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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 that is transforming the global payments landscape. Some developing countries have surprisingly overtaken advanced economies in adopting the mobile payment innovation. We construct a dynamic model with sequential payment innovations to explain this phenomenon. Our estimated model matches cross-country patterns of payment technology adoption well and uncovers how advanced economies' past success in adopting card-payment technology holds them back in the mobile-payment race. Our analysis also shows that in the presence of payment externalities, subsidizing mobile payment adoption may enhance social welfare and can be more beneficial for developing countries.

Keywords: Technology Adoption, Payment Innovation, Financial Development
JEL Classification: E4, G2, O3

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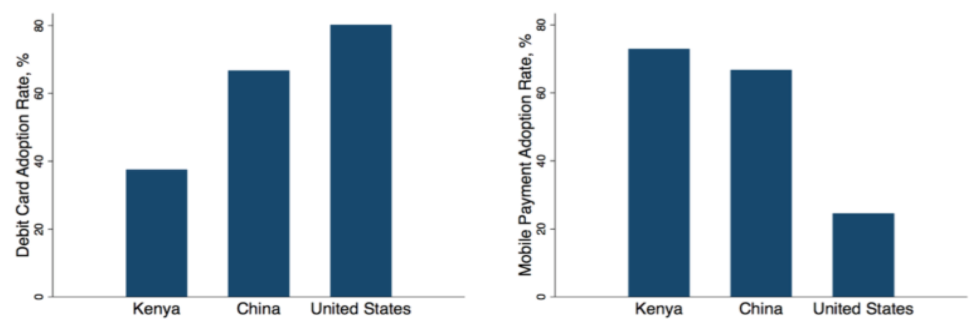
1 Introduction

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

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



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

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

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

These observations raise concerns about the efficiency and innovativeness of the U.S. payments system and lead to important questions. Why did developing countries lag in adopting card payments but some of them leapfrog in adopting mobile payments? Have

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

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

advanced economies lost their leadership in the payment area? What government policies, if any, should be considered to facilitate mobile payment development?

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

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

Our estimated model matches cross-country adoption patterns of both card and mobile payments well. Based on the model, we conduct counterfactual and welfare analysis. We find that lagging behind in mobile payment adoption does not necessarily imply that advanced

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

economies fall behind in overall payment efficiency, even though they may benefit less from the mobile payment innovation. Down the road, greater technological progress is needed for advanced economies to catch up in the mobile payment race, and we quantify welfare gains from introducing mobile payments across countries.

By focusing on the role of income heterogeneity, our baseline model abstracts from market imperfections. We then extend the model to incorporate network externalities associated with payments. The payment market is two-sided, in which consumers and merchants jointly use each payment technology in transactions. As underscored in Rochet and Tirole (2002, 2006) and the following two-sided market literature, a fundamental friction in the two-sided payment market is price coherence: Merchants typically do not price differentiate based on payment means. Consequently, consumers would not internalize the payment externalities they generate on merchants and through merchant pricing onto other consumers. Essentially, a consumer adopting a more efficient payment technology subsidizes those who do not. By incorporating such externalities into our analysis, we show that the positive economic findings of our baseline model continue to hold and we gain additional normative economic insights. We find that policy interventions such as subsidizing mobile payment adoption enhance welfare in the presence of payment externalities, and can be more beneficial for developing countries by speeding up their transition from cash to electronic payments.

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

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

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

More broadly, our paper contributes to the literature of technology diffusion. The non-monotonic relationship that we discover between payment technology adoption and per capita income is a novel empirical finding to the literature (e.g., Comin and Hobijn, 2004). Our theory, à la Manuelli and Seshadri (2014) and others, explains technology adoption as the moving equilibrium of a frictionless model. We find that incumbent technology curse can help explain the leapfrogging in mobile payment adoption. This echoes with studies in the firm investment literature which show that in the presence of sequential innovations, some firms may get stuck with old technologies due to their past investments in technology-specific learning (e.g., Parente, 1994, Jovanovic and Nyarko, 1996, and Klenow, 1998).

Our paper is also related to the growing literature on the rise of digital payments and FinTech firms. According to Berg et al. (2022), the rise of FinTech payment firms is one of the most significant changes to the financial industry over the last decade. This has had positive impacts on financial inclusion and welfare (e.g., Jack and Suri (2014) on mobile payments in Kenya and Muralidharan et al. (2016) on smartcard payments in India). Digital payment services provided by FinTech firms also transform the lending business (e.g., Ouyang, 2021, Parlour et al., 2022, Ghosh et al., 2023). Our paper complements those works in the sense that we take a structural approach to study how cost savings of different electronic payments affect payment efficiency and drive different adoption patterns across countries.

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

The remainder of this paper is structured as follows. Section 2 provides the background of mobile payments and summarizes stylized facts regarding cross-country adoption patterns. Section 3 introduces the baseline model and solves for the equilibrium. Section 4 estimates the baseline model and explores model implications. Section 5 extends the model to a two-sided market setting with payment externalities. Section 6 provides robustness checks and additional 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, regardless of whether the phone actually accesses the mobile network to make the payment. Mobile payment technology can also be used to send money from person to person.

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

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

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

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

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

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

2.1 Alternative mobile payment technologies

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

2.1.1 Card-substituting mobile payment

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

Following the success in Kenya, M-PESA was emulated in many other developing countries. This category of mobile payment methods is defined as "Mobile Money" by the Global System for Mobile Communications Association (GSMA) that must meet the following four conditions. First, the payment method must include transferring money as well as making and receiving payments using a mobile phone. Second, the payment method must be available to the unbanked (i.e., people who do not have access to a formal account at a financial institution). Third, the payment method must offer a network of physical transactional

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

points (that can include agents) widely accessible to users. Fourth, mobile-banking-related payment services (such as Apple Pay and Google Wallet) that offer the mobile phone as just another channel to access a traditional banking product do not satisfy this definition of Mobile Money.

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

2.1.2 Card-complementing mobile payment

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

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

2.2 Data and stylized facts

To study the global adoption pattern of mobile payments, we assembled a novel dataset on debit card and mobile payment adoption in 94 countries.[9] The countries in our sample accounted for 91.4% of world GDP in 2017.

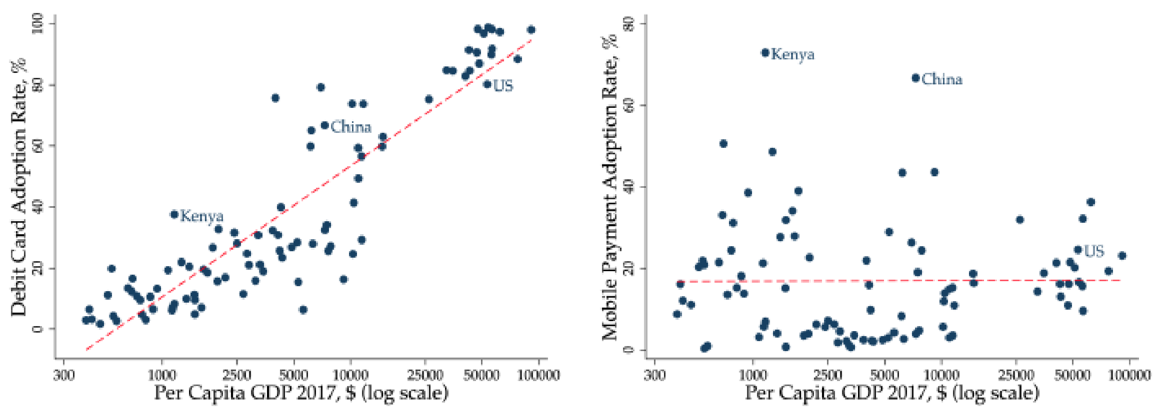
Our data are drawn from the following sources (See Internet Appendix II for more details). First, the data on the adoption rates of card-substituting mobile payment services in 2017 are

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

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

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

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



(A) Debit Card Adoption

(B) Mobile Payment Adoption

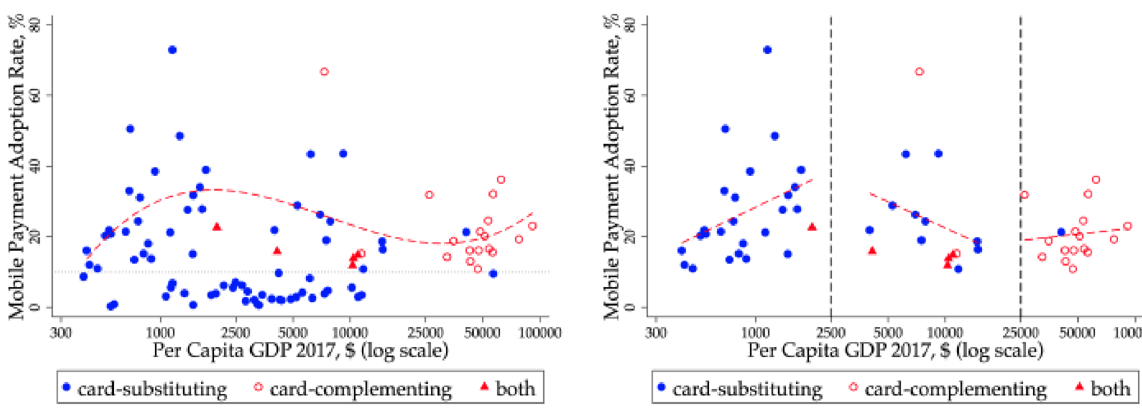
Figure 2. Card and Mobile Payment Adoption across Countries

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

However, some subtle patterns of mobile payment adoption emerge as we delve further into the data. First, we distinguish mobile payment technologies used in each country in our sample. As shown in Figure 3A, most countries in the highest income group adopt

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

card-complementing mobile payments, while most other countries choose card-substituting ones. Also, considering that mobile payment is a fairly recent technological innovation, it is possible that some countries may not have fully introduced it due to information or coordination frictions. We then leave out the observations that have a very low adoption rate (i.e., <10%)[11] and fit the remaining data with a smooth nonparametric curve.[12] It becomes evident that mobile payment adoption displays a non-monotonic relationship with per capita GDP.



(a) Nonparametric fit (b) Linear fit

Figure 3. Cross-Country Mobile Payment Adoption

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

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

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

regression model or excluding two outlier countries that have exceptionally high mobile payment adoption rates (i.e., Kenya and China). Also, the non-monotonic mobile payment adoption pattern continues to hold after controlling for a variety of additional factors. All the regression results are reported in Internet Appendix III.

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

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

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

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

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

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

3 Baseline model

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

3.1 Setup

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

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

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

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

[14] One example of intangible adoption costs is learning different payment technologies and evaluating the associated benefits and risks. Learning may require time and efforts. While lower-income agents may face lower time costs, they may be confronted with higher effort costs. In our analysis, we assume agents face the same fixed adoption cost to reduce free parameters.

