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# Technology Adoption and Leapfrogging: Racing for Mobile Payments

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# 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 early 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]

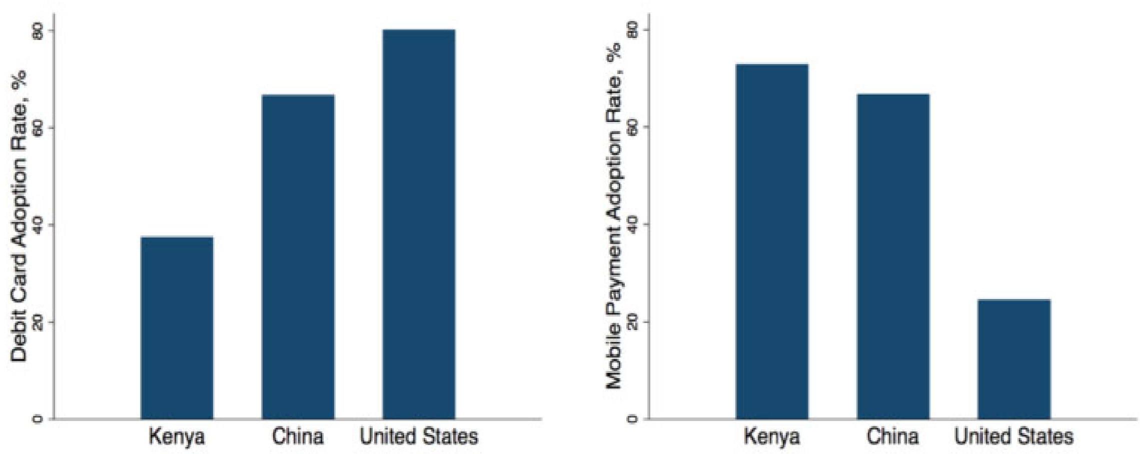
As a stark contrast, the United States appears to be lagging in mobile payment adoption. To illustrate, Figure 1 compares the adoption rates of card and mobile payments around 2017 in three countries: Kenya, China, and the United States. Figures 1A and 1B report the percentage of the adult population (age 15 and above) having a debit card and using a mobile payment service, respectively.[2] As depicted in Figure 1A, 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 favors 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 have fallen 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 studying how electronic payments affect financial inclusion and social well-being. 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 works in the sense that we study how cost savings brought by electronic payments affect payment efficiency and drive different adoption patterns between developing and advanced economies.

Finally, our paper contributes to the broad literature of technology diffusion. For a long time, researchers in that field have been interested in the relationship between the adoption of new technologies and the heterogeneity of potential adopters (e.g., Griliches, 1956). Some more recent works (e.g., Comin and Hobijn, 2004) explore cross-country adoption patterns of major technologies and match them with alternative theoretical explanations. We add to this literature a study of the diffusion of a latest payment innovation and uncover a novel non-monotonic relationship between technology adoption and per capita income.

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 helped 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

[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.

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.

## 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.

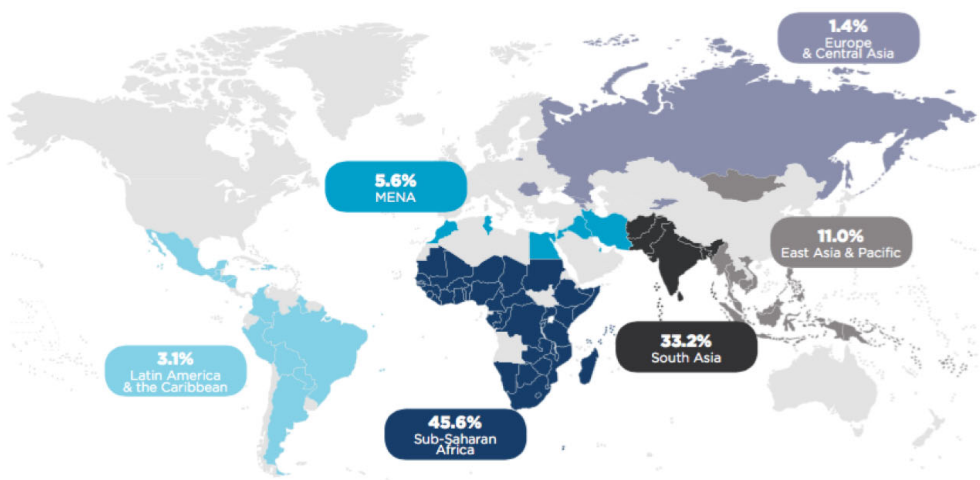



Figure 2. Global Adoption of Mobile Money Payment

The global adoption of Mobile Money payment in 2018 is illustrated in Figure 2.[7] The 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.

### 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.

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

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 being 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.[8] 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.

