

# **The Real Impact of FinTech: Evidence from Mobile Payment Technology\***

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# **The Real Impact of FinTech: Evidence from Mobile Payment Technology**

## **Abstract**

We utilize the introduction of QR-code payment technology by the largest bank in Singapore in 2017 to study how mobile payment technology reshapes economic activities and stimulates business creation. After the introduction, business-to-consumer industries witnessed a higher growth rate of business creation by 8.9% per month relative to business-to-business industries, with the effect driven by small firms and more pronounced among industries with a higher cost of cash handling. Underlying this pattern is a strong adoption of mobile payment and a large decline in cash ATM withdrawals during the post-shock period, as well as closure of ATM machines by the bank. The reduced transaction cost also allows consumers to increase their spending capacity, which further fosters business growth. Interestingly, part of the increased consumer demand is captured by credit card spending, which associates with more credit card opening and higher credit limit provision by the bank. We develop a model to rationalize the responses and extend the empirical evidence to understand the key structural parameters that drive the effects of mobile payment technology.

Keywords: FinTech, Mobile payment, Cash, Credit card, Real effect, Small business, Business creation, Entrepreneurship, Consumption, Banking, Digital economy, Transaction cost, Inclusive growth

JEL codes: E42, D12, D14, G21, O43

## I. Introduction

The recent rapid development in FinTech transforms the financial service industry, ranging from investment, lending, and payment services. One of the most significant progress in providing financial services is the introduction of mobile payment technology. For example, in China, the transaction amount of mobile payment witnessed an annual growth rate of 96% from 2013 to 2018, reaching 42 trillion USD in 2018 (source: People's Bank of China). In developed countries, mobile payment also gains popularity: the penetration rate of mobile payment in the US reaches 20.2% as of 2018 (source: eMarketer).

Mobile payment offers a key advantage over cash payment by reducing costs and alleviating frictions in economic transactions. By removing the need to carry cash, mobile payment improves convenience for consumers. Comparatively, merchants, especially cash-reliant businesses, benefit enormously from the reduction in cash-handling cost. Besides the operating cost, firms suffer from cash leakage. Association of Certified Fraud Examiners (ACFE 2014) estimates that business losses due to employee theft can reach 5% of total business revenues per year, with theft of cash accounts for 48% of the total losses of employee theft (Kennedy 2014).

These cost reduction benefits accumulate to exert a more profound impact on the real economy. Easing frictions in the business operation encourages business growth, and more importantly, promotes entry of businesses that would otherwise be deterred due to high cash handling cost. The incremental benefit of mobile payment's convenience facilitates a wide adoption by consumers. In addition, a lower transaction cost for consumers increases their spending capacity and spurs demand for more products and services. Consequently, consumers' adoption of mobile payment and their boosted consumer demand reinforce mobile payment's direct benefits to merchants, creating more conducive forces to encourage business growth. Notably, benefits brought by mobile payment technology likely accrue disproportionately more to small businesses, which are ex-ante more sensitive to the cost of handling cash and demand conditions. Since small business is a vital component of the economy and has long been recognized as a key engine of economic growth (Hause and Du Rietz, 1984; Klapper, Laeven, and Rajan, 2006), mobile payment technology can have a sizable aggregate impact through fostering particularly small business growth.

It's important to recognize that these implications apply more directly to a cash-dominant society. While most countries to date heavily rely on cash in daily economic activities, other cashless payment methods—such as credit card—exist as popular alternative payment choices. On the one hand, merchants likely favor mobile payment to credit cards due to the latter's higher setup and maintenance cost as well as the transaction-based commission paid to card payment service providers.<sup>1</sup> On the other hand, consumers' preference ordering between mobile payment and credit

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<sup>1</sup> On top of the initial fixed cost for payment terminals (which typically consumes at least 200 dollars), the transaction costs of credit cards are typically higher than the transaction costs associated with cash payment, mainly due to the transaction fees charged by banks (typically ranging from 1% to 3% of transaction amount) and the tender-time cost to complete a card transaction (Economist Incorporated, 2014).

card remains unclear because both payment methods circumvent the hassle dealing with cash and because some consumers may enjoy the distinct aspects of credit cards such as liquidity provision. Furthermore, credit card is an important source of revenue for banks. Though it is in banks' best interest to promote mobile payment adoption to replace costly cash-based services, profit-maximizing banks will at the same time strive to maintain the market share of its credit card business. These offsetting factors potentially impede an active use of mobile payment, dampening its effect on (small) business growth. Consequently, the magnitude as well as the distribution of gains to mobile payment is an open question.