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

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

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

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

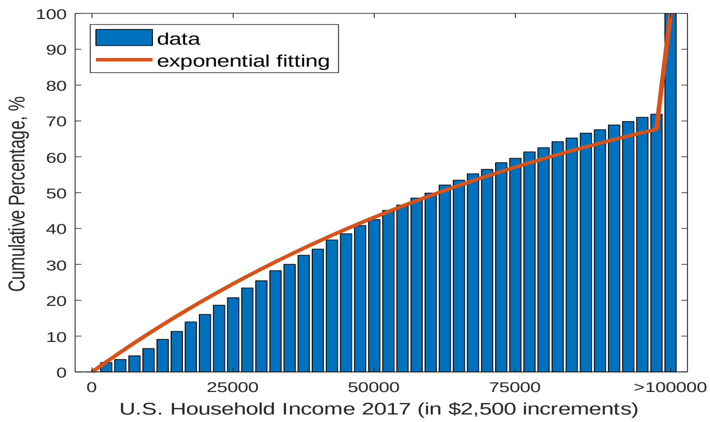


Figure 4. Exponential Income Distribution

An agent has a linear utility $u = c$, where c is her consumption. We assume there is no storage technology, and thus each agent consumes all her income net of payment costs each period. We also assume payment services and merchant services are provided via competitive markets. A consumer always uses her favorite payment technology and the private cost to the consumer equals the social cost.[19] In Sections 5 and 6, we will relax these assumptions and introduce market imperfections in the analysis.

3.2 Equilibrium

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

3.2.1 Cash payment

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

[18] In Section 6.2, we extend the analysis by assuming a log-logistic income distribution and allow for country-specific Gini coefficients, and the findings are very similar.

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

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

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

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

and β is the discount rate.

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

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

3.2.2 Card payment

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

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

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

which yields

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

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

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

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

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

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

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

which requires

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

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

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

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

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

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

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

3.2.3 Mobile payment

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

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

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

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

[21] This is a simplifying assumption, and we will relax it in Section 6.1 to consider anticipated arrival of mobile payments.

which yields

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

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

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

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

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

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

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

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

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

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

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

where the value function of a card user now becomes

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

This yields the income threshold I_m^a for adoption:

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

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

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

which increases with per capita income across countries.

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

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

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

4 Baseline model: Estimation and implications

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

4.1 Model estimation

The unit of time is year and we set 2017 as the year T_m when mobile payment became widely available. In the model estimation, we assume each country offers only one mobile payment option, either the card-substituting one or the card-complementing one, whichever yields the higher mobile payment adoption (cf. Eqs. (16) and (19)). We then show in Section 4.2.1 that allowing each country to offer both mobile payment options would change little the data fitting.

Table 1. Parameter Values for the Baseline Model

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

There are eight parameters in the baseline model. To discipline the model estimation, we assume that all countries share the same model parameter values. Allowing countries to have different parameter values would otherwise provide too many degrees of freedom for the model to fit the data. We calibrate four parameters (i.e., β, g, τ_h, and τ_d) by a priori information and they are reported in panel A of Table 1. Specifically, we follow the convention and set the annual discount factor $\beta = 0.95$ and the annual income growth rate $g = 2\%$. According to a study of the European Central Bank (Schmiedel et al., 2012) on retail payment costs in 13 participating countries, the average social cost of using cash is 2.3% of the transaction value, while that of using debit cards is 1.4%. Hence, we set $\tau_h = 2.3\%$ and $\tau_d = 1.4\%$ accordingly.

The other four parameters (i.e., k_d, τ_m, k_m, and k_m^a) cannot be pinned down by a priori information and we estimate them by matching the model predictions with six data targets: the mean and standard deviation of card payment adoption rates across countries, per capita income at both the peak and trough of mobile payment adoption, as well as the mean and standard deviation of mobile payment adoption rates across countries.[22] These six targeted moments are chosen based on their sensitivity to changes in the payment cost parameters and we delineate detailed identification strategy in Internet Appendix IV.

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

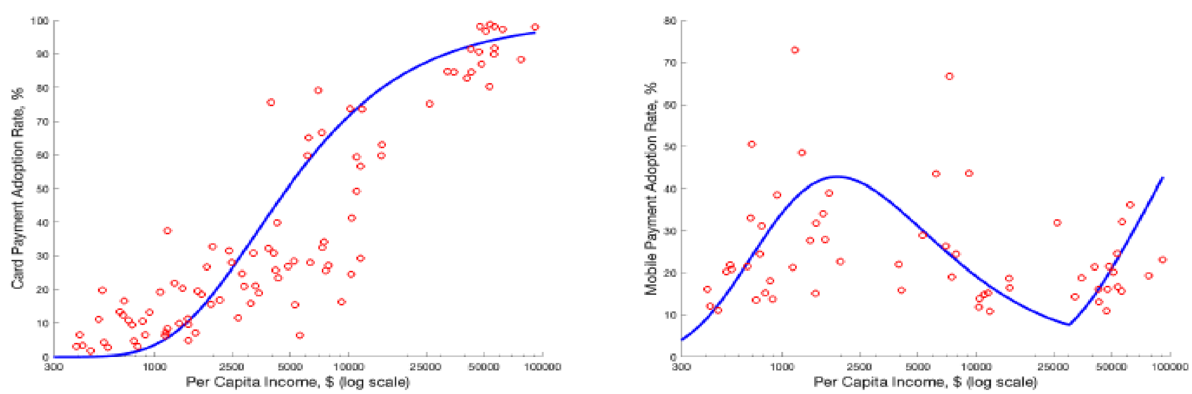
[22] The data moments on mobile payment are based on countries whose mobile payment adoption rate are above 10%. The data moments on card payment are based on the same set of countries. The data targets on per capita income at the peak and trough of mobile payment adoption are obtained by nonparametric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

compare our benchmark estimates of adoption costs with micro-level evidence and the results are consistent.[23]

Table 2: Model Fit with Data, Targeted Moments

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

Table 2 shows that our estimated model matches the targeted data moments well. Furthermore, we plot the model predictions of card and mobile payment adoption rates at each level of per capita income in Figure 5.



(A) Card Payment Adoption

(B) Mobile Payment Adoption

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

[23] We obtain individual consumer survey data on debit card and mobile payment adoption in 2017 from the 26 low-income countries in our sample (i.e., countries where per capita GDP<\$2,500 and mobile payment adoption rate>10% in 2017). We then estimate card and mobile adoption costs k_d and k_m from individual consumer data for each country. We find that the estimates follow consistent ranking condition $k_d > k_m$ as our benchmark results, and our benchmark estimates ($k_d = \$589.83$ and $k_m = \$175.76$) lie between the 25th percentile and 75th percentile of the k_d and k_m estimated from the individual consumer data across the 26 countries (see Internet Appendix VII for details). The finding that the estimated adoption costs k_d and k_m are in hundreds of U.S. dollars in low-income countries reflect that consumers in those countries face high adoption hurdles relative to their income, likely due to the lack of basic literacy (including financial literacy) in those countries.

Figure 5 shows that our estimated model fits the cross-country observations well. It matches the three stylized facts identified above: (1) *Positive relationship between per capita income and card adoption; (2) Non-monotonic relationship between per capita income and mobile payment adoption*; (3) *Overtaking in mobile payment adoption.*

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

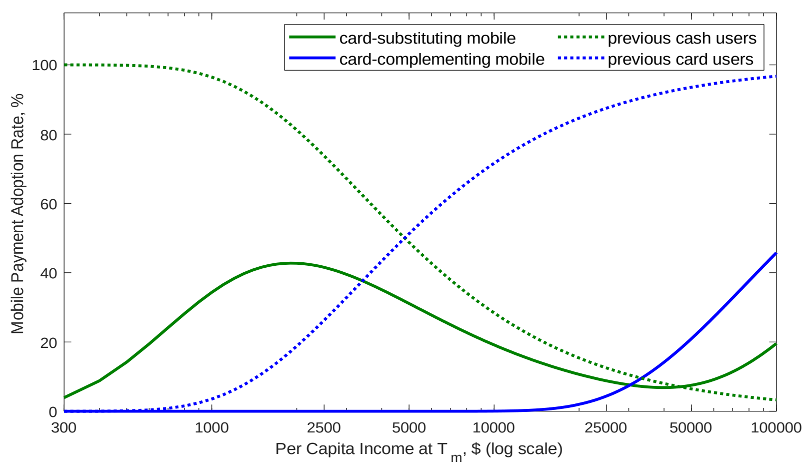


Figure 6. Mobile Payment Technoloy Choices

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

4.2 Counterfactuals

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

4.2.1 Mobile payment options

We first investigate how mobile payment options affect the cross-country adoption pattern.

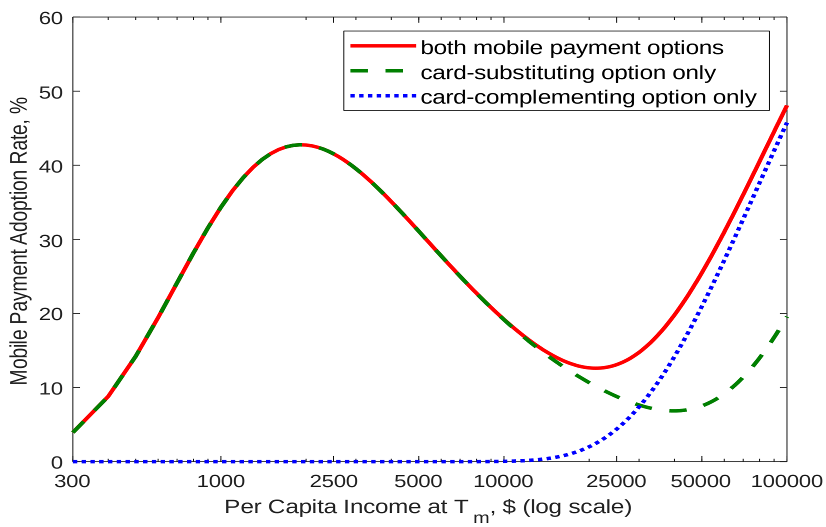


Figure 7. Mobile Payment Options

In Figure 7, the green dashed line and the blue dotted line each depict the mobile payment adoption pattern if the card-substituting technology or the card-complementing technology is the only option offered in each country (cf. Eqs. (16) and (19), respectively). The upper envelope of these two lines then tracks the adoption rate if each country chooses to offer one of the two mobile payment options whichever achieves the higher adoption rate, which is the adoption fitting curve shown in Figure 5(B). In comparison, the red solid line in the figure shows the adoption pattern if both mobile payment options are offered in each country (cf. Eq. (20)). This exercise provides the following insights.