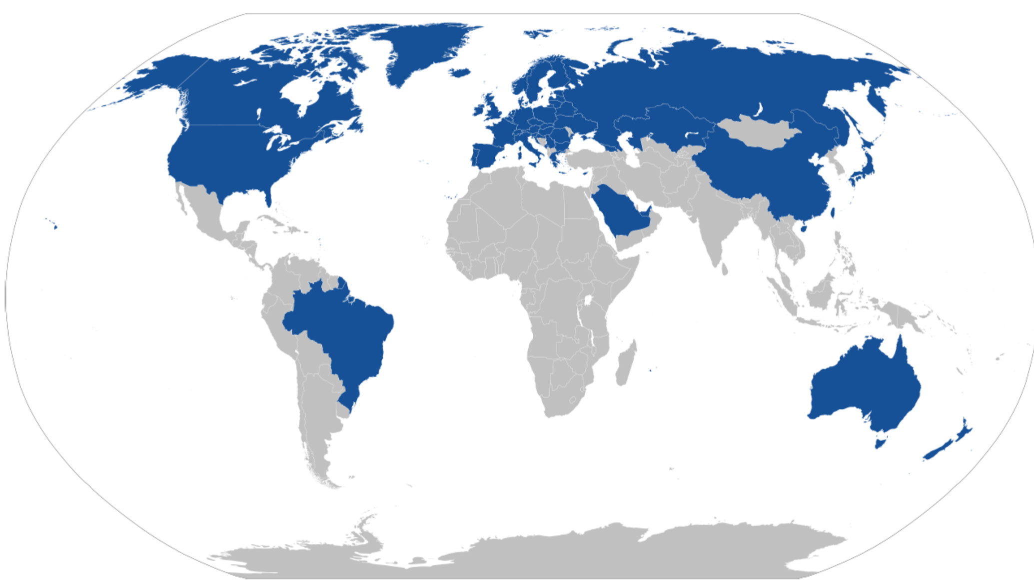


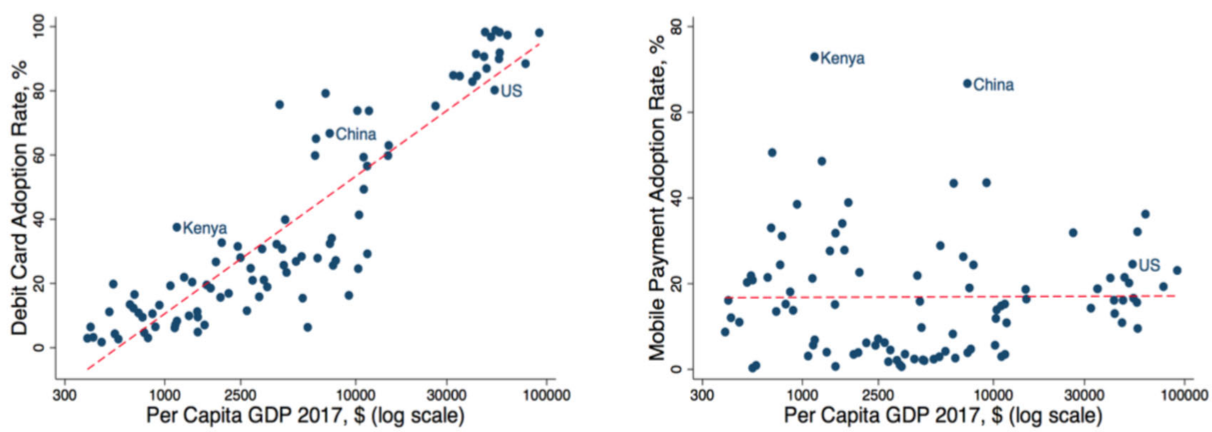
Figure 3. Global Availability of Apple Pay

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

## 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. 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 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.

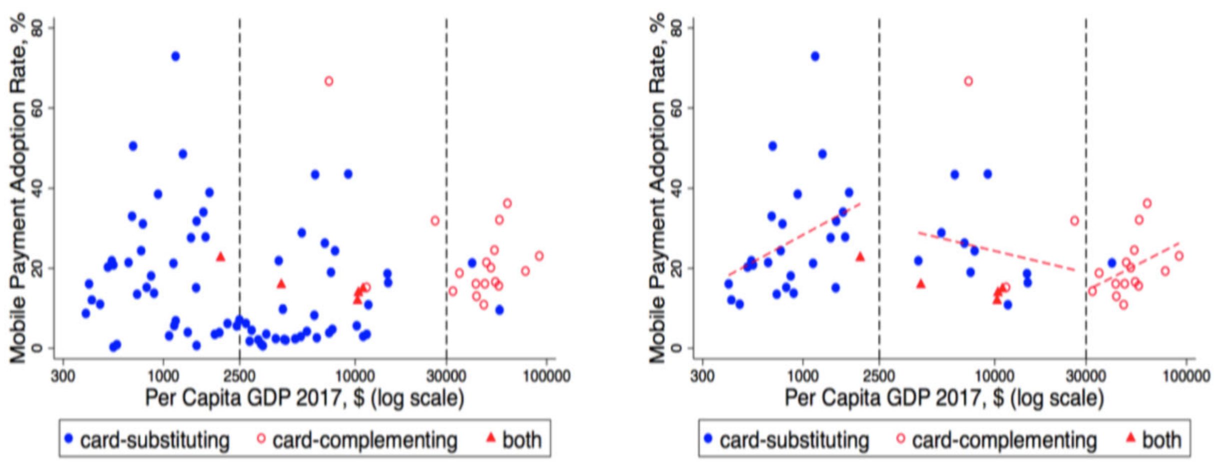



(A) Debit Card Adoption (B) Mobile Payment Adoption

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.[9] The results are shown in Figure 5B. It becomes visible that

[9]Removing observations with mobile payment adoption rate below 10% only affects countries from the Global Findex Database that use Mobile Money payment services. Presumbly, the eMarketer dataset on mobile proximity payment adoption has implicitly applied a similiar selection rule.

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 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.* – For low- and middle-income countries, the mobile payment technologies adopted are almost entirely the card-substituting ones, 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 rate (i.e., $<10\%$) in Section 6.

# 3 Model

## 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 $\tau_h$ 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 $\tau_d$ and $\tau_m$ 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 $G_t(I_t) = 1 - \exp(-I_t/\lambda_t)$.[10] Note that the exponential distribution has a fixed Gini coefficient at 0.5 and the mean is $\lambda_t$. Over time, each agent's income $I_t$ grows at a constant rate $g$, i.e., $I_{t+1} = I_t(1+g)$. This implies that the mean income of the economy also grows at the same rate, 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.[11]

## 3.2 Equilibrium

We derive the equilibrium adoption patterns of cash, card, and mobile payment technologies as they arrive sequentially in an economy.

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

[11] 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.