This paper provides a comprehensive study of how mobile payment technology stimulates business creation. Exploiting a unique FinTech innovation in Singapore, we start the analysis with empirical evidence on the responses from multiple sectors—merchants, consumers, and banks—to the introduction of a new mobile payment technology. Next, we develop a model that rationalizes the responses of each sector in a unifying framework and use the model to understand the key structural parameters that drive the effect of the mobile payment technology.

Singapore offers a great setting for the following reasons. First, Singapore is a developed economy that relies heavily on cash. At the same time, consumers have long and widely used other cashless payments such as credit cards. Using our representative sample of consumers from its largest bank, we find that cash usage accounts for 43% of total monthly spending and credit card spending explains 16% of total monthly spending in 2016. Second, Singapore actively promotes technology use in advancing their financial services, including innovating the payment service (as described below). These features allow us to directly assess the responses empirically after the mobile payment introduction and to incorporate the nuanced role other cashless payment methods play in understanding the effect.

In April 2017, the leading bank in Singapore, DBS, introduced a new mobile payment technology – Quick Response (QR) code payment. This mobile payment technology allows consumers to make transactions or transfer funds by displaying or scanning QR codes on their mobile phones. Compared with existing mobile payment technologies, the QR-code payment is more straightforward, efficient, and secure, which can significantly lower the cost of mobile payment. In July 2017, another mobile payment technology that allows for mobile interbank fund transfer was introduced, which further facilitated the usage of mobile payment. We find a strong adoption of mobile payment after the QR-code introduction, in particular after the introduction of mobile interbank fund transfer: in the first year subsequent to the QR code introduction, the number of consumers who signed up (used) mobile payment increased by 53.8% (304%).

We rely on two sources of datasets to empirically investigate our research question. Our data of business creation comes from the administrative business registry data that contains the population of firms created in Singapore. To investigate how business creation interacts with banks' operation and consumers' demand as a response to the technology shock, we also look at a large panel of consumer financial transaction dataset obtained from DBS, the largest bank in Singapore

servicing about 5 million retail customers, or 82 percent of the entire country's population. For a random, representative sample of 250,000 individuals, we can observe their transaction-level disaggregated information of bank accounts, credit cards, and debit cards. We also observe the transaction-level information of ATM transactions of all the ATM machines at the bank.

To empirically study the impact of mobile payment technology on business creation, our identification strategy relies on the cross-industry variation in customer type, based on the idea that industries with retail customers are directly affected by the QR-code payment technology. Specifically, we rely on a difference-in-differences estimation, using business-to-consumer industries as the treatment group and business-to-business industries as the control group. Only firms in the treated industries enjoy the benefits of the QR-code payment technology; at the same time, our DID estimation allows us to use the post-shock change in the control group to capture the contemporaneous shocks that affect both the treatment and the control groups.

We first document the causal effect of QR-code introduction on business creation. After the shock, monthly business creation among business-to-consumer industries increased by 8.9% more than for business-to-business industries, which is equivalent to a monthly increase of 156 business-to-consumer firms. The effect is entirely driven by small businesses. To facilitate a causal interpretation, we show that there were no differential trends in business creation between the treated industries and the control industries before the QR-code introduction, and there was no effect in the tourism areas where foreign visitors are major customers and mobile payment is less accessible for them. Moreover, the post-shock business creation is more pronounced in public housing communities, low-house-price areas, and non-prime districts, suggesting a positive role of mobile payment technology in promoting inclusive growth and mitigating inequality in development.

What are the economic forces that underly the increase in small business creation? As argued earlier, mobile payment technology provides direct and indirect benefits to all three sectors—merchants, consumers, and banks. To begin, mobile payment technology directly introduces cost-saving benefits for small merchants. By exploiting the cross-industry variation in the cash-handling cost (Arango and Taylor, 2008), we show a stronger business creation in the high cash-cost industries, lending support to the hypothesis.