First, in the case that each country offers both mobile payment technologies, the adoption pattern (i.e., shown by the red line) is very similar to the one that each country only offers one of the two mobile payment options that delivers the higher adoption rate (i.e., the upper envelope of the green dashed line and the blue dotted line). The difference between the former and the latter is almost invisible in low- and middle-income countries. In high-income countries, there is a small difference because of a small number of cash-mobile switchers who would not exist if only card-complementing technology is offered. This comparison suggests that the parameter values we estimated (cf. Table 1) would allow the model to fit the cross-country mobile payment adoption pattern well even if both mobile payment options are offered in each country. In our counterfactual and welfare analysis, we will consider scenarios where both mobile payment technologies are available in each country.

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

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

4.2.2 Income growth and technological progress

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

According to our theory, long-run income growth would eventually lift all the card adopters (who exist before date T_m) to cross the mobile payment adoption threshold. Once that happens, mobile payment adoption would be solely driven by cash-mobile switchers and the adoption rate would become monotonically increasing in per capita income. However, our quantitative exercise suggests that it would take very long for income growth to overturn the non-monotonic adoption pattern. Recall that we assume per capita income grows at 2% annually in each country. Figure 8A tracks each country by per capita income at T_m and plots mobile payment adoption rates at year T_m (red solid line), $T_m + 50$ (pink dashed line), $T_m + 100$ (green dotted line), and $T_m + 160$ (blue dash-dotted line). The figure shows that mobile payment adoption increases in every country as per capita income grows. Nevertheless, the adoption rate continues to be non-monotonic in per capita income. Ultimately, it takes about 160 years to converge to an adoption curve that strictly increases in per capita income.[24]

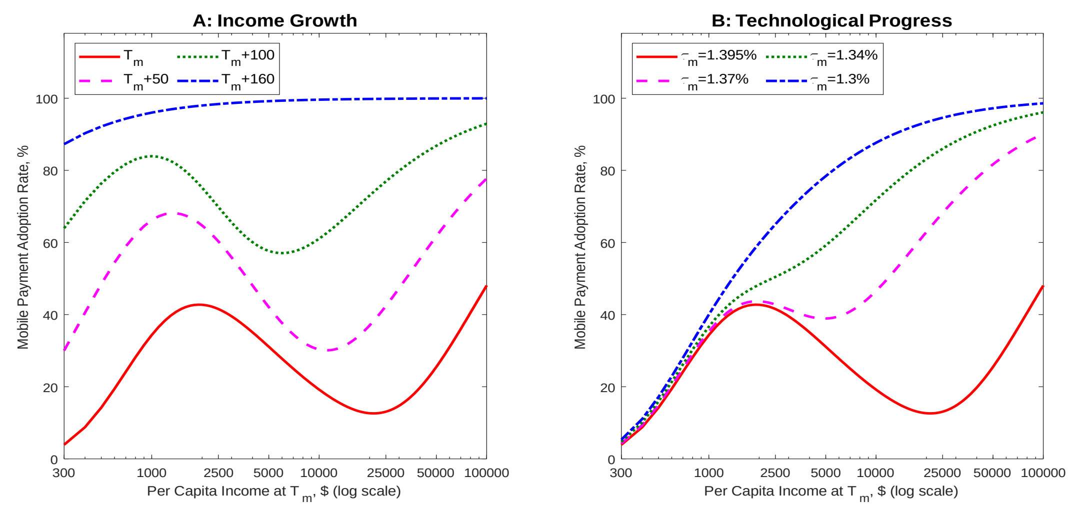


Figure 8. Income Growth and Technoloigical Progress

In contrast, the effect of mobile payment technological progress is more striking. According to our theory, advanced economies are stuck with card payment primarily because the value added of mobile payment is not substantial enough to induce some middle-income card adopters to switch. Therefore, greater technological progress of mobile payment would not only increase the adoption in every country, but could also restore advanced economies to the leading positions in the mobile payment race if the technological progression becomes sufficiently large. To evaluate the effect of technological progress on mobile payment, we reduce

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

the variable mobile payment cost τ_m. As shown in Figure 8B, greater technological progress (i.e., smaller values of τ_m) promotes the mobile payment adoption rate in every country and advanced economies are especially benefitted. If the technological progress is sufficiently large, mobile payment adoption becomes strictly increasing with per capita income across countries.

4.3 Welfare findings

In this section, we use our estimated baseline model to gauge payment efficiency and welfare gains.

4.3.1 Payment efficiency

For a symmetric comparison, we assume every country offers both mobile payment options in the analysis. We will show in Section 4.3.2 that the welfare comparison results would be similar if we assume that low- and middle-income countries only offer card-substituting mobile payment while high-income countries only offer card-complementing mobile payment.

We first introduce some notations. Denote $\bar{V}_h(I)$ as the value function of an agent with income I at date t who would permanently use cash payment. Note that we drop the subscript t in $\bar{V}_h(I)$ and I to ease notations. By Eq. (1), we know

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

where the value function takes into account that agent income grows at rate g. Similarly, we denote $\bar{V}_d(I)$ and $\bar{V}_m(I)$ as the value functions of an agent with income I at date t who would permanently use card or mobile payment, respectively:

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

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

With $\bar{V}_h(I)$ given by Eq. (21), the present-value welfare of a pure cash economy $W_{t<T_d}$ equals

$$W_{h,t} = \int_0^\infty \bar{V}_h(I) dG_t(I). \tag{23}$$

With $\bar{V}_d(I)$ given by Eq. (22), the present-value welfare of the economy at T_d is

$$\begin{aligned} W_{T_d} &= W_{h,T_d} + \int_{I_d}^{\infty} \left(\bar{V}_d(I) - k_d - \bar{V}_h(I)\right) dG_{T_d}(I) \\ &+ \sum_{s=1}^{\infty} \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_d(I(1+g)^s) - k_d - \bar{V}_h(I(1+g)^s)\right) dG_{T_d}(I), \end{aligned} \tag{24}$$

where $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is from Eq. (5). Note that the first term of the right-hand side of Eq. (24) is the present value of welfare for all the agents if they continue using cash forever. The second term is the additional welfare gains for card adopters at date T_d, and the last term is the additional welfare gains for future card adopters.

Finally, we derive the present value of welfare for the economy at T_m to be

$$\begin{aligned} W_{T_m} &= \int_{0}^{I_d(1+g)} \bar{V}_h(I) dG_{T_m}(I) + \int_{I_m}^{I_d(1+g)} \left(\bar{V}_m(I) - k_m - \bar{V}_h(I)\right) dG_{T_m}(I) \\ &+ \sum_{s=1}^{\infty} \int_{\frac{I_m}{(1+g)^s}}^{\frac{I_m}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_m(I(1+g)^s) - k_m - \bar{V}_h(I(1+g)^s)\right) dG_{T_m}(I) \\ &+ \int_{I_d(1+g)}^{\infty} \bar{V}_d(I) dG_{T_m}(I) + \int_{\max(I_m^a, I_d(1+g))}^{\infty} \left(\bar{V}_m(I) - k_m^a - \bar{V}_d(I)\right) dG_{T_m}(I) \\ &+ \sum_{s=1}^{\infty} \int_{\max(\frac{I_m^a}{(1+g)^s}, I_d(1+g))}^{\max(\frac{I_m^a}{(1+g)^{s-1}}, I_d(1+g))} \beta^s \left(\bar{V}_m(I(1+g)^s) - k_m^a - \bar{V}_d(I(1+g)^s)\right) dG_{T_m}(I), \end{aligned} \tag{25}$$

where $I_m = \frac{(1-\beta)k_m}{(\tau_h - \tau_m)}$ is given by Eq. (10), and $I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d - \tau_m)}$ is given by Eq. (18). Note that the first term of the right-hand side of Eq. (25) is the present-value welfare for all the cash users at $T_m - 1$ if they continue using cash at date T_m and forever. The second term is the additional welfare gains of cash-mobile switchers at date T_m, and the third term is the additional welfare gains for future cash-mobile switchers. The fourth term is the present-value welfare for all the card adopters at $T_m - 1$ if they continue using card at date T_m and forever. The fifth term is the additional welfare gains of card-mobile switchers at date T_m, and the last term is the additional welfare gains for future card-mobile switchers.

With the exponential income distribution, one can solve Eqs. (23), (24), and (25) explicitly (see Internet Appendix V for the solution details). We define the payment efficiency of an economy, $X_t(\lambda_t)$, as the ratio between the present value of aggregate welfare with and without incurring payment costs at date t:

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

Using the parameter values in Table 1, we can now compare payment efficiency across countries under each payment technology. We assume that mobile payment technologies arrive at $T_m = 2017$, and the card payment technology arrives at $T_d = T_m - 30$.[25] Figure 9 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.

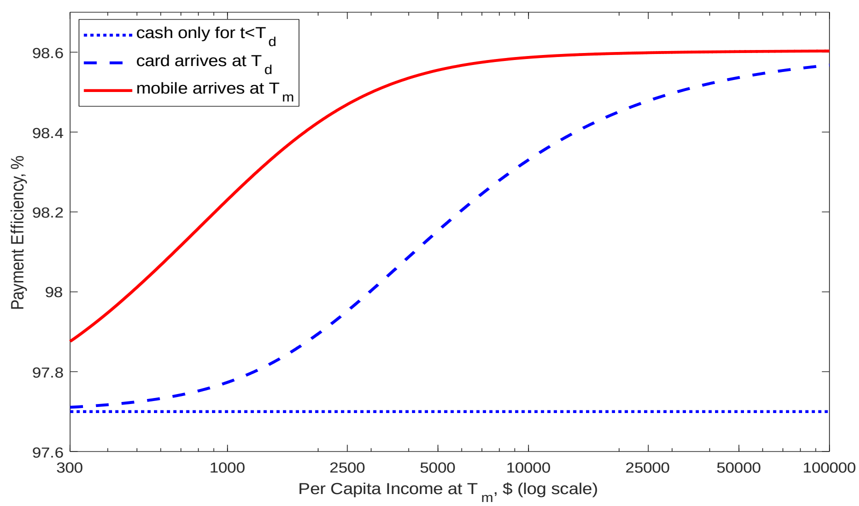


Figure 9. Payment Efficiency by Per Capita Income

As depicted in Figure 9, every country has the same payment efficiency when cash is the only payment means (i.e., $X_{t<T_d} = 1 - \tau_h$). Once the card technology arrives, the payment efficiency improves in every country, and the efficiency improvement increases in per capita income across countries. Hence, high-income countries gain the most from the card payment adoption. The arrival of mobile payments also benefits every country, though disproportionately. The relative welfare gain $(X_{T_m} - X_{T_d})/X_{T_d}$ peaks at the per capita income around \$1,900, but richest countries remain leaders in terms of overall payment efficiency. In contrast, the poorest countries do not gain much from either card or mobile payment innovations because most of their consumers are stuck with cash.

[25] The large-scale introduction of debit cards started in the U.S. in the mid-1980s (see Hayashi et al., 2017), so we set $T_d = T_m - 30$ accordingly.