### 3.2.1 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

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

where

$$I_{t+1} = I_t(1 + g),$$

and $\beta$ is the discount rate. Accordingly, $V_h(I_{t+1}) = (1 + g)V_h(I_t)$, and we derive

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

### 3.2.2 Card payment

At 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 is $I_t$ 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

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

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

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

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

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

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 $\lambda_t$ 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 several counterfactual exercises to explore the model implications.

## 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. 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 $\tau_h$ and $\tau_d$ 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 $k^a_m = 100$ ($< k_m$) to fit the cross-country mobile payment adoption pattern in 2017.[12]

Table 1. Parameter Values for Model Calibration

| Parameter | Value | Description | Source of Identification |
|---|---|---|---|
| $\beta$ | 0.95 | Discount factor | Standard |
| $g$ | 2% | Income growth rate | Standard |
| $\tau_h$ | 2.3% | Cash variable cost | ECB (2012) |
| $\tau_d$ | 1.4% | Card variable cost | ECB (2012) |
| $k_d$ | 500 | Card adoption cost | Cross-country card payment adoption pattern, Figure 6A |
| $\tau_m$ | 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 |

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.*

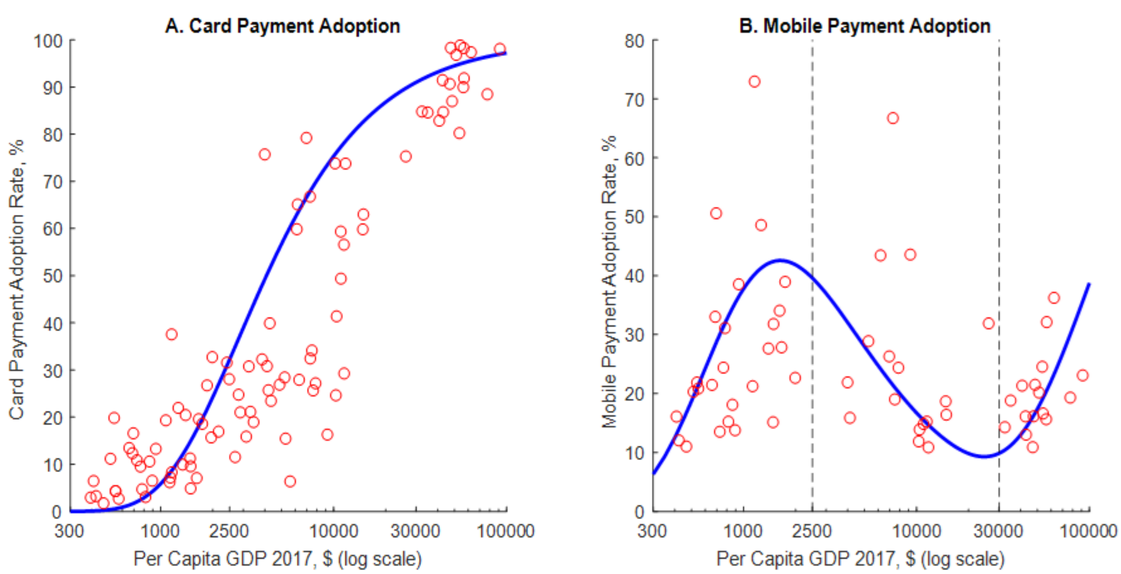



Figure 6. Model Fit with Data

[12]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 any of the analysis and findings.

Figure 7 below shows that our calibration also matches the fourth stylized fact: (4) *Different technology choice across countries.*

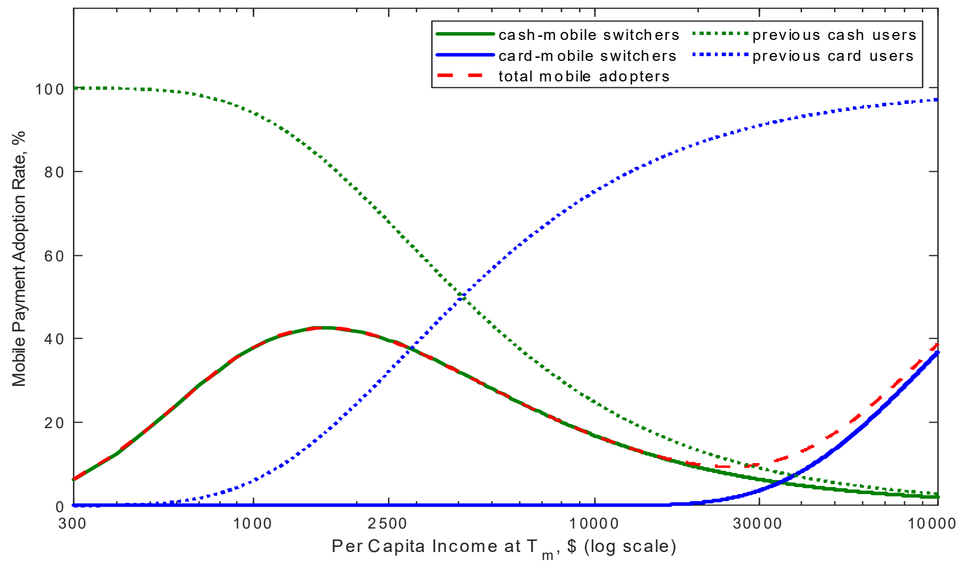



Figure 7. Composition of Mobile Payment Adopters

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 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-augmenting technologies.

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 that, we provide several counterfactual exercises to illustrate the implications of the model.

### 4.2.1 Mobile payment options

First, we 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.