The cost saving benefit also implies consumers' adoption of mobile payment. Indeed, consumers switch from cash usage to mobile payment after the QR-code introduction. Using the bank's financial transaction data under a diff-in-diff framework, we classify consumers who are more (less) receptive to mobile payment before the QR code event as the treatment (control) group. After matching the treated and control consumers based on their demographic and financial information, we find that the treated consumers—those who were *ex ante* more receptive to mobile payment—increased their mobile payment amount by 25.4% after the shock, relative to their matched control group. Our estimate implies that the aggregate increase in mobile payment spending as a response to the QR-code payment technology is at least SGD 4.5 million per month.

At the same time, the treatment group significantly decreased their cash withdrawal amount by 2.7% afterwards, which is driven by the reduction in ATM cash withdrawal amount. Consistent with the observed decline in ATM cash withdrawal by consumers, ATMs at the bank closed at an increasing rate after the QR payment introduction. Moreover, areas that experienced a higher acceleration of ATM closure coincide with those that witnessed a larger increase in small business creation.

Furthermore, the added convenience associated with the QR-code payment technology can stimulate consumers' demand and further benefit merchants. We document that the consumers increased their total spending by 4.2% per month after the introduction of mobile payment technology. Notably, a large portion of the total spending increase is unexplained by spending using mobile payment. Consumers also significantly increased their credit card spending by 3.3% during the post-shock period.

To understand the increase in credit card spending, we note that banks may endogenously respond in their provision of credit card payment service given its high profit margin (as well as credit card's appealing features that meet consumer needs). Consistently, treated consumers are more likely to start using a credit card or increase the number of credit cards after the QR code introduction. Conditional on owning a credit card account, treated consumers also witnessed a rise in their credit limit. These results echo the earlier argument regarding a more nuanced effect of mobile payment in the presence of credit cards. To the extent that credit cards remain unpopular among small merchants after the QR code introduction, part of the increased consumer demand is diverted into existing large businesses as well as the banking sector, potentially muting the aggregate impact of mobile payment on business creation.

To wrap up the empirical analysis, we use our bank data to assess the business performance by studying the income change of entrepreneurs after the QR-code introduction. Specifically, self-employed consumers, who are more likely to be an owner of small businesses, experienced a significant increase in their bank account inflow and total spending after the introduction of QR-code payment, compared with the non self-employed.

Our empirical results show that the QR-code technology affects multiple sectors (i.e., consumers, merchants, and banks) in the economy. To link these empirical findings together, we develop a model that rationalizes the responses of each sector. In the model, consumers choose a payment method; mobile technology is modeled as a decrease in the transaction cost for mobile payment. Merchants decide on whether to enter the market based on the expected profit. Banks decide the optimal number of ATMs and credit supply to maximize the profit. We estimate the model to match empirical moments, which are i) consumers' choices of payment methods, ii) the number of merchant entries, iii) the number of ATMs, and iv) the credit supply offered by banks over time. The estimates find that consumers' choices of payment methods are sensitive to the QR-code technology. Small merchants' profits increase when more consumers switch from cash to mobile payment. Moreover, relative to mobile payment, banks have a higher profit margin for

credit cards and a lower profit margin for cash. The model predicts that, consistently with the empirical evidence, after the mobile payment technology, banks lower the number of ATMs to facilitate the substitution from the less profitable sector (i.e., cash) to more profitable sectors (i.e., mobile payment and credit cards).

Using the estimated model, we perform a series of counterfactual analyses to understand the key structural parameters that drive the effects of mobile payment technology. The results highlight the importance of financial intermediary (i.e., banks) on the impact of mobile payment technology, leading to distinct implications of the mobile payment across countries. In markets where the credit card's profit margin is higher (e.g., US), banks provide a lower number of ATMs and a higher credit supply to retain its profitable credit card business, diluting the effect of mobile payment technology. On the other hand, if the mobile payment has a higher profit margin than what we document in Singapore (e.g., China), banks have a lower incentive to steer consumers from mobile payment to credit cards, amplifying the effect of mobile payment technology. We also find that mobile technology has a larger impact when fewer consumers use credit cards or more consumers use cash before the introduction. Overall, counterfactual analyses are consistent with the different patterns when mobile payment technology was introduced in other countries, strengthening the external validity of our findings.

