacing cash early on, but their sunk costs in adopting card payments later set a higher threshold for adopting the mobile payment innovation. Also, the same sunk costs make it more attractive for card-intensive countries to adopt mobile payment methods complementary to cards, while cash-intensive countries favor card-substituting mobile solutions.

Our model calibration matches cross-country adoption patterns of card and mobile payments well. Based on the quantitative model, we find that lagging behind in mobile payment adoption does not necessarily mean that advanced economies fall behind in overall payment efficiency. Moreover, slower adoption can be an optimal choice given that the incremental benefit of switching from card payment to the current mobile payment technology is not large enough. Down the road, greater technological advances in mobile payments are needed for advanced economies to regain leading positions in the payment race, and governments may play positive roles in facilitating technological progress and market coordination.

While our paper focuses on payment services, a major payment innovation like the mobile may have impact beyond payments. For example, it may help extend financial services to the unbanked population and reduce poverty. Meanwhile, the rise of nonbank payment service providers, particularly telecom companies and fintech firms, may pose new challenges to financial stability and regulations. Those would be interesting topics for future research. On the other hand, leapfrogging is a relevant issue for the adoption of other major innovations. For example, mobile phone has enabled developing countries to skip the old fixed-line technology and move straight to the mobile technology, and solar energy technologies may allow developing countries to skip an energy infrastructure based on fossil fuels but jump directly into the Solar Age. Our analysis on mobile payment might help shed light on this broad issue.

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Appendix

I. Data sources.

The mobile payment data introduced in Section 2.2 are drawn from two sources. First, the data on the adoption rate 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 the GSMA MMU database indicates that mobile money accounts were available at the time the survey was carried out) were surveyed for mobile money adoption: "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 on the adoption rate for card-complementing mobile payments around 2017 were 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 had 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, so 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 United States, 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.

II. Regression results.

This appendix section provides the regression results related to Figures 4 and 5.

Table A1 reports the OLS results for estimating the card and mobile payment adoption. Across the 94 countries in the sample, the regression (1) shows that the card adoption rate in 2017 is significantly and positively related to per capita GDP in 2017. In contrast, the regression (2) shows 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 we would have had a better fit if we simply had run a regression with only a constant. However, a pattern starts to emerge once we remove the countries that have very low adoption rates of mobile payments (i.e., adoption rate $<$ 10%) and group the remaining ones by income. The regression (3) shows that mobile payment adoption increases in per capita GDP for low-income countries (i.e., per capita GDP $<$ \$2,500) and high-income countries (i.e., per capita GDP $>$ \$30,000), but decreases in per capita GDP for middle-income countries (i.e., \$2,500 $\leq$ per capita GDP $\leq$ \$30,000).

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 would increase mobile payment adoption by 11.3% for the low-income countries. The coefficient estimate of ln(GDP per capita) $\times 1\{\text{High Income}\}$ is small and not statistically significant, suggesting that the marginal effect of per capita GDP on mobile payment adoption in high-income countries is not different from that in low-income countries. On the other hand, the coefficient estimate of ln(GDP per capita) $\times 1\{\text{Middle Income}\}$ is -0.163 and statistically significant. This implies that the marginal effect of per capita GDP on mobile payment adoption in middle-income countries is significantly lower than that in low-income (and high-income) countries. The coefficient difference, 0.113-0.163, suggests that doubling per capita GDP is associated with a 5% reduction in mobile payment adoption rate among middle-income countries.

Table A1. Cross-Country Payment Adoption: OLS Regressions

	Card	Mobile	
	(1)	(2)	(3)
ln(GDP per capita)	0.186***	0.001	0.113**
	(0.009)	(0.010)	(0.053)
ln(GDP per capita) $\times 1\{$Middle Income$\}$			-0.163*
			(0.084)
ln(GDP per capita) $\times 1\{$High Income$\}$			-0.007
			(0.133)
$1\{$Middle Income$\}$			1.197*
			(0.692)
$1\{$High Income$\}$			-0.456
			(1.365)
Constant	-1.179***	0.163*	-0.497
	(0.079)	(0.083)	(0.362)
Observations	94	94	59
Adjusted R^2	0.81	-0.01	0.07

The results in Table A1 are based on the Ordinary Least Squares (OLS) models. The dependent variable is the debit card adoption rate of 2017 in regression (1) or the mobile payment adoption rate around 2017 in regressions (2) and (3). The independent variables include the GDP per capita of 2017 and a constant in regressions (1) and (2), plus two dummy variables (i.e., Middle Income and High Income) and their interaction terms with the GDP per capita in regression (3). Standard errors are reported in the parentheses. *** Significance at 1% level, ** at 5% level, and * at 10% level.