4.3.2 Social benefit of mobile payments

Introducing mobile payments requires investing in the related infrastructures and it is important to evaluate the social return of such investment. Our model can help inform such decisions by quantifying the social benefit of introducing mobile payments given a country's per capita income level.[26]

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

$$\begin{aligned}\tilde{W}_{T_m} &= W_{h,T_m} + \int_{I_d(1+g)}^{\infty} \left(\bar{V}_d(I) - \bar{V}_h(I)\right) dG_{T_m}(I) + \int_{I_d}^{I_d(1+g)} \left(\bar{V}_d(I) - k_d - \bar{V}_h(I)\right) dG_{T_m}(I) \\ &\quad + \sum_{s=1}^{\infty} \int_{\frac{I_d}{(1+g)^s}}^{\frac{I_d}{(1+g)^{s-1}}} \beta^s \left(\bar{V}_d(I(1+g)^s) - k_d - \bar{V}_h(I(1+g)^s)\right) dG_{Tm}(I), \end{aligned} \tag{27}$$

where $I_d = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}$ is from Eq. (5). Note that Eq. (27) is similar to Eq. (24) except that the income distribution is measured at date T_m (instead of T_d) and agents who have already adopted card before T_m no longer need to pay the card adoption cost k_d. Given the exponential income distribution, one can solve $\tilde{W}_{T_m}$ explicitly.

With the parameter values in Table 1, we calculate $W_{T_m} - \tilde{W}_{T_m}$ using Eqs. (25) and (27) to quantify per capita welfare gain from introducing two mobile payment options (i.e., card-substituting and card-complementing ones) in each country at $T_m = 2017$ in dollar value. We also calculate per capita welfare gain from introducing just one mobile payment option, denoted as $W_{T_m}^{Subs} - \tilde{W}_{T_m}$ for the card-substituting one and $W_{T_m}^{Comp} - \tilde{W}_{T_m}$ for the card-complementing one.[27] The results, plotted in the left panel of Figure 10, are similar to the mobile payment options and adoption patterns shown in Figure 7.

According to Figure 10A, the per capita welfare gain from introducing both mobile payment options is low for the poorest countries (e.g., welfare gain is \$14 per capita for countries with per capita income at \$300) as well as for some relatively high-income countries (e.g.,

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

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

welfare gain is $35 per capita for countries with per capita income at $28,000). In contrast, the welfare gain peaks at $125 per capita for countries with per capita income at $2,100. For a rich country at the U.S.-level of per capita income ($53,356 in 2017), the welfare gain is $51 per capita.

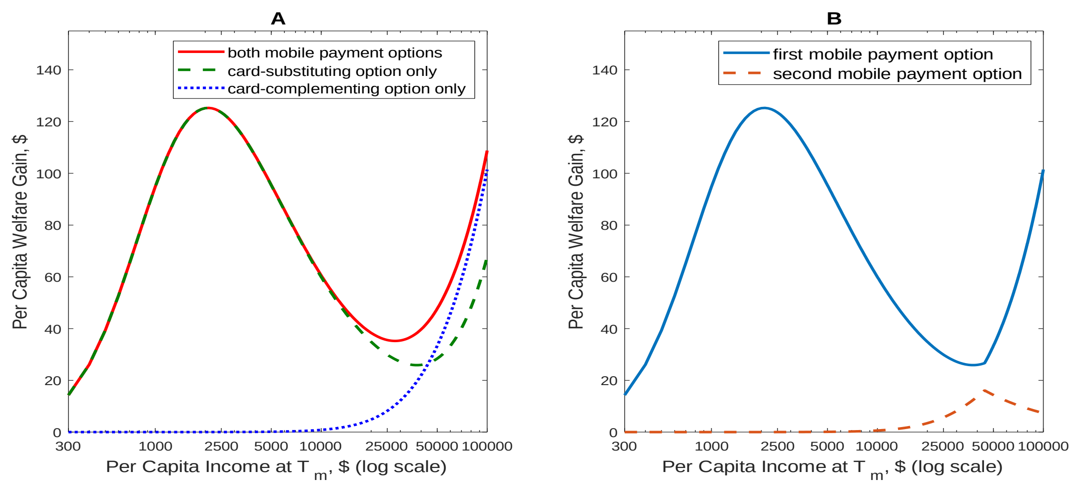


Figure 10. Welfare Gain from Mobile Payments

Figure 10A also suggests that the incremental welfare gain from introducing the second mobile payment option is relatively small and varies by per capita income. To make it clearer, we plot in Figure 10B each country's per capita welfare gain from its more desirable choice of the two mobile payment options (i.e., $\max(W^{Subs}_{T_m} - \tilde{W}_{T_m}, W^{Comp}_{T_m} - \tilde{W}_{T_m})$), and we then plot the per capita welfare gain from adding the second option (i.e., $W_{T_m} - \max(W^{Subs}_{T_m}, W^{Comp}_{T_m})$). The result shows that countries with per capita income below $12,000 would derive little per capita welfare gain (< $0.99) from introducing card-complementing mobile payment as the second option. In contrast, a country with per capita income at $44,300 could gain $16.1 per capita by introducing card-substituting mobile payment as the second option, but that benefit would decline for countries with higher per capita income.

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

So far our baseline model does not incorporate any market imperfection and the market outcome is socially optimal. Payments markets, however, likely involve externalities. In the next section, we extend our baseline model to allow payment externalities that distort consumers' payment decisions. We show the positive economic findings from our baseline model continue to hold, and we gain additional normative insights from the extended model.

5 An extended model with payment externalities

In this section, we extend our baseline model to incorporate payment externalities. It is well known that payment market is two-sided, in which consumers and merchants jointly use each payment technology in transactions. A major friction in this market is price coherence: Merchants often charge consumers the same retail price no matter how they pay.[28] Consequently, consumers do not internalize the payment externalities they generate on merchants and through merchant pricing onto other consumers. We show that our baseline model can be extended to incorporate payments externalities and yield useful normative implications.

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

5.1 Price differentiation

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

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

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

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

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

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

$$1 - \tau_i = (1-\tau_{b,i})(1-\tau_{s,i}). \tag{28}$$

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

5.2 Price coherence

Alternatively, if merchants do not price differentiate based on payment means, consumers would pay the same retail price regardless of payment technologies they use. This is termed "price coherence" in the two-sided market literature, under which each consumer's adoption and usage of payment technologies would impose externalities on others. According to Rochet and Tirole (2002, 2006) and the following two-sided market studies, price coherence is a key friction in the two-sided payment markets that causes efficiency losses.[30] In the following,

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

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

we extend our model to incorporate the friction.

5.2.1 Card adoption

Our analysis remains unchanged for a cash economy. Once the card technology arrives at date T_d, a price-coherent merchant would set a single price p_t regardless of payment means for any date $t \geq T_d$. This price is time varying because the composition of card and cash users as well as their spending evolve with income growth.

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

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

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

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

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

$$p_t = \frac{R_t}{Q_t} = \frac{(1 - \tau_{b,h})\lambda_t + (\tau_{b,h} - \tau_{b,d}) \exp(-I_{d,t}/\lambda_t)(\lambda_t + I_{d,t})}{(1 - \tau_h)\lambda_t + (\tau_h - \tau_d) \exp(-I_{d,t}/\lambda_t)(\lambda_t + I_{d,t})}, \tag{29}$$

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

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

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

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

$$I_{d,t} = \frac{(1 - \beta)k_d}{(\tau_{b,h} - \tau_{b,d})} p_t. \tag{30}$$

In contrast to our baseline model, the income threshold $I_{d,t}$ for card adoption now depends on $(\tau_{b,h} - \tau_{b,d})$ instead of $(\tau_h - \tau_d)$ because under price coherence, consumers would only consider the buyer-side but not seller-side payment savings. The threshold $I_{d,t}$ also depends on the retail price p_t, which is time-varying. With the exponential income distribution, the card adoption rate is $F_{d,t} = \exp(-I_{d,t}/\lambda_t)$, and we can rewrite Eq. (30) to pin down $F_{d,t}$ as a function of per capita income λ_t and other parameters:

$$-\lambda_t \ln(F_{d,t}) = \frac{(1-\beta)k_d}{(\tau_{b,h}-\tau_{b,d})} \frac{(1-\tau_{b,h}) + (\tau_{b,h}-\tau_{b,d})\, F_{d,t}(1-\ln(F_{d,t}))}{(1-\tau_h) + (\tau_h - \tau_d)\, F_{d,t}(1-\ln(F_{d,t}))}. \tag{31}$$

5.2.2 Mobile payment adoption

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

$$R_t = \left\{ \begin{array}{c} (1-\tau_{b,h}) \int_0^{I_{m,t}} I dG_t(I) + (1-\tau_{b,m}) \int_{I_{m,t}}^{I_{d,T_m-1}(1+g)^{(t-T_m+1)}} I dG_t(I) \\ + (1-\tau_{b,d}) \int_{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}^{I^a_{m,t}} I dG_t(I) + (1-\tau_{b,m}) \int_{I^a_{m,t}}^{\infty} I dG_t(I) \end{array} \right\} \tag{32}$$

from customers, and provides the quantity of numeraire goods

$$Q_t = \left\{ \begin{array}{c} (1-\tau_h) \int_0^{I_{m,t}} I dG_t(I) + (1-\tau_m) \int_{I_{m,t}}^{I_{d,T_m-1}(1+g)^{(t-T_m+1)}} I dG_t(I) \\ + (1-\tau_d) \int_{I_{d,T_m-1}(1+g)^{(t-T_m+1)}}^{I^a_{m,t}} I dG_t(I) + (1-\tau_m) \int_{I^a_{m,t}}^{\infty} I dG_t(I) \end{array} \right\}. \tag{33}$$

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

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

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

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

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

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

$$I_{m,t}^a = \frac{(1-\beta)k_m^a}{(\tau_{b,d} - \tau_{b,m})} p_t. \tag{35}$$

Equations (34) and (35) suggest that $I_{m,t}$ and $I_{m,t}^a$ are connected so that

$$I_{m,t}^a = z I_{m,t}, \text{ where } z = \frac{k_m^a(\tau_{b,h} - \tau_{b,m})}{k_m(\tau_{b,d} - \tau_{b,m})}. \tag{36}$$

Denote $F_{e,t}$ the fraction of consumers who have adopted any electronic payments (card or mobile) by date t. The exponential income distribution implies that $F_{e,t} = \exp(-I_{m,t}/\lambda_t)$, and we can pin down $F_{e,t}$ via Eq. (34) together with Eqs. (32), (33) and (36) as follows:

$$-\lambda_t \ln(F_{e,t}) \frac{(\tau_{b,h} - \tau_{b,m})}{(1-\beta)k_m} = \tag{37}$$

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

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

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

$$-\lambda_t \ln(F_{e,t}) = \frac{(1-\beta)k_m}{(\tau_{b,h} - \tau_{b,m})} \frac{(1-\tau_{b,h}) + (\tau_{b,h} - \tau_{b,m}) F_{e,t}(1 - \ln(F_{e,t}))}{(1-\tau_h) + (\tau_h - \tau_m) F_{e,t}(1 - \ln(F_{e,t}))}, \tag{38}$$

and then derive the other endogenous variables.