Our paper directly adds to the emerging literature on FinTech and digitization, with a specific focus on its real impact. One strand of literature documents that by mitigating credit constraint faced by small merchants, FinTech credit can boost their sales growth (Hau, Huang, Shan, and Sheng, 2018), reduce sales volatility (Chen, Huang, Lin, and Sheng, 2019), and facilitate the accumulation of customer capital (Huang, Lin, Sheng, and Wei, 2019). FinTech influences consumers' spending behavior (Agarwal, Ghosh, Li, and Ruan, 2019; Carlin, Olafsson, and Pagel, 2019; D'Acunto, Rossi, and Weber, 2019; D'Acunto, Rauter, Scheuch, and Weber, 2019). The closest paper to ours is Agarwal, Qian, Yeung, and Zou (2019), which also investigates the effect of mobile payment technology. However, it focuses on a narrow perspective by examining how the improved payment convenience for consumers benefits debit card and credit card sales at existing merchants that accept card payment.

We provide a comprehensive and structured analysis on how mobile payment reshapes economic activities and stimulates the real economy (as measured by small business growth). While existing studies focus on a single aspect of the economy, this paper emphasizes the role of multiple sectors—merchants, consumers, and banks—in driving the effect of mobile payment technology. Specifically, we model and delineate responses by all sectors that are affected by the technology, using the key insight that mobile payment technology reduces frictions for both consumer and merchant sectors. One novel insight from our paper is the role of financial intermediaries in advancing FinTech given the tradeoff among various payment methods.

We also contribute to the literature on the implication of technologies on inclusive growth and inequality (Chava et al. 2018; Fuster et al., 2018; Chen and Qian 2019; Mihet, 2019; Philippon,

2019). Gupta, Ponticelli, and Tesei (2019) document mobile phone coverage promotes the adoption of high yielding variety seeds, chemical fertilizers, and credit access in rural India. Fan, Tang, Zhu, and Zou (2018) shows that by reducing the fixed cost of setting up a brick-and-mortar store, E-commerce increases the accessibility of cheaper products from distant locations, thereby mitigating spatial consumption inequality. We add to the literature by documenting that mobile payment technology can promote inclusive growth by fostering the creation of small businesses, especially those located in poorer communities.

The remainder of the paper is organized as follows. Section II provides the institutional background of the mobile payment technology shock we exploit in this study. Section III describes the details of our dataset. Section IV explains the identification and empirical strategy, along with summary statistics. Section V shows the empirical results. Section VI provides a model that rationalizes and extends the empirical evidence. Finally, section VII concludes.

## **II. Institutional background**

Before 2017, Singapore had already possessed a well-developed infrastructure for mobile payment. It is one of the first countries to adopt the FAST (Fast and Secure Transfers) payment system, which allows consumers to perform 24/7 instant fund transfer. The proportion of the banked population is also among the highest in the world (98%). The high penetration rate of smartphones (>73% as of 2016) also demonstrates technological readiness for mobile payments.

In early 2014, several major commercial banks in Singapore, including our bank, launched mobile payment applications that allow consumers to make person-to-person (P2P) fund transfers within the bank's customers. However, the utilization of mobile devices for payments remains relatively small: only 3% of the retail businesses choose mobile payment as their preferred payment instrument (Monetary Authority of Singapore, 2016). On the other hand, consumers in Singapore still show a strong preference for cash: 60% of retail transactions are fulfilled by cash (Monetary Authority of Singapore, 2016). The slow settlement of payment, high transaction and management cost, and concerns for fraud and security constitute the significant reasons that hinder the promotion of cashless payment.<sup>2</sup>

As one of the pillars of achieving the Smart Nation Vision, in 2017, mobile payments in Singapore took a major step forward. On 13th April 2017, the leading bank in Singapore, DBS, became the first bank in Singapore to launch QR (Quick Response) code payment in the city-state. After that, an increasing number of local banks started to advocate QR code payment. This mobile payment technology allows consumers to make transactions or transfer funds by displaying or scanning QR codes on their mobile phones. Compared with the existing mobile payment

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<sup>2</sup> The low adoption rate is also likely to be driven by coordination problems, as suggested by Crouzet, Gupta, and Mezzanotti (2019).



technology, the QR-code payment is more straight-forward, efficient, and secure, which can significantly reduce transaction costs, especially for small and new businesses (Agarwal et al. 2019). Importantly, unlike existing cashless payment technologies, such as credit cards, which charge a high level of transaction fees (up to 2-3%), mobile payment charges no transaction costs for individuals and small merchants.<sup>3</sup> In November 2017, Network for Electronic Transfers (NETS), the leading Singaporean electronic payment service provider, launched the first unified QR code that is universally applicable for consumers of six leading local commercial banks, which further strengthened the infrastructure of QR-code payment in Singapore.