For robustness checks, we re-run the regressions using the Fractional Logit (FL) model to address the fractional nature of the dependent variable, which is bounded by 0 and 1. The estimated marginal effects, shown in Table A2, are very similar to the OLS results in Table A1.

We also re-run the regressions using the Two-Stage Least Squares (2SLS) model to address a potential endogeneity concern that the adoption of a payment innovation may have reverse impact on contemporaneous per capita GDP. To purify the potential reverse impact, we bring in per capita GDP in 2004 (which is more than a decade ago and well before the mobile payment was introduced) as an instrument for per capita GDP in 2017, and the first-stage results are highly significant. The second-stage results, shown in Table A3, are consistent with the OLS findings that card adoption has a positive relationship with per capita income, while mobile payment adoption has a non-monotonic relationship.

Table A2. Cross-Country Payment Adoption: FL Regressions

	Card	Mobile	
	(1)	(2)	(3)
ln(GDP per capita)	0.229***	0.001	0.106***
	(0.012)	(0.008)	(0.039)
ln(GDP per capita) ×1{Middle Income}			-0.155**
			(0.070)
ln(GDP per capita) ×1{High Income}			0.014
			(0.061)
1{Middle Income}			1.149*
			(0.589)
1{High Income}			-0.647
			(0.575)
Observations	94	94	59

Regressions in Table A2 are based on the Fractional Logit (FL) models. The dependent and independent variables in the regressions are the same as 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. *** Significance at 1% level, ** at 5% level, and * at 10% level.

Table A3. Cross-Country Payment Adoption: 2SLS Regressions (Second-Stage Results)

	Card	Mobile	
	(1)	(2)	(3)
ln(GDP per capita)	0.186***	0.002	0.100*
	(0.009)	(0.010)	(0.055)
ln(GDP per capita) ×1{Middle Income}			-0.203**
			(0.087)
ln(GDP per capita) ×1{High Income}			0.039
			(0.144)
1{Middle Income}			1.592**
			(0.723)
1{High Income}			-0.891
			(1.495)
Constant	-1.179***	0.155*	-0.407
	(0.079)	(0.083)	(0.373)
Observations	94	94	59

Regressions in this table are based on the Two-Stage Least Squares (2SLS) models. The dependent and independent variables in the regressions are the same as in Table A1 except that the independent variable ln(GDP per capita 2017) is instrumented by its value of 2004. Standard errors are reported in the parentheses. *** Significance at 1% level, ** at 5% level, and * at 10% level.

III. Present-value welfare of aggregate economies.

This appendix section calculates the present-value welfare of aggregate economies.

Recall that $\bar{V}_h(I)$ is the value function of an agent I who would permanently use the cash technology, given by Eq. (20). Accordingly, the present-value welfare of a pure cash economy, $W_{h,t}$, at any time t is

$$W_{h,t} = \int_0^\infty \bar{V}_h(I) dG_t(I) = \frac{(1-\tau_h)\lambda_t}{1-\beta(1+g)}. \tag{27}$$

Thus, the present-value welfare of an economy, denoted by W_t, equals $W_{h,t}$ for any $t < T_d$.

Recall that $\bar{V}_d(I)$ is the value function of an agent I who would permanently use the card technology, given by Eq. (21). Accordingly, the present-value welfare of the economy, W_{T_d}, at time T_d when card technology arrives is

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

where $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is given by 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 time T_d, and the last term is the additional welfare gains for future card adopters.