5.3 Quantitative analysis

To conduct quantitative analysis for the price-coherent model, we use parameter values consistent with the baseline model, as shown in Table 3. Without loss of generality, we assume that cash, card and mobile each yield symmetric benefits to consumers and merchants: $\tau_{b,i} = \tau_{s,i}$ for $i \in \{h, d, m\}$. Accordingly, Eq. (28) implies that $\tau_{b,i} = \tau_{s,i} = 1 - \sqrt{(1 - \tau_i)}$, where $\tau_h = 2.3\%$, $\tau_d = 1.4\%$ and $\tau_m = 1.395\%$. We then show that for the price-coherent model to fit data equally well as the baseline model, one needs to reduce the adoption costs (i.e., k_d, k_m and k_m^a) by half from their previous values.[31] For ease of notations, we round the values of k_d, k_m and k_m^a to the nearest integer in Table 3.

Table 3. Parameter Values for Two-sided Market Model

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

We plot model predictions of card and mobile payment adoption rates at each level of per capita income in Figure 11. The results show that with the same adoption cost values, the adoption of card and mobile payments would be lower under the price-coherent regime (drawn with red dotted lines) than under the price-differentiation regime (drawn with blue dashed lines) because under the former consumers would only consider savings of payment costs on the buyer side but not on the seller side. In comparison, once we reduce the adoption costs (i.e., k_d, k_m and k_m^a) by half, the price-coherent model replicates almost the same adoption patterns generated by the price-differentiation model (which is equivalent to our baseline model), as shown by the yellow solid lines in the figure.

[31] This equally applies to the adoption cost estimation using individual consumer data, and the findings continue to align between our benchmark estimation based on country-level data and the logit estimation based on individual consumer data (see Internet Appendix VII).

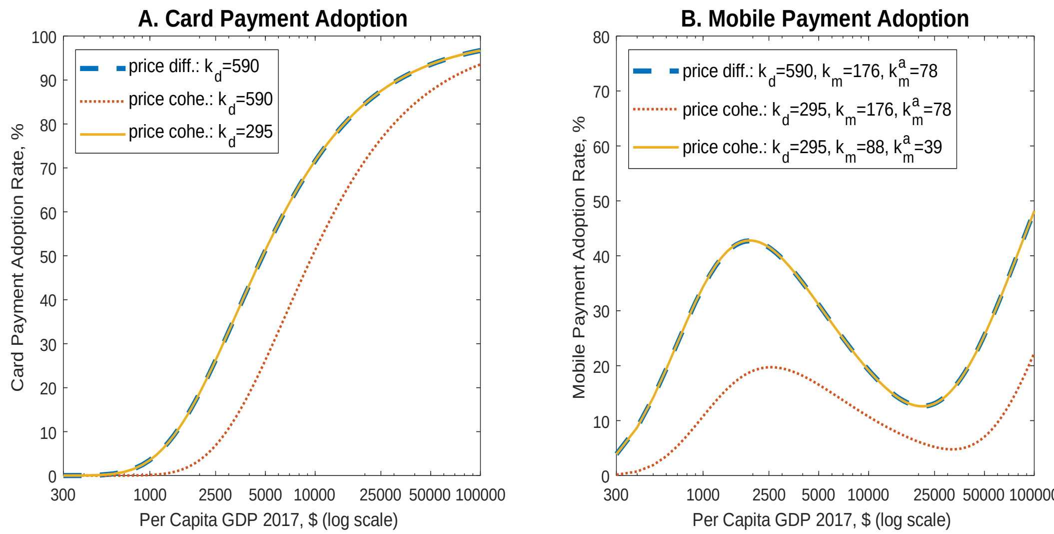


Figure 11. Payment Adoption under Price Coherence

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

$$I_{d,t}^{disc} = \frac{(1-\beta)k_d}{(\tau_h - \tau_d)} \quad \text{vs.} \quad I_{d,t}^{cohe} = \frac{(1-\beta)k_d}{(\tau_{b,h} - \tau_{b,d})} p_t. \tag{39}$$

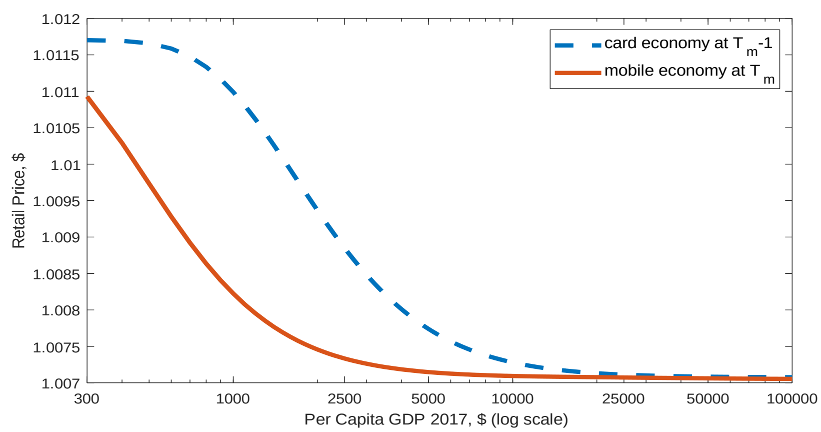


Figure 12. Retail Price under Price Coherence

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

$p_t = \frac{1-\tau_{b,d}}{1-\tau_d} = 1.0071$ (see Figure 12). Because $(\tau_{b,h} - \tau_{b,d}) \approx (\tau_h - \tau_d)/2$, halving k_d under the price-coherent regime would then generate an adoption threshold $I_{d,t}^{cohe}$ very close to the one $I_{d,t}^{disc}$ under the price differentiation regime. A similar analysis applies to comparing mobile payment adoption between the two regimes.

5.4 Welfare and policy analysis

5.4.1 Payment efficiency and social welfare

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

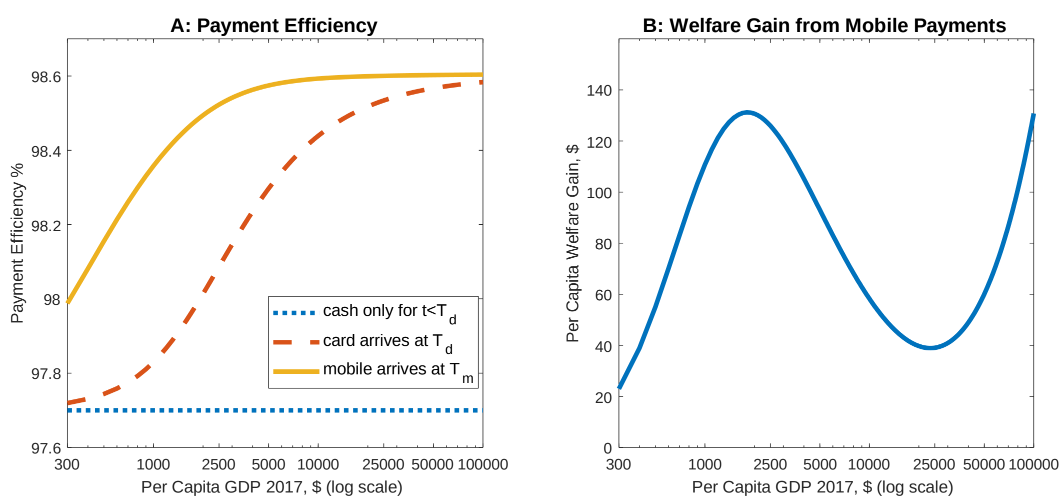


Figure 13. Welfare Results under Price Coherence

Figure 13A plots payment efficiency for an economy, defined by Eq. (26). The patterns are similar to our findings from the baseline model (cf. Figure 9). Figure 13B computes the welfare gain from introducing mobile payments at date T_m (i.e., $W_{T_m} - \tilde{W}_{T_m}$). Again, the cross-country pattern is similar to our finding from the baseline model (cf. Figure 10A), but the magnitude of welfare gains from introducing mobile payments becomes higher due to the lower values of adoption costs.

5.4.2 Policy interventions

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

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

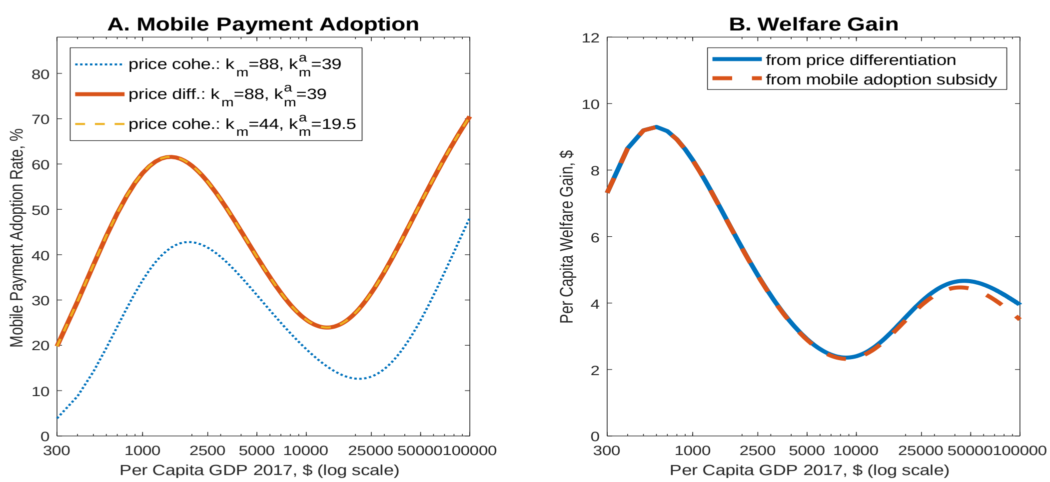


Figure 14. Effects of Policy Interventions

The results plotted in Figure 14 show that switching from price coherence to price differentiation increases mobile payment adoption and social welfare. This suggests that price differentiation policies, such as surcharging cash use or rewarding mobile payment use at the point of sale can be welfare enhancing. However, in practice, it can be difficult for merchants to price differentiate based on payment means. Alternatively, policymakers could subsidize mobile payment adoption costs k_m and k_m^a financed by a non-distortionary tax. The subsidy would induce consumers to adopt mobile payments close to the socially optimal level. In our numerical example, subsidizing half of k_m and k_m^a would achieve nearly the social optimum. Moreover, Figure 14B shows that low-income countries would benefit more from these policies than middle- and high-income countries. This is because for the low-income countries, internalizing payment externalities would convert more consumers from cash users to mobile payment users and lead to a larger decline in retail prices for all consumers. Such a policy would also benefit middle- and high-income countries but to a lesser extent because the incremental benefit of switching from card to mobile payment is limited.