On 10th July 2017, the Association of Banks in Singapore introduced another mobile payment technology, Paynow. As an enhanced peer-to-peer (P2P) payment instrument on mobile phones, Paynow allows retail consumers to perform instant free-of-charge fund transfer by just using counterparties' mobile phone numbers or national ID number. More importantly, unlike the previously introduced mobile payment technology, Paynow allows for inter-bank fund transfer, which further facilitates the usage of mobile payment.

The introduction of the new mobile payment technology significantly reduced the cost of mobile payment and therefore boosted its usage. Figure 1 shows the time trend of mobile payment usage around the launch of the QR code payment, based on a random, representative sample of our bank's retail customers composed of 250,000 individuals. As shown in Panel A, the first year subsequent to QR code introduction witnessed an increase in the number of consumers who signed up (used) mobile payment by 53.8% (304%). In addition, the total dollar amount of mobile payment transactions exhibited a significantly larger increase by 9.8 times (shown in Panel B), suggesting mobile payment adopters become more active after the technology shock. Notably, in both figures, mobile payment adoption shows a further acceleration after the introduction of mobile interbank fund transfer (i.e., Paynow), suggesting this second shock reinforced the effect of QR-code payment and further promoted mobile payment usage.

*[Insert Figure 1 here]*

### **III. Data**

Our data mainly comes from two sources, which we describe separately in this section.

#### *3.1 Data for business creation analysis*

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<sup>3</sup> Similarly, WeChat Pay and Alipay, the largest mobile payment service providers in China, also charge no transaction fees for individuals and small merchants.

Our data of business creation comes from the administrative business registry data maintained by the Accounting and Corporate Regulatory Authority (ACRA), the national regulator of business entities in Singapore. As per section 5 of the Business Names Registration Act, generally, all forms of businesses must be registered with the ACRA. Therefore, our registry data contains the population of the firms created in Singapore. For each newly created firm, we can observe the firm name, date of registration, registered office address, the Singapore Standard Industrial Classification (SSIC) code, as well as firm's legal status (i.e., Sole Proprietorship, Partnership or Corporation).

For the purpose of evaluating the effect of mobile payment on business creation, we aggregate the monthly number of firms created at the 4-digit SSIC industry level. Our full sample period runs from January 2016 to December 2018. In the main analysis, we focus on the sample period from January 2016 to April 2018, which is the 12<sup>th</sup> month after the introduction of QR-code payment, so as to alleviate the potential concern of other confounding events.

### *3.2 Data of consumer financial transaction*

Our data of consumer financial transactions comes from a unique, proprietary dataset obtained from DBS, the largest and dominant bank in Singapore serving about 5 million retail customers, or 82 percent of the entire city state's population. We observe the consumer financial transaction information of 250,000 individuals, which is a random, representative sample of the bank's retail customers, in a 36-month period between 2016:01 and 2018:12. Specifically, our bank data has four parts. The monthly statement information of credit cards, debit cards, and bank accounts include the balance, total debit and credit amount (for bank accounts), card spending (for credit and debit cards), credit card limit, credit card payment, and debt. The transaction-level disaggregated information of bank accounts, credit cards, and debit cards contains each transaction's type (e.g., ATM cash withdrawal, mobile payment, or card spending), transaction amount, date, merchant category code (for credit and debit cards), and merchant name. We also observe the transaction-level information of ATM transactions of all the DBS ATMs, including transaction amount, transaction timestamp, location, and masked consumer ID. Lastly, the dataset also contains a rich set of demographic information about each individual, including age, gender, income, property type (HDB or private), nationality, ethnicity, and occupation.