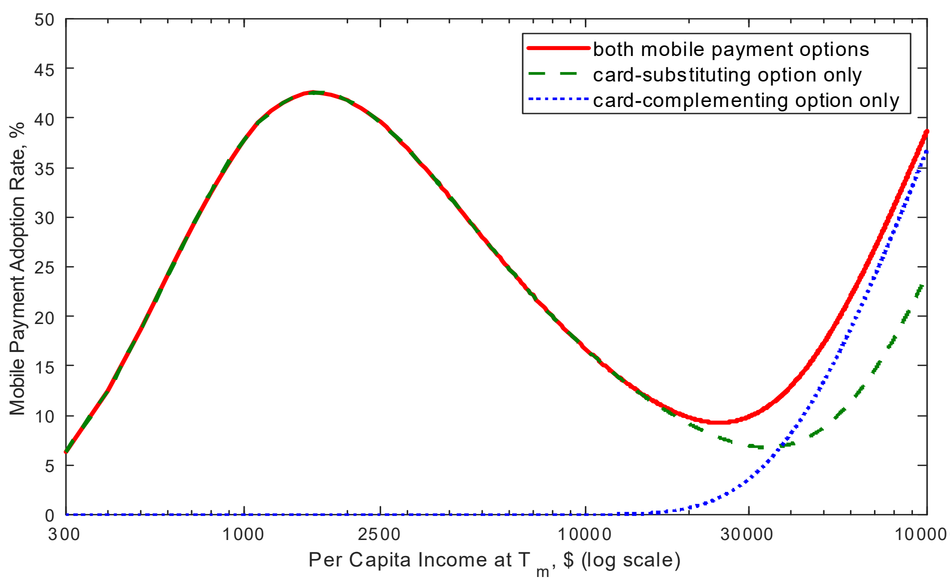



Figure 8. Mobile Payment Options and Adoption Patterns

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

1. The availability of both mobile payment options in each country increases adoption rate, especially for high-income countries (i.e., the red line is on top of both the green dash line and the blue dash line).

2. 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.

3. 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.

4. 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., there might exist a minimal 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.[13]

#### 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 mobile adoption rate would become

[13] Note that 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, as shown by Figure 8, this alternative calibration would not change much of the data fitting, and the counterfactual analyses would be very similar.

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.

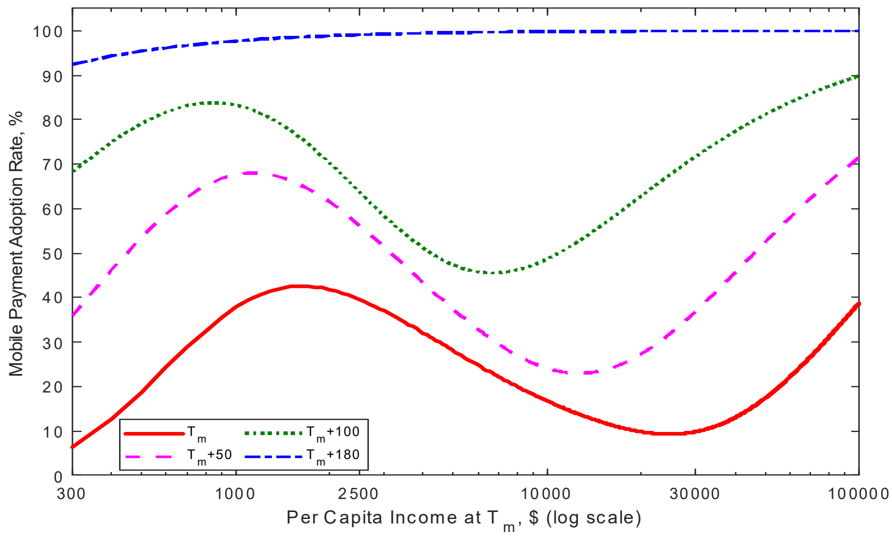



Figure 9. Income Growth and Mobile Payment Adoption

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).[14] 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.

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

[14] Note that when $\frac{\lambda_t}{\lambda_{T_m-1}} = (1+g)^{t-(T_m-1)} > \frac{I_{m'}}{I_d} = \frac{k_m^a(\tau_h-\tau_d)}{k_d(\tau_d-\tau_m)}$, all the agents who have adopted card at $T_m - 1$ would have crossed the mobile payment adoption threshold. Once that happens, the mobile payment adoption rate only depends on the fraction of cash-mobile switchers so that $F_{m,t} = \exp(-\frac{I_m}{\lambda_t}) = \exp(-\frac{(1-\beta)k_m}{(\tau_h-\tau_m)\lambda_t})$, which increases in per capita income $\lambda_t$. Based on our calibrated parameter values, this would take 180 years to happen.

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.