Finally, we compare the counterfactuals where government subsidizes one or two mobile payment technologies. The results, plotted in Figure 15, suggest that low-income countries would benefit primarily from subsidizing card-substituting mobile payments while high-income countries would benefit most from subsidizing card-complementing ones.

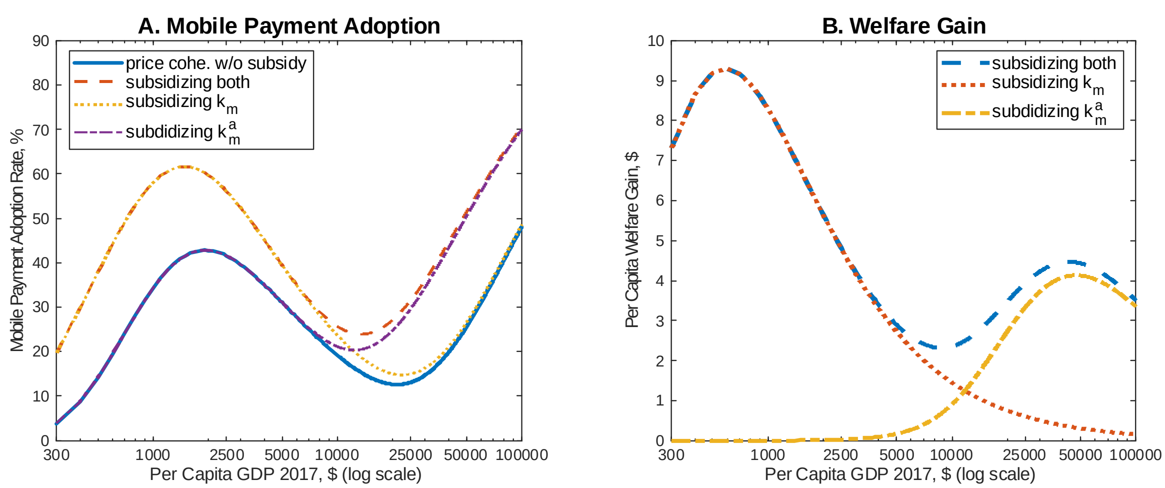


Figure 15. Subsidizing Mobile Payment Adoption

6 Additional discussions

We have shown that incorporating payment externalities in the analysis, while yielding useful policy implications, does not alter our baseline model's explanation of the leapfrogging. In this section, we conduct additional robustness checks on the baseline model and provide some further discussions.

6.1 Anticipation for mobile payments

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

Formally, we assume that at date $T_m - n$, agents receive news that two mobile payments options (i.e., card-substituting and card-complementing ones) may arrive at a Poisson rate ρ starting from next period in each country.[32] We then characterize how this information affects the income threshold of card adoption and the card and mobile adoption rates as follows.

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

$$\tilde{V}_h(I_t) = (1-\tau_h)I_t + \beta \left\{ \begin{array}{c} \rho \max\left[V_h(I_{t+1}), V_m(I_{t+1}) - k_m\right] \\ +(1-\rho)\max\left[\tilde{V}_h(I_{t+1}), \tilde{V}_d(I_{t+1}) - k_d\right] \end{array} \right\}, \tag{40}$$

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

$$\tilde{V}_d(I_t) = (1-\tau_d)I_t + \beta \left\{ \begin{array}{c} \rho \max\left[V_d(I_{t+1}), V_m(I_{t+1}) - k_m^a\right] \\ +(1-\rho)\tilde{V}_d(I_{t+1}) \end{array} \right\}. \tag{41}$$

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

$$\tilde{V}_d(I_d^\rho) - \tilde{V}_h(I_d^\rho) = k_d. \tag{42}$$

Evaluating Eqs. (40) and (41) at I_d^ρ and inserting them into Eq. (42) then pins down I_d^ρ (see

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

Internet Appendix VI for the solution details).

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

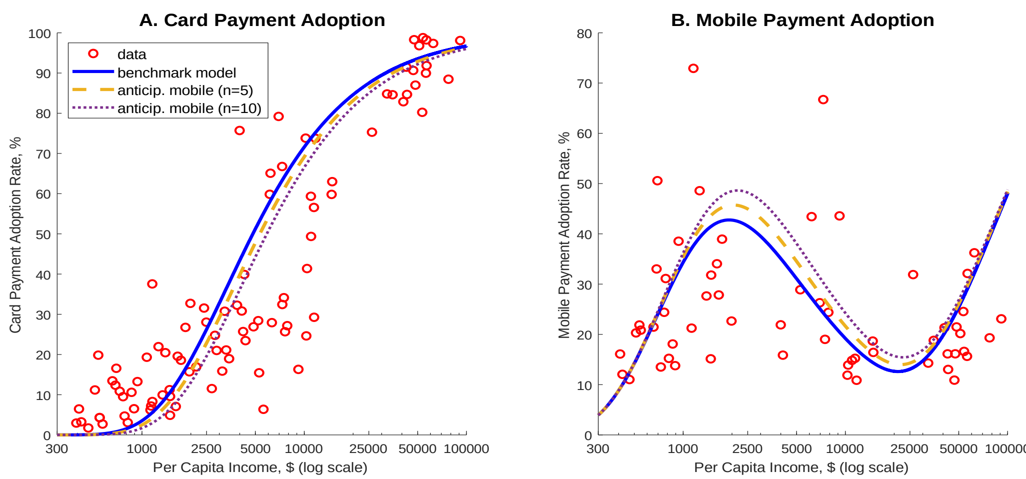


Figure 16. Anticipated Mobile Payments

Using the set of parameter values in Table 1, we compute I_d^ρ and conduct the following counterfactual analysis. We consider two scenarios: Agents anticipate mobile payments 5 years (i.e., $n = 5$ and $\rho = 1/n = 0.2$) or 10 years (i.e., $n = 10$ and $\rho = 1/n = 0.1$) ahead of the actual arrival at $T_m = 2017$. The resulting card and mobile adoption patterns are plotted in Figure 16. In either scenario, an increased card adoption threshold satisfies $I_d^\rho > I_d(1+g)^n$, which induces agents who otherwise would have adopted card between $T_m - n$ and $T_m - 1$ to postpone their card adoption. Once mobile payments arrive at date T_m, those delayed card adopters become additional mobile payment adopters. The earlier the anticipation, the more the delayed card adopters, and the higher the mobile payment adoption. However, as Figure 16 shows, comparing with our baseline model where mobile payments arrive unexpectedly, the effect of anticipation is quantitatively small.[33]

[33] Note that our findings are robust to any alternative values of $\rho \in [0, 1]$. When $\rho = 0$, we are back to the

6.2 Income distribution and Gini coefficient

We so far have assumed an exponential income distribution in the analysis. While this is a simplifying assumption and fits the data well, one may wonder if our findings are robust under alternative distributional assumptions. Moreover, the property that the exponential distribution has a fixed Gini coefficient at 0.5 raises the question of how much of the cross-country payment technology adoption pattern is affected by country-specific Gini coefficients outside the model.

To address these questions, we extend the model by assuming a log-logistic income distribution, which has also been popularly used in empirical studies (e.g., see Fisk, 1961). Figure 17 presents an example of fitting the U.S. household income distribution in 2017 with a log-logistic distribution. The log-logistic distribution has two parameters that capture the mean and the Gini coefficient separately.

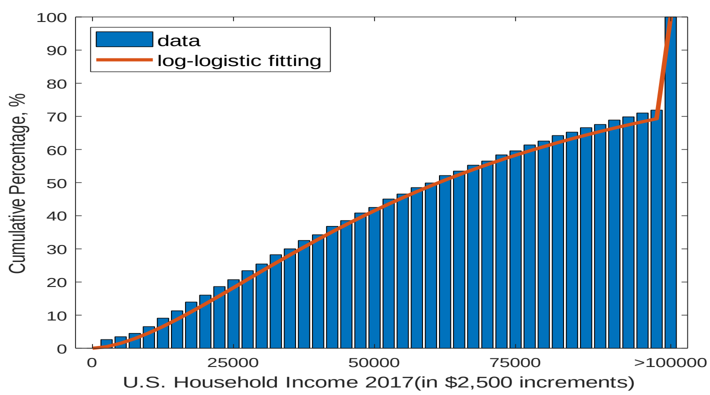


Figure 17. Log-logistic Income Distribution

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

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

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

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

We assume that each country offers both mobile payment technologies.[34] The analysis is the same as the baseline model except that we now replace the card adoption equation (6) with Eq. (43) and replace the mobile adoption equation (20) with Eq. (44) as follows:

$$F_{d,t} = \frac{1}{1 + \left(\frac{(1-\beta)k_d}{(\tau_h-\tau_d)\lambda_t}\right)^{\frac{1}{\eta}} \Phi}, \tag{43}$$

$$F_{m,t} = \frac{1}{1 + \left(\frac{(1-\beta)k_m}{(\tau_h-\tau_m)\lambda_t}\right)^{\frac{1}{\eta}} \Phi} - \frac{1}{1 + \left(\frac{(1-\beta)k_d}{(\tau_h-\tau_d)\lambda_{T_m-1}}\right)^{\frac{1}{\eta}} \Phi} + \frac{1}{1 + \left(\frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)\lambda_t}\right)^{\frac{1}{\eta}} \Phi}. \tag{44}$$

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

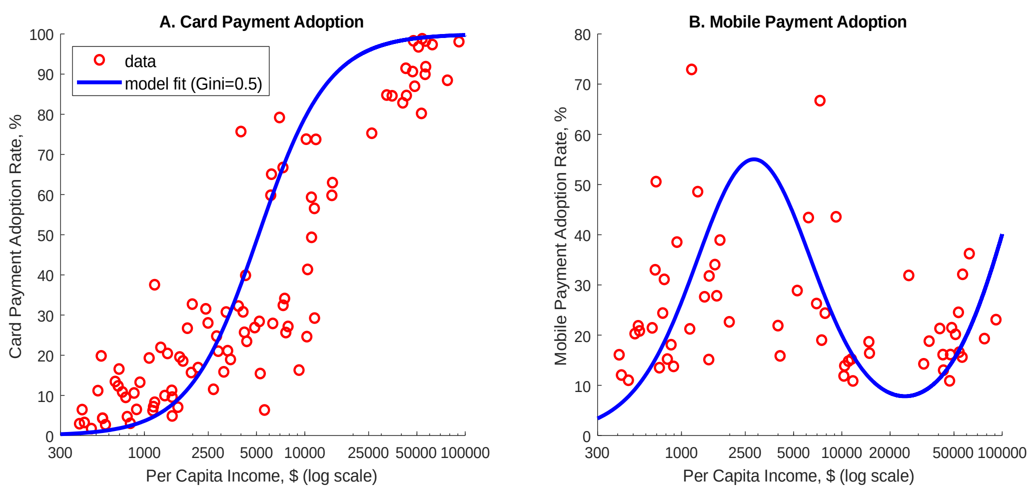


Figure 18. Log-logistic Model Fit (Gini =0.5).