For our purpose, we aggregate consumers' financial transaction data at the individual-month level. Following Agarwal and Qian (2014, 2017), in order to capture the full picture of consumers' financial transactions, we only include consumers who have both bank account and credit card account with our bank at the same time. We also exclude inactive consumers as of the event time (i.e., consumers with zero monthly spendings for at least half of the sample period as of the event time). Out of 250,000 consumers in our sample, there are 138,448 active consumers who have both

bank account and credit card account with our bank. Consistent with the analysis of business creation, for the bank data, we also restrict our sample period from January 2016 to April 2018.

#### IV. Identification and Empirical Strategy

To identify the impact of the mobile payment technology on business creation, we exploit the cross-industry variation in the exposure to retail consumers using the QR-code payment technology. Specifically, only firms providing goods or services to retail consumers benefit from the convenience of the QR-code payment technology. We, therefore, employ a difference-in-differences approach, using business-to-consumer industries as the treatment group, and business-to-business industries as the control group.<sup>4</sup> The classification of the treatment status is at the 4-digit SSIC industry level. Table 1 shows the summary statistics of the treated and control industries.

We first plot the unconditional means of the numbers of businesses created in the treatment and control group around the time of the technology introduction (January 2016–April 2018). As shown in Figure 2, the levels and trends of business creation in the treatment and control groups are very similar before the technology introduction, which supports the parallel-trends assumption. In addition, the two lines start to diverge significantly after the technology shock, which provides suggestive evidence of the impact of mobile payment on business creation. Consistent with the pattern of mobile payment adoption in Figure 1, the increase in business creation is more pronounced after the introduction of mobile interbank fund transfer.

We then perform our difference-in-differences analysis using the following specification:

$$Y_{it} = \beta \times Treatment_i \times Post_t + \alpha_i + \delta_t + \theta_{dy} + \epsilon_{it} \quad (1)$$

Specifically, the dependent variable,  $Y_{it}$ , is the log number of newly created firms in month  $t$  industry  $i$ .<sup>5</sup>  $Treatment_i$  is a dummy variable equal to 1 for business-to-consumer industries, and 0 for business-to-business industries.  $Post_t$  is a dummy that equals 1 for the months after the introduction of QR-code payment technology (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark period in our estimation.  $\alpha_i$  represents a vector of industry fixed effects;  $\delta_t$  represents a vector of year-month fixed effects; the  $\theta_{dy}$  is the 2-digit industry division $\times$ year fixed effects, aimed to absorb the time-variant common shocks at the 2-digit

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<sup>4</sup> Business-to-consumer industries are those that provide goods or services directly to retail consumers, including retail trade, food and beverage service, education, health, entertainment, and other personal/household services (e.g., plumbing, domestic cleaning services, etc.).

<sup>5</sup> To avoid undefined dependent variable when a given industry has no firm created in a given month, we use  $\log(1+\text{number of new firms created})$  as the dependent variable. As a robustness test, in Table A1, we repeat our main result using the inverse hyperbolic sine transformation as an alternative of log transformation (which allows retaining zero-valued observations), and find similar results.

industry-division level.<sup>6</sup>  $\beta$  captures the average percentage change in the number of monthly firm creation in the treatment group (relative to the average change in the control group) after the introduction of QR-code payment technology (compared with the benchmark period, i.e., January 2016–March 2017).

We also estimate the dynamic effect of mobile payment on firm creation. Specifically, we estimate the following distributed lag model:

$$Y_{it} = \sum_{s=0}^{12} \beta_s \times Treatment_i \times 1_{month\ s} + \alpha_i + \delta_{dy} + \epsilon_{idt} \quad (2)$$

The estimates of Equation (2) can be interpreted as an event study. The coefficient  $\beta_s$  measures the average change in the log number of newly created firms (relative to the average change in the control industries) in the  $s^{th}$  month after the QR-code payment introduction (compared with the benchmark period, i.e., January 2016–March 2017), with  $s$  ranging from 0 (i.e., April 2017) to 12 (i.e., April 2018). Therefore, the cumulative estimated coefficient  $b_s \equiv \sum_{t=0}^s \beta_t$  describes the cumulative increase in business creation after  $s$  months.