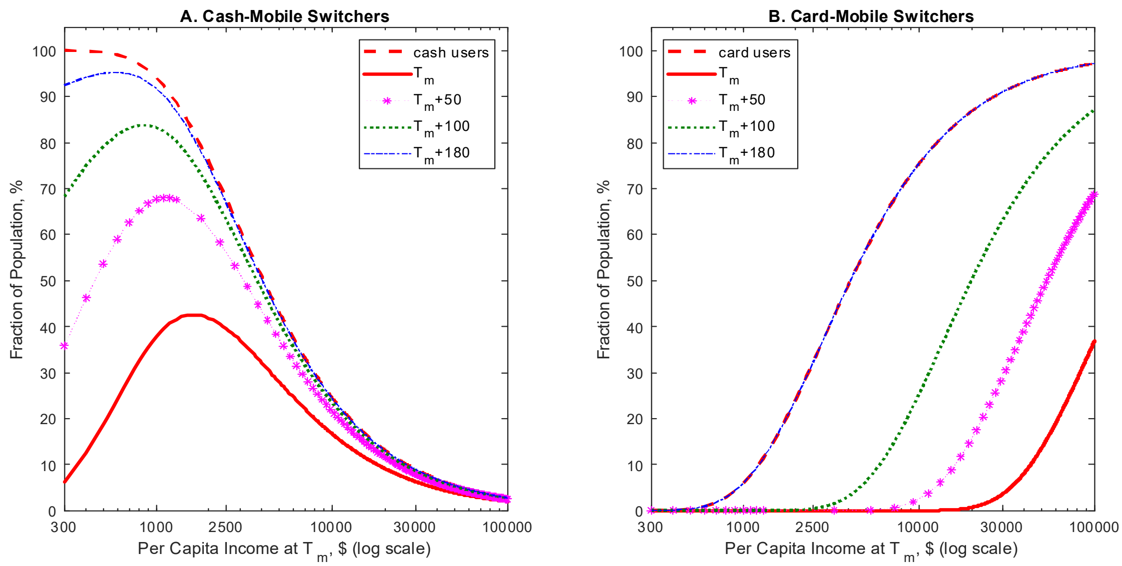



Figure 10. Income Growth and Mobile Payment Adopters

### 4.2.3 Technology progress

Comparing with income growth, the effect of technology 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 $\tau_m$. Figure 11 plots the result. It shows that with larger technological progress (i.e., smaller values of $\tau_m$), the mobile payment adoption rate gets higher in every country and advanced economies are especially benefitted. If the technology progress is sufficiently large, mobile payment adoption becomes strictly increasing in per capita income across countries.

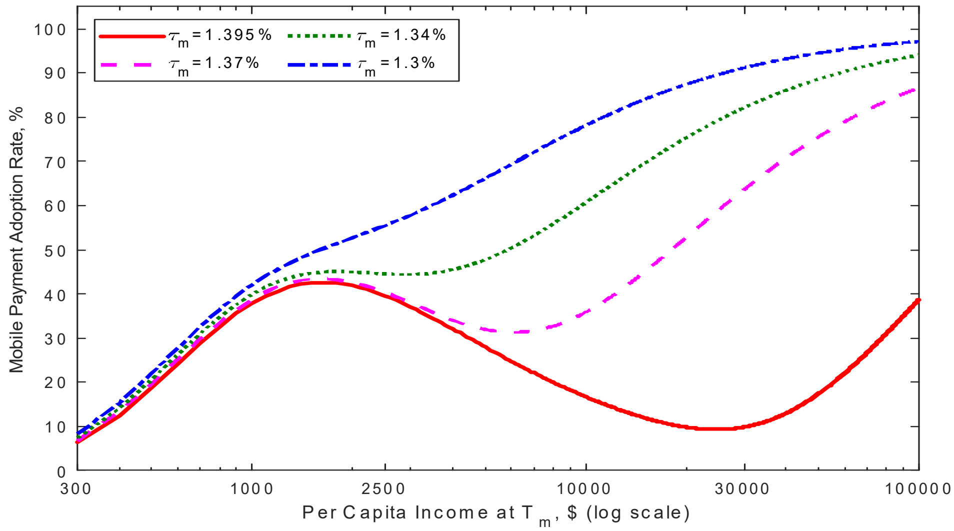



Figure 11. Technology Progress and Mobile Payment Adoption

Taking a step further, Figure 12 decomposes mobile payment adopters into cash-mobile switchers and card-mobile switchers. One can see that technology progress mainly boosts mobile payment adoption among previous card users, which explains why high-income countries benefit more. Therefore, should some major technology 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.

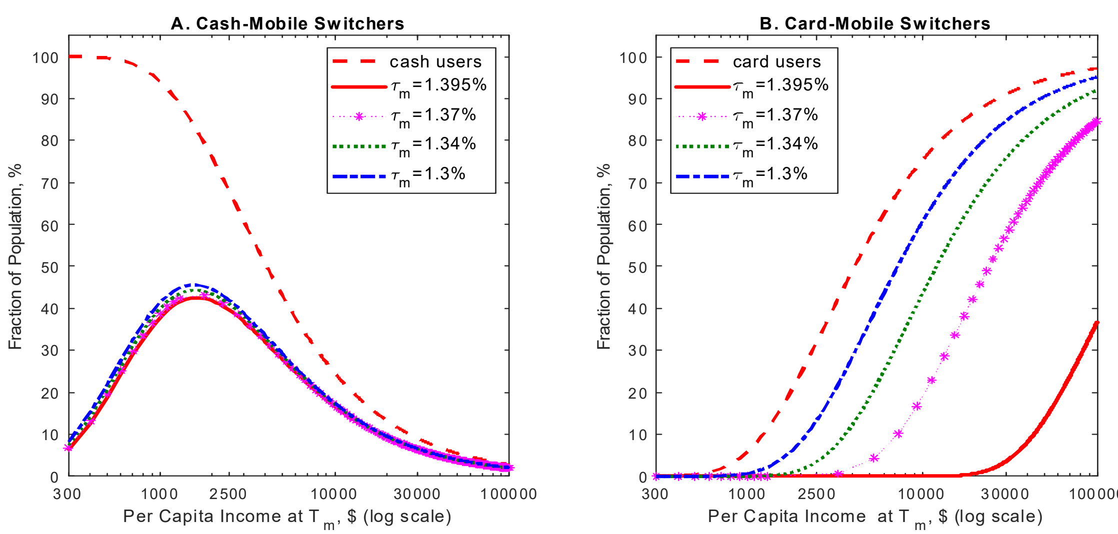



Figure 12. Technology Progress and Mobile Payment Adopters

# 5 Welfare and policy analyses

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

## 5.1 Payment efficiency

Given our model framework, an intriguing question is to evaluate which group of countries might be the biggest winner in adopting new payment technologies. To address this question, we conduct a welfare analysis. For ease of notation, we denote each agent by her income level $I$ (without the time subscript) in the analysis.