To compare directly with our previous findings, we first assume a log-logistic income distribution with $\eta = 0.5$, the same value of the Gini coefficient under the exponential

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

distribution, for every country in the sample. Using the same set of parameter values in Table 1, we plot the card and mobile payment adoption rates at each level of per capita income in Figure 18. The results are similar to the baseline model.[35]

We then compute the mobile payment adoption rates while allowing each country to have the actual country-specific Gini coefficient in the data.[36] In Figure 19, we plot the results and contrast them with those assuming a uniform Gini coefficient = 0.5. The comparison suggests that the cross-country card and mobile adoption patterns are mainly governed by the level of per capita income, and the difference in Gini coefficient only plays a small role quantitatively. This finding is consistent with the regression results reported in Tables A3 and A4 of Internet Appendix III, which show that the cross-country mobile payment adoption pattern is significantly correlated with per capita income but not the Gini index.

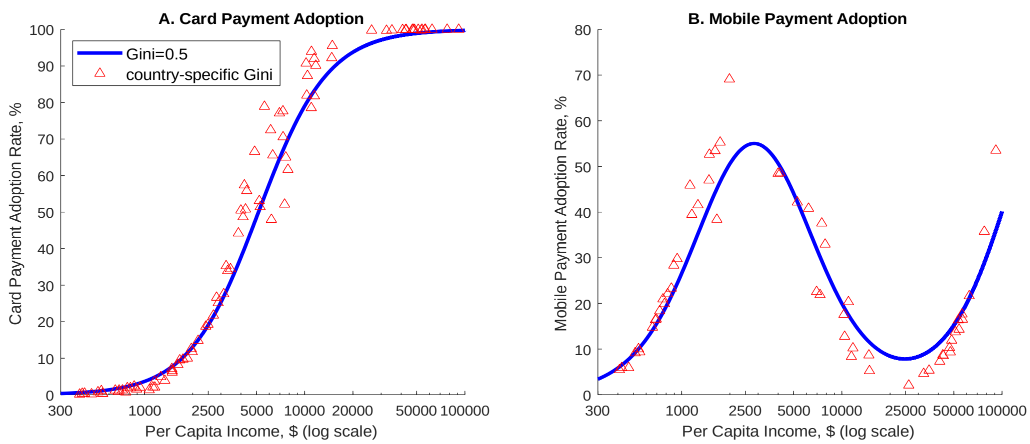


Figure 19. Log-logistic Models (Country-specific Gini vs. Gini =0.5).

6.3 Payment user cost

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

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

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

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

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

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

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

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

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

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

Table 4. Model Parameterization with User Cost Wedges

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

Figure 20 plots the welfare results with $s = 0.25$. Comparing the figure with Figures 9 and 10A, we find that the results of the welfare analysis (in terms of payment efficiency and user welfare from introducing mobile payments) are very similar to the baseline case where $s = 0$, though the levels become lower due to the payment user cost wedges.[37]

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

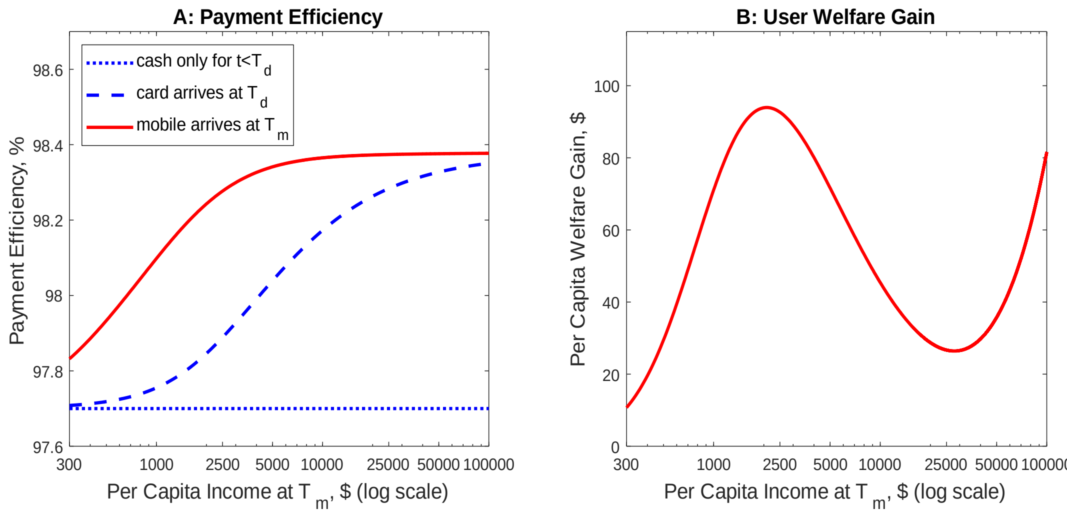


Figure 20. Welfare Results with User Cost Wedges

6.4 Other factors

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

Nevertheless, by focusing on income heterogeneity, our theory provides a parsimonious model to explain cross-country payment technology adoption patterns without being bogged down by idiosyncratic details. It is known from consumer surveys that income is a key factor explaining card adoption at household level (e.g., see Greene and Shy, 2022), which is consistent with our finding that per capita GDP positively correlates with card adoption across countries. It is striking that such a positive relation is absent for mobile payments, and our model offers a coherent explanation in the context of sequential payment innovations.[38] Our

[38] Through the lens of our model, the non-monotonic relationship between mobile payment adoption and

estimated model fits the cross-country mobile payment adoption pattern well and provides a convenient framework for welfare and policy analysis. Incorporating additional factors into the analysis may further enhance our understanding of payment technology adoption across countries, especially the variations in the data that are not accounted for by our theory, and those will be valuable venues for future research.

7 Conclusion

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

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

Our estimated model matches the cross-country payment technology adoption patterns well. We find that lagging behind in mobile payment adoption does not necessarily mean that advanced economies fall behind in overall payment efficiency. Rather, slower adoption may simply reflect that the incremental benefit of switching from card to the current mobile payment technology is not large enough. Our analysis also shows that in the presence of payment externalities, subsidizing mobile payment adoption may enhance social welfare and

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

can be more beneficial for developing countries.

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

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

I. Global pattern of mobile payments

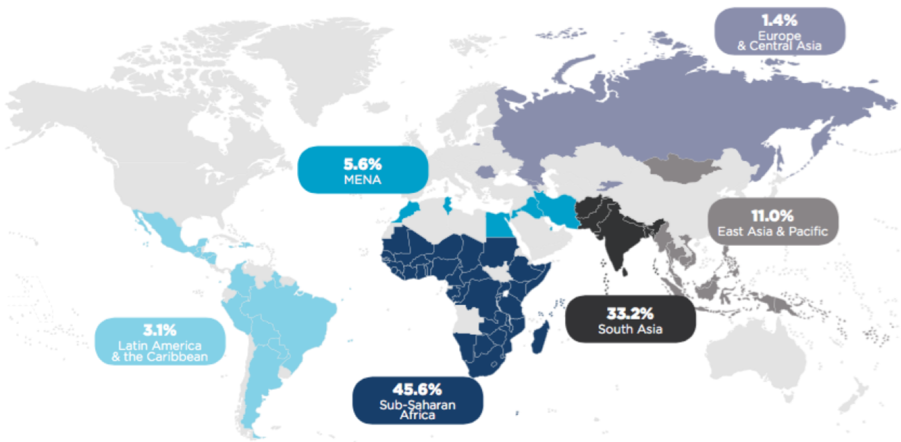


Figure A1. Global Adoption of Mobile Money

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

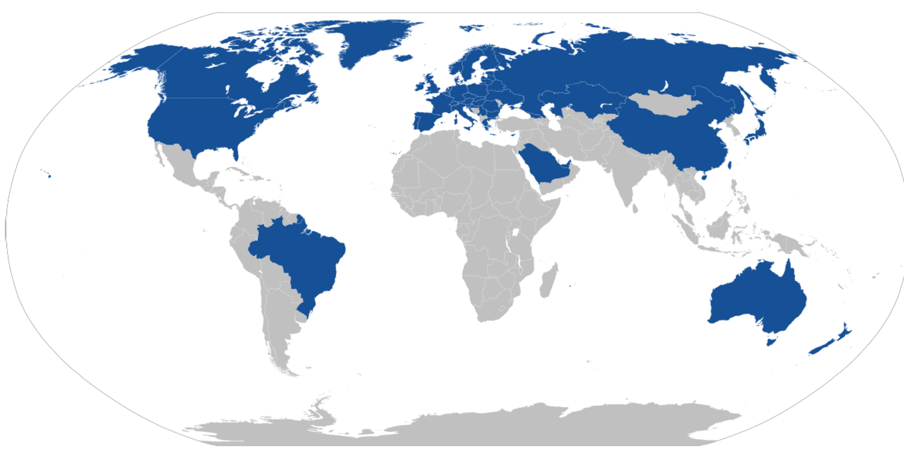


Figure A2. Global Deployment of Apple Pay

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

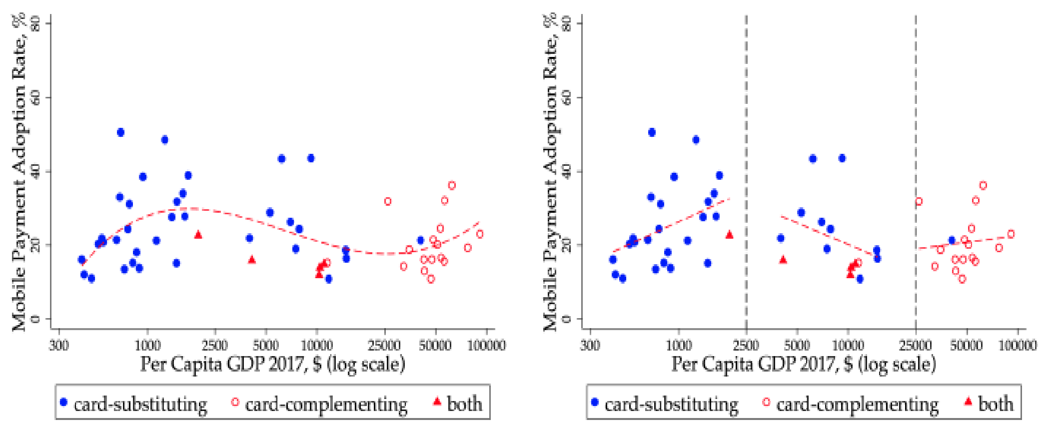
II. Data sources

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

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

III. Regression results

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



(A) Nonparametric fit (B) Linear fit

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

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

Table A1. Cross-Country Payment Adoption: OLS Regressions

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

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

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

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

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

Table A2. Cross-Country Payment Adoption: FL Regressions

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

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

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

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

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

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

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

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

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

IV. Baseline model estimation: Identification strategy

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

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

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

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

V. Present-value welfare of aggregate economies

Given the exponential distribution $G_t(I)$, Eq. (23) yields that the present-value welfare of a cash economy at date t ($< T_d$) is