## V. Empirical Evidence

### 5.1 Main results

In Column 1 of Table 2, we report the results of the average treatment effect of mobile payment technology on business creation. The coefficient on the interaction term of “*Treated*” and “*Post*” suggests a both statistically and economically significant treatment effect: after the QR-code payment introduction, business creation among business-to-consumer industries increased by 8.9% per month more than business-to-business industries, relative to the pre-introduction period. Given that, on average, there are 1,758 firms created per month in the business-to-consumer industries during the pre-event window (Table 1), the mobile payment technology shock increased the number of firms created from business-to-consumer industries by 156.4 per month.

Figure 3 shows the dynamic effect of mobile payment on firm creation estimated according to Equation (2). Consistent with the pattern of mobile payment adoption in Figure 1, the treatment effect on business creation is more pronounced after the introduction of mobile interbank fund transfer. The cumulative effect by the 12<sup>th</sup> month after the QR code introduction, or  $b_{12}$ , is 124.5%,

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<sup>6</sup> Note that the treatment status is defined at the 4-digit industry level. Within a 2-digit industry division, there are significant variation of the treatment status. For example, the industry division “Rental and leasing activities” includes both B2C industries (e.g., Renting and leasing of personal and household goods) and B2B industries (e.g., Leasing of non-financial intangible assets).

equivalent to an increase of 2,188 firms from the treated industries, suggesting a persistent and economically large impact.

Column 2 shows the test of parallel-trends assumption. Specifically, we additionally control for  $Treated \times Pre$ , with  $Pre$  equal to 1 for the nine months immediately the technological shock (i.e., July 2016-March 2017). The corresponding coefficient estimate suggests that the treatment effect during the pre-event window is statistically insignificant and economically small.

We then use the legal entity type to measure the size of businesses: we define sole-proprietorship or partnership businesses as small businesses and define companies as large businesses. In Column 3, we repeat the analysis in Column 1 but restrict the sample to small businesses only. The number of small businesses created among the treated industries grew by 12.3% per month after the QR code introduction, relative to the control industries. Column 4 shows that the effect during the pre-event window is economically small and statistically insignificant, which further supports the parallel trend assumption. On the other hand, as shown in Column 5, large businesses do not exhibit a significant treatment effect.

Given that the effect of business creation is concentrated in small businesses, unless stated otherwise, the remaining of the analysis is based on non-companies only.

## 5.2 Falsification test

In this section, we perform a falsification test by looking at the business creation among areas with low mobile-payment penetration. Tourists are a major contributor to the Singapore economy. Tourism areas, where merchants serve a higher fraction of foreign visitors that do not have access to this domestic-user-oriented mobile payment technology, should experience a smaller growth in business creation after the technology shock.<sup>7</sup> Consistently, the effect concentrates on the non-tourism areas, while the change in small business creation in the tourism areas is negligible statistically and economically (the p-value for the Chow test on the two coefficient estimates' difference is 0.012). This result further shows that the effect on business creation is driven by the introduction of mobile payment (see Table A2 of the Internet Appendix).

## 5.3 Heterogeneous effect in different regions

To the extent that the QR-code technology is an extremely low-cost service that can help mitigate the frictions in the real world, we conjecture that mobile payment technology can promote

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<sup>7</sup> As per Wikipedia, tourism areas include the Sentosa island, the Orchard area, the Marina bay area, the Raffles place area, Singapore zoo, River Safari, Botanic garden, Changi Airport, Jurong Bird Park, and Night Safari. (<https://en.wikipedia.org/wiki/Singapore#Tourism>)

inclusive growth. In this section, we investigate whether the effect of mobile payment is stronger among less wealthy communities.

We first use residential house prices as a proxy for the average wealth of a community. At the 2-digit postal sector level, we define an area as a low-house-price area if its average residential property transaction price during the pre-event window (from January 2016 to March 2017) is below the median of all postal sectors. As shown in Table 3 Panel A, after the QR-code payment introduction, small business creation increased by 12.8% per month in low-house-price areas, while the treatment effect is only 6.1% in high-house-price areas (the p-value for the Chow test is 0.090).