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

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

Accordingly, the present-value welfare of a cash economy, $W_t$, at time $t$ ($< T_d$) is

$$W_{t<T_d} = \int_0^\infty \bar{V}_h(I) dG_t(I) = \frac{(1-\tau_h)\,\lambda_t}{1-\beta(1+g)}. \tag{21}$$

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 the card technology. By Eq. (2), we know

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

Accordingly, we can derive the present-value welfare of the economy, $W_{T_d}$, at time $T_d$ :

$$\begin{aligned} W_{T_d} &= W_{h,T_d} + \int_{I_d}^{\infty} \left(\bar{V}_d(I) - k_d - \bar{V}_h(I)\right) dG_{T_d}(I) \\ &\quad + \sum_{s=1}^{\infty} \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_d(I(1+g)^s) - k_d - \bar{V}_h(I(1+g)^s)\right) dG_{T_d}(I), \end{aligned} \tag{23}$$

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. (23) 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.

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

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

We can then derive the present value of welfare for the economy, $W_{T_m}$, at time $T_m$ :

$$\begin{aligned} W_{T_m} \;=\; & \int_0^{I_d(1+g)} \bar{V}_h(I) dG_{T_m}(I) + \int_{I_m}^{I_d(1+g)} \left(\bar{V}_m(I) - k_m - \bar{V}_h(I)\right) dG_{T_m}(I) \\ & + \sum_{s=1}^{\infty} \int_{\frac{I_m}{(1+g)^s}}^{\frac{I_m}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_m(I(1+g)^s) - k_m - \bar{V}_h(I(1+g)^s)\right) dG_{T_m}(I) \\ & + \int_{I_d(1+g)}^{\infty} \bar{V}_d(I) dG_{T_m}(I) + \int_{\max(I^a_{m'}, I_d(1+g))}^{\infty} \left(\bar{V}_m(I) - k^a_m - \bar{V}_d(I)\right) dG_{T_m}(I) \\ & + \sum_{s=1}^{\infty} \int_{\max(\frac{I^a_{m'}}{(1+g)^s}, I_d(1+g))}^{\max(\frac{I^a_{m'}}{(1+g)^{s-1}}, I_d(1+g))} \beta^s \left(\bar{V}_m(I(1+g)^s) - k^a_m - \bar{V}_d(I(1+g)^s)\right) dG_{T_m}(I), \end{aligned} \tag{25}$$

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. (25) is the present value of welfare for all the cash users at time $T_m - 1$ 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 of welfare for all the card adopters by time $T_m - 1$ 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.

With the exponential income distribution, we can solve Eqs. (21), (23), and (25) explicitly (see Appendix III). Define the payment efficiency of an economy, $X_t$, as the ratio between the present value of aggregate welfare with and without incurring payment costs at time $t$:

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

Note that the first-best payment efficiency is 1 in a frictionless economy without any payment costs, so $X_t$ gauges the fraction of the first-best welfare level that can be achieved under available payment technologies at time $t$.

Using the parameter values in Table 1, we can compare the change of payment efficiency across countries due to payment innovations. Consider a thought experiment that the card technology arrives at $T_d$, and the mobile payment technology arrives at $T_m = T_d + 1$. Figure 13 plots the payment efficiency of each economy for $t < T_d$ (i.e., cash only), $t = T_d$ (i.e., card technology becomes available), and $t = T_m$ (i.e., mobile payments becomes available), according to their per capita income level at $T_m$.

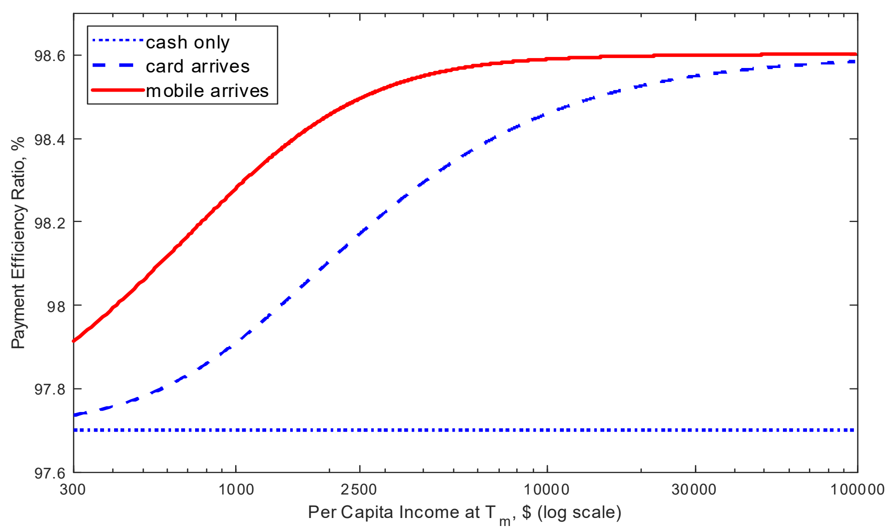



Figure 13. Payment Efficiency by Per Capita Income

Figure 13 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 14, the relative welfare gain $(X_{T_m} - X_{T_d})/X_{T_d}$ peaks for countries with per capita income around \$1,200. Figures 13 and 14 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 both card and mobile payment innovations, and they lag far behind in overall payment efficiency. Therefore, despite the promise of mobile payments 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.

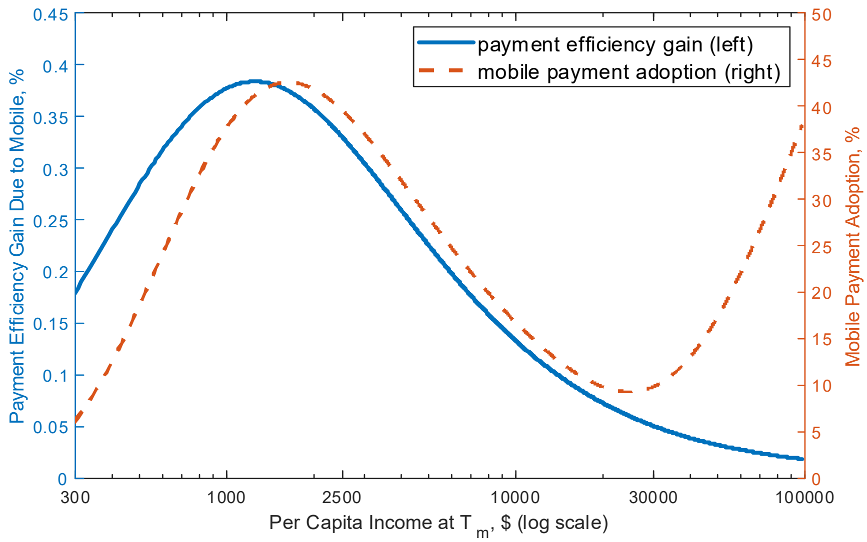



Figure 14. Payment Efficiency Gain by Per Capita Income

## 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 mobile payment technology progress 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 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 adapting Eq. (25) to the new adoption thresholds:

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

Figures 15 and 16 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.