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

Given the exponential distribution $G_{T_d}(I)$, Eq. (24) yields that

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

Denote that ϕ satisfies $\frac{I_m^a}{(1+g)^\phi} > I_d(1+g)$ and $\frac{I_m^a}{(1+g)^{\phi+1}} \leq I_d(1+g)$. Eq. (25) implies

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

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

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

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

VI. Anticipation for mobile payments: Solution details

Denote I_d^{ρ} as the income threshold at which an agent is indifferent between adopting card and continuing with cash at any dates between T_m-n and T_m-1. Given the mobile payment news, the income threshold of adopting card becomes higher, which means $I_d^{\rho}>I_d>I_m$. At income I_d^{ρ}, Eqs. (40) and (41) imply that

$$\tilde{V}_h(I_d^{\rho})=(1-\tau_h)I_d^{\rho}+\beta\left\{\begin{array}{c}\rho\left[V_m(I_d^{\rho}(1+g))-k_m\right]\\ +(1-\rho)\left[\tilde{V}_d(I_d^{\rho}(1+g))-k_d\right]\end{array}\right\}, \tag{45}$$

and

$$\tilde{V}_d(I_d^{\rho})=(1-\tau_d)I_d^{\rho}+\beta\left\{\begin{array}{c}\rho\max\left[V_d(I_d^{\rho}(1+g)),V_m((I_d^{\rho}(1+g))-k_m^a\right]\\ +(1-\rho)\tilde{V}_d(I_d^{\rho}(1+g))\end{array}\right\}. \tag{46}$$

Inserting Eqs. (45) and (46) into Eq. (42) yields

$$\begin{aligned} k_d-\beta(1-\rho)k_d &= (\tau_h-\tau_d)I_d^{\rho}+\beta\rho\max\left[V_d(I_d^{\rho}(1+g)),V_m((I_d^{\rho}(1+g))-k_m^a\right] \\ &\quad -\beta\rho\left[V_m(I_d^{\rho}(1+g))-k_m\right]. \end{aligned} \tag{47}$$

To solve I_d^{ρ}, we can use Eq. (47) with a guess-and-verify method. We first guess that $I_d^{\rho}(1+g)\geq I_m^a=\frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$. Equation (47) then yields

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

which pins down

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

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

We then guess $I_d^\rho(1+g) < I_m^a = \frac{(1-\beta)k_m^a}{(\tau_d-\tau_m)}$. Equation (47) now yields

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

From Eq. (7), we know

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

From Eq. (17), we have

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

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

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

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

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

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

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

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

$$\begin{aligned} F_{h\to m,t} &= 1 - F_{d,T_m-1} - G_t(I_m) \\ &= \exp\left(-\frac{I_m}{\lambda_t}\right) - \max\left(\exp(-\frac{I_d}{\lambda_{T_m-n-1}}), \exp(-\frac{I_d^{\rho}}{\lambda_{T_m-1}})\right). \end{aligned} \tag{48}$$

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

$$F_{d\to m,t} = 1 - G_t(I_m^a) = \exp\left(-\frac{I_m^a}{\lambda_t}\right) \tag{49}$$

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

VII. Estimating payment adoption costs: Micro-level evidence

In the paper, we estimated the fixed costs associated with adopting card and mobile payments $k_d = \$589.83$ and $k_m = \$175.76$ using minimum distance estimation based on the data of country-level adoption rates. To cross check our benchmark estimates, we compare them with micro-level evidence. To do that, we obtain individual consumer survey data on payment technology adoption in 2017 from 26 low-income countries, and estimate the payment adoption costs in each country. Below, we delineate our estimation strategy and report the estimation results. The estimates based on individual consumer survey data are in line with our benchmark estimates and hence provide supporting evidence.

Estimation strategy. —We first delineate our estimation strategy using individual consumer data on payment technology adoption. Consider in each country, the micro-level payment adoption data set $\{y_i, I_i\}_{i=1}^N$ contains N individuals where I_i is the income of individual i, and y_i takes the value of one if individual i adopts a particular payment technology and zero otherwise.

In our baseline model, three payment technologies–cash, card, and mobile–arrive sequentially. Newer technologies lower the variable costs of making payments, but they require a fixed cost to adopt. Hence, in equilibrium each individual follows a cutoff strategy to adopt a new payment technology (i.e., an individual adopts a new payment technology if her income is above a particular threshold).

Specifically, individual i would adopt a debit card if her income I_i is above the following threshold:

$$I_i \geq \frac{(1-\beta)k_d}{(\tau_h - \tau_d)}. \tag{50}$$

In this expression, β is the discount factor, k_d refers to the one-time fixed adoption cost associated with card, and τ_h and τ_d are the variable costs (per dollar of transaction) associated with using cash and card, respectively. Intuitively speaking, individual i would adopt card if the flow benefit of adoption $(\tau_h - \tau_d)I_i$ can cover the flow cost $(1-\beta)k_d$.

The adoption decision (50) gives rise to a latent variable setting to estimate the cost parameters from individual consumer data. To be specific, consider an auxiliary random variable $y_i^* = \frac{(\tau_h - \tau_d)}{1-\beta} I_i - k_d + \epsilon_i$, where ϵ_i is the idiosyncratic error term. The card adoption outcome y_i can be viewed as an indicator for whether the latent variable y_i^* is positive:

$$y_i = \begin{cases} 1, & \text{if } \ y_i^* > 0 \\ 0, & \text{otherwise} \end{cases} = \begin{cases} 1, & \text{if } \frac{(\tau_h - \tau_d)}{1-\beta} I_i - k_d + \epsilon_i > 0 \\ 0, & \text{otherwise} \end{cases}.$$

To estimate the card adoption cost k_d, we can regress the individual card adoption indicator against the individual income and a constant term using a logit model:

$$y_i = \begin{cases} 1, & \text{if } a_d I_i + b_d + \epsilon_i > 0 \\ 0, & \text{otherwise} \end{cases}.$$

The coefficient estimates of the individual income and the constant term are denoted by a_d and b_d, respectively. The ratio of b_d and a_d, together with other parameters in the threshold condition (50) then pins down the adoption cost k_d as follows:

$$\frac{b_d}{a_d} = \frac{-k_d}{\frac{(\tau_h - \tau_d)}{1-\beta}} \Longrightarrow k_d = -\frac{b_d}{a_d}\frac{(\tau_h - \tau_d)}{1-\beta}. \tag{51}$$

Following the common practice, we set the annual discount factor $\beta = 0.95$. Consistent with Schmiedel et al. (2012), we set $\tau_h = 2.3\%$ and $\tau_d = 1.4\%$. With individual consumer data on debit card adoption, we obtain the coefficient estimates a_d and b_d using a logit model and the card adoption cost k_d can then be deduced from Eq. (51).

Analogously, the adoption cost of card-substituting mobile payment k_m can be obtained from

$$k_m = -\frac{b_m}{a_m}\frac{(\tau_h - \tau_m)}{1-\beta}. \tag{52}$$

In this expression, a_m and b_m refer to the logit coefficient estimates of the individual income and the constant term in the card-substituting mobile payment adoption regression, and $\tau_h(= 2.3\%)$ and $\tau_m(= 1.395\%)$ are the variable costs associated with using cash and mobile payment, respectively.

Estimation results. —To estimate the payment adoption costs, we obtain individual consumer survey data on payment technology adoption in 2017 from the Global Financial Inclusion (Global Findex) Database of the World Bank. Our sample consists of the group of 26 low-income countries in the paper (i.e., per capita GDP<\$2,500 and mobile payment adoption rate>10% in 2017). Each country has about 1,000 survey respondents (except for Haiti and India where the number of survey respondents is 491 and 2,980, respectively).

To check how our benchmark estimates compare with estimates based on micro-level data, we first run logit regression for each country using individual consumer data. We then derive k_d (card payment adoption cost) and k_m (card-substituting mobile payment adoption cost) for each country based on Eqs. (51) and (52) respectively, and we report the summary statistics of the estimated k_d and k_m in Table A5 below.

Since consumers' payment adoption decision features a cutoff strategy, the richest individuals could be less informative in the payment adoption estimation compared with their poorer counterparts (who may better reflect the adoption decision of the marginal adopters). Hence, for robustness checks, we exclude individuals in the top income quintile in each country and reran the regressions. We report the estimation results in the last three columns in Table A5.

In both cases (i.e., including or excluding the top income quintile), we find that the estimates from individual consumer data follow the same ranking condition that $k_d > k_m$ as our benchmark estimates. Moreover, the estimated adoption costs (k_d = \$589.83 and

k_m = \$175.76) from our benchmark estimation lie between the 25^{th} percentile and the 75^{th} percentile of the estimated k_d and k_m reported in Table A5.[39] This consistency provides supporting external validation for our benchmark estimation results.

Table A5: Adoption cost estimates based on micro-level data

	Full sample			Excluding the richest quintile		
Adoption cost	p25	p50	p75	p25	p50	p75
k_d (card)	\$404.24	\$639.28	\$793.68	\$360.32	\$498.47	\$823.34
k_m (mobile)	\$189.68	\$444.88	\$748.81	\$143.04	\$349.04	\$527.67

Model extension and adoption cost estimation. —The above estimation of payment adoption costs is based on our baseline model where consumers bear the social variable costs of using a payment technology. With the model extension in Section 5 of the paper, we have shown that in the presence of payment externalities, consumers may only bear a fraction of the social costs. Nevertheless, such an extension would have the same effect on the two estimation approaches (i.e., our benchmark estimation based on country-level data and the logit estimation based on individual consumer data), and the findings from these two approaches continue to be consistent.

Specifically, this can be shown by comparing Eqs. (51) and (52) in this note with their counterparts Eqs. (30) and (34) in Section 5 of the paper (together with the discussion of Eq. (39)). In the case that consumers only bear a fraction of the social variable costs of using a payment technology, one just needs to scale down the adoption cost estimates proportionally for both estimation approaches, and the estimates from these two approaches continue to align with each other.

[39] Our benchmark estimate k_m = \$175.76 is close to the 25^{th} percentile of the estimated k_m from the full-sample individual consumer data, and lies between the 25^{th} percentile and the 75^{th} percentile of the estimated k_m when we exclude the top income quintile in the regressions.