Given the exponential distribution $G_{T_d}(I) = 1 - \exp(-I/\lambda_{T_d})$, Eq. (28) yields that

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

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. (23). We can then derive the present value of welfare for the economy, W_{T_m}, at time T_m when mobile technology arrives:

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

where $I_m = \frac{(1-\beta)k_m}{(\tau_h - \tau_m)}$ is given by Eq. (10), and $I^a_{m'} = \frac{(1-\beta)k^a_m}{(\tau_d - \tau_m)}$ is given by Eq. (17). 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 time T_m and forever. The second term is the additional welfare gains of cash-mobile switchers at time 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 time T_m and forever. The fifth term is the additional welfare gains of card-mobile switchers at time T_m, and the last term is the additional welfare gains for future card-mobile switchers.

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

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

Given the exponential distribution $G_{T_m}(I) = 1 - \exp(-I/\lambda_{Tm})$, this yields

$$
\begin{aligned}
W_{T_m} \quad = \quad & \frac{(1-\tau_h)}{1-\beta(1+g)}\left(\lambda_{T_m} - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g))\right) \\
& + \frac{(\tau_h - \tau_m)}{1-\beta(1+g)}\left(\exp(-\frac{I_m}{\lambda_{T_m}})(\lambda_{T_m} + I_m) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g))\right) \\
& - k_m\left(\exp(-\frac{I_m}{\lambda_{T_m}}) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})\right) \\
& + \sum_{s=1}^{\infty}\beta^s\left(\frac{(\tau_h - \tau_m)(1+g)^s}{1-\beta(1+g)}\right)\begin{pmatrix} \exp(-\frac{I_m}{(1+g)^s\lambda_{T_m}})(\lambda_{T_m} + \frac{I_m}{(1+g)^s}) \\ -\exp(-\frac{I_m}{(1+g)^{s-1}\lambda_{T_m}})(\lambda_{T_m} + \frac{I_m}{(1+g)^{s-1}}) \end{pmatrix} \\
& - k_m\sum_{s=1}^{\infty}\beta^s\left(\exp(-\frac{I_m}{(1+g)^s\lambda_{T_m}}) - \exp(-\frac{I_m}{(1+g)^{s-1}\lambda_{T_m}})\right) \\
& + \frac{(1-\tau_d)}{1-\beta(1+g)}\exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g)) \\
& + \left(\frac{(\tau_d - \tau_m)}{1-\beta(1+g)}\right)\exp(-\frac{I^a_{m'}}{\lambda_{T_m}})(\lambda_{T_m} + I^a_{m'}) - k^a_m\exp(-\frac{I^a_{m'}}{\lambda_{T_m}}) \\
& + \sum_{s=1}^{\phi}\beta^s\frac{(\tau_d - \tau_m)(1+g)^s}{1-\beta(1+g)}\begin{pmatrix} \exp(-\frac{I^a_{m'}}{(1+g)^s\lambda_{T_m}})(\lambda_{T_m} + \frac{I^a_{m'}}{(1+g)^s}) \\ -\exp(-\frac{I^a_{m'}}{(1+g)^{s-1}\lambda_{T_m}})(\lambda_{T_m} + \frac{I^a_{m'}}{(1+g)^{s-1}}) \end{pmatrix} \\
& - k^a_m\sum_{s=1}^{\phi}\beta^s\left(\exp(-\frac{I^a_{m'}}{(1+g)^s\lambda_{T_m}}) - \exp(-\frac{I^a_{m'}}{(1+g)^{s-1}\lambda_{T_m}})\right) \\
& + \beta^{\phi+1}\frac{(\tau_d - \tau_m)(1+g)^{\phi+1}}{1-\beta(1+g)})\begin{pmatrix} \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m} + I_d(1+g)) \\ -\exp(-\frac{I^a_{m'}}{(1+g)^{\phi}\lambda_{T_m}})(\lambda_{T_m} + \frac{I^a_{m'}}{(1+g)^{\phi}}) \end{pmatrix} \\
& - k^a_m\beta^{\phi+1}\left(\exp(-\frac{I_d(1+g)}{\lambda_{T_m}}) - \exp(-\frac{I^a_{m'}}{(1+g)^{\phi}\lambda_{T_m}})\right).
\end{aligned}
$$