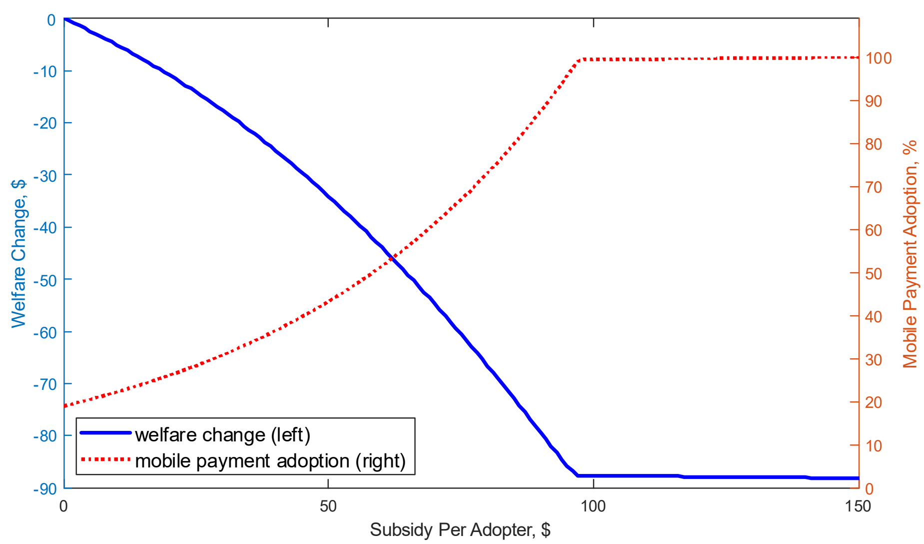



Figure 15. Effects of Mobile Payment Adoption Subsidy

Figure 15 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.

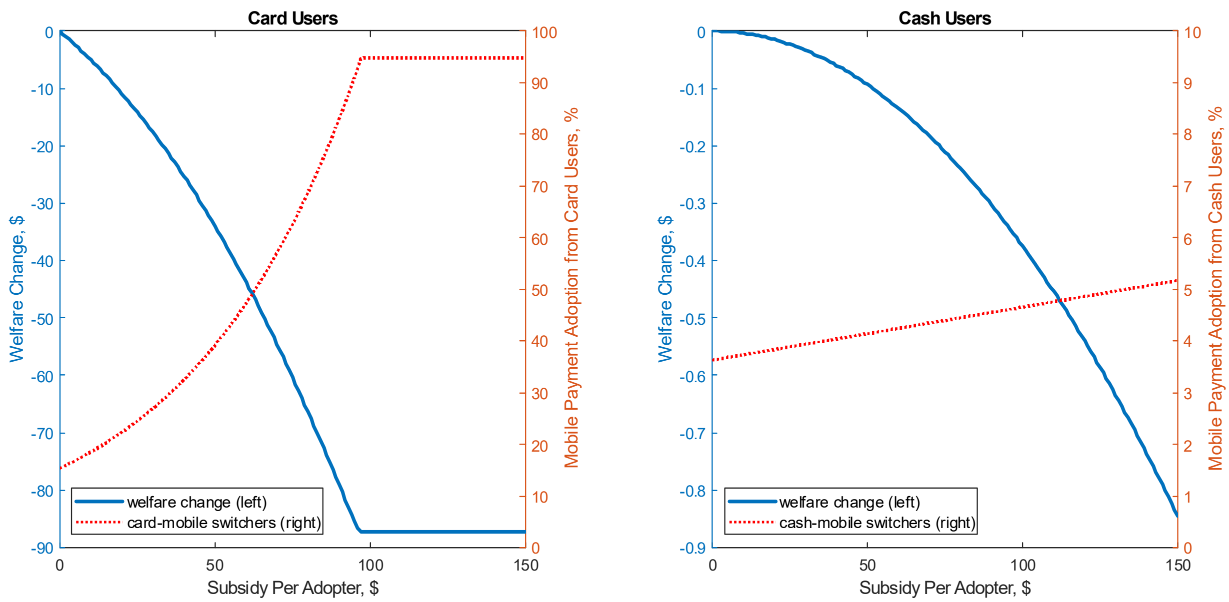



Figure 16. Effects of Mobile Payment Subsidy on Card and Cash Users

Figure 16 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.

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, remain 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 before 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 $i \in \{h, d, m\}$, 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 $\tau_i$ 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 benefits. 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 valuable 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 easily 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-egg" dynamic often arises in network industries, and coordination becomes a relevant issue. 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. 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. Their extraordinary performance may have idiosyncratic components beyond the theory that we offer to explain the average cross-country pattern.

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 strict assumption is not intended to fit extreme 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 $\tau_m$) or less costly (i.e., a lower $k_m$), or the card technology is less efficient (i.e., a higher $\tau_d$) or more costly (i.e., a higher $k_d$). These factors are certainly 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 $\tau_d$. In contrast, the mobile payment service providers in each country, Safaricom in Kenya and Alibaba and Tencent in China, are very innovative and successful players, which may suggest a lower $k_m$ or $\tau_m$.

Some factors outside our model may also play important roles. 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. This may have additional implications on payment pricing and adoption decisions. 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) find that the mobile payment innovation, M-PESA, is also popularly used for urban-rural remittances in Kenya, providing an important risk-sharing function. 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. 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, 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 have fallen 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.

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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) $\times 1\{\text{Middle Income}\}$ | | | -0.163* |
| | | | (0.084) |
| ln(GDP per capita) $\times 1\{\text{High Income}\}$ | | | -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. Welfare calculation.

Eq. (21) shows that the present-value welfare of a cash economy at time $t$ ($< T_d$) is

$$W_{t<T_d} = \frac{(1-\tau_h)\,\lambda_t}{1-\beta(1+g)}. \tag{27}$$

Eq. (23) implies that the present-value welfare when card technology arrives at $T_d$ is

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

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

$$\begin{aligned} W_{T_d} &= \frac{(1-\tau_h)\,\lambda_{T_d}}{1-\beta(1+g)} + \left(\frac{\tau_h-\tau_d}{1-\beta(1+g)}\right)\exp(-\frac{I_d}{\lambda_{T_d}})(\lambda_{T_d}+I_d) - k_d\exp(-\frac{I_d}{\lambda_{T_d}}) \\ &+\sum_{s=1}^{\infty}\beta^s\left(\frac{(\tau_h-\tau_d)\,(1+g)^s}{1-\beta(1+g)}\right)\left(\begin{array}{c}\exp(-\frac{I_d}{(1+g)^s\lambda_{T_d}})(\lambda_{T_d}+\frac{I_d}{(1+g)^s}) \\ -\exp(-\frac{I_d}{(1+g)^{s-1}\lambda_{T_d}})(\lambda_{T_d}+\frac{I_d}{(1+g)^{s-1}})\end{array}\right) \\ &-\sum_{s=1}^{\infty}\beta^s\left(\exp(-\frac{I_d}{(1+g)^s\lambda_{T_d}}) - \exp(-\frac{I_d}{(1+g)^{s-1}\lambda_{T_d}})\right)k_d. \end{aligned} \tag{28}$$

Denote that $x$ satisfies $\frac{I^a_{m'}}{(1+g)^x} > I_d(1+g)$ and $\frac{I^a_{m'}}{(1+g)^{x+1}} \leq I_d(1+g)$. Eq. (25) implies the present value of welfare when the mobile payment technology arrives at $T_m$ is

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

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

$$
\begin{aligned}
W_{T_m} \;=\; & \frac{(1-\tau_h)}{1-\beta(1+g)}\left(\lambda_{T_m} - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m}+I_d(1+g))\right) \qquad (29)\\
& +\frac{(\tau_h-\tau_m)}{1-\beta(1+g)}\left(\exp(-\frac{I_m}{\lambda_{T_m}})(\lambda_{T_m}+I_m) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m}+I_d(1+g))\right)\\
& -k_m\left(\exp(-\frac{I_m}{\lambda_{T_m}}) - \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})\right)\\
& +\sum_{s=1}^{\infty}\beta^s\left(\frac{(\tau_h-\tau_m)\,(1+g)^s}{1-\beta(1+g)}\right)\left(\begin{array}{c} \exp(-\frac{I_m}{(1+g)^s\lambda_{T_m}})(\lambda_{T_m}+\frac{I_m}{(1+g)^s}) \\ -\exp(-\frac{I_m}{(1+g)^{s-1}\lambda_{T_m}})(\lambda_{T_m}+\frac{I_m}{(1+g)^{s-1}}) \end{array}\right)\\
& -k_m\sum_{s=1}^{\infty}\beta^s\left(\exp(-\frac{I_m}{(1+g)^s\lambda_{T_m}}) - \exp(-\frac{I_m}{(1+g)^{s-1}\lambda_{T_m}})\right)\\
& +\frac{(1-\tau_d)}{1-\beta(1+g)}\exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m}+I_d(1+g))\\
& +\left(\frac{(\tau_d-\tau_m)}{1-\beta(1+g)}\right)\exp(-\frac{I^a_{m'}}{\lambda_{T_m}})(\lambda_{T_m}+I^a_{m'}) - k^a_m\exp(-\frac{I^a_{m'}}{\lambda_{T_m}})\\
& +\sum_{s=1}^{x}\beta^s\frac{(\tau_d-\tau_m)\,(1+g)^s}{1-\beta(1+g)}\left(\begin{array}{c} \exp(-\frac{I^a_{m'}}{(1+g)^s\lambda_{T_m}})(\lambda_{T_m}+\frac{I^a_{m'}}{(1+g)^s}) \\ -\exp(-\frac{I^a_{m'}}{(1+g)^{s-1}\lambda_{T_m}})(\lambda_{T_m}+\frac{I^a_{m'}}{(1+g)^{s-1}}) \end{array}\right)\\
& -k^a_m\sum_{s=1}^{x}\beta^s\left(\exp(-\frac{I^a_{m'}}{(1+g)^s\lambda_{T_m}}) - \exp(-\frac{I^a_{m'}}{(1+g)^{s-1}\lambda_{T_m}})\right)\\
& +\beta^{x+1}\frac{(\tau_d-\tau_m)\,(1+g)^{x+1}}{1-\beta(1+g)})\left(\begin{array}{c} \exp(-\frac{I_d(1+g)}{\lambda_{T_m}})(\lambda_{T_m}+I_d(1+g)) \\ -\exp(-\frac{I^a_{m'}}{(1+g)^x\lambda_{T_m}})(\lambda_{T_m}+\frac{I^a_{m'}}{(1+g)^x}) \end{array}\right)\\
& -k^a_m\beta^{x+1}\left(\exp(-\frac{I_d(1+g)}{\lambda_{T_m}}) - \exp(-\frac{I^a_{m'}}{(1+g)^x\lambda_{T_m}})\right).
\end{aligned}
$$