Using the same method, in Panel B, we investigate the heterogeneous treatment effects among prime versus non-prime districts.<sup>8</sup> The results show that the treatment effect is significantly larger among the non-prime areas than among the prime areas ( $p=0.047$ ). Lastly, in Panel C, we measure the average wealth of a community by whether it is close to a public housing area. The public housing in Singapore, or Housing and Development Board (HDB) flats are built primarily to provide affordable housing for the less wealthy. We define HDB areas to be those within a 500-meter radius of an HDB building. Consistently, HDB areas show significantly larger treatment than non-HDB areas ( $p=0.066$ ).

#### *5.4 Heterogeneous effect: the role of cash-handling costs*

We then move on to analyze the underlying economic forces that explain the increase in small business creation. We start with the mobile payment's direct cash-saving benefits for small merchants by exploiting the cross-industry variation in the cash-handling cost. Based on a survey for more than 400 merchants in the retail and food industry divisions, Arango and Taylor (2008) show that food and grocery stores, gas stations, and miscellaneous retailers have a relatively higher cost of handling cash, compared with other types of merchants in the retail trade and food industry divisions. Using this classification, we group industries in the retail and food industry divisions into high-cash-handling-cost and low-cash-handling-cost industries.<sup>9</sup> To the extent that industries with higher costs of cash transaction can enjoy more cost savings from the mobile payment technology shock, we expect a larger treatment effect among high-cash-handling-cost industries.

Table 4 Column 1 shows the treatment effect of high-cash-handling-cost retail and food industries. Specifically, we estimate a DID regression that compares the small business creation in

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<sup>8</sup> In Singapore, the prime districts include postal district 1, 2, 6, 9, 10 and 11

<sup>9</sup> Specifically, high-cash-handling-cost retail and food industries include retail sale in non-specialized stores with predominantly food and beverages products; retail sale of food in specialized stores; retail sale of automotive fuel in specialized stores; retail sale of handicrafts and fancy goods, flowers, plants and pet animals in specialized stores; retail sale of other goods in specialized stores; retail sale via stalls and markets; fast food outlets, food courts, and food kiosks; stalls selling cooked food and prepared drinks.

high-cash-handling-cost retail and food industries with the small business creation in all B2B industries. After the QR-code payment introduction, the number of small business creation in high-cash-handling-cost industries increased by 43.7% per month. By the same token, in Column 2, we estimate the treatment effect among low-cash-handling-cost retail and food industries and find the effect statistically insignificant and discernibly smaller. (The difference between the two estimates is statistically significant, with  $p=0.026$ .)

Within the high-cash-handling-cost industries, some industries are targeted by a mobile payment promotion campaign while some are not. From November 2017 to March 2018, NETS, along with the top 3 Singapore local banks, provided rebates for consumers who make frequent mobile-payment purchases in hawker centers and food stalls. To the extent that promotions can boost the adoption of mobile payment, we expect a stronger treatment effect among the industries targeted by the campaign.<sup>10</sup>

In Table A3 of the Internet Appendix, we separately estimate the treatment effect among industries targeted by the promotion campaign (in Column 1) and the treatment effect among high-cash-handling-cost retail and food industries that do not enjoy the promotion (in Column 2). Consistently, industries that enjoy the mobile-payment promotion show a significantly larger treatment effect than those not targeted by the promotion campaign ( $p=0.003$ ). In addition, the small business creation among the high-cash-handling-cost industries that do not enjoy the promotion also exhibits a significant increase (by 23.5%), which lends further support to the role of the lowered cash handling costs absent promotion.

### *5.5 Mobile payment and consumers' cash usage response*

In addition to the direct cost-saving effect on small merchants, the QR-code payment technology brings convenience to consumers by removing their need to carry cash. With reduced reliance on cash, consumers face lower transaction costs, which can boost their demand and, in turn, benefit the merchants. Nevertheless, given the prevalence of other existing cashless payment methods, such as credit card, the incremental effect of mobile payment on consumers' cash usage is unclear. In this section, we examine whether the newly introduced mobile payment technology managed to encourage consumers' switch from cash usage to mobile payment.

We employ a difference-in-differences approach, using consumers with higher-level exposure to the technology shock as the treatment group and consumers with lower-level exposure as the control group. Conceptually, consumers with previous experience of mobile payment usage are more receptive to the newly-introduced mobile payment technology. Thus, we define consumers who signed up for mobile payment with our bank before the event as the treatment group, and

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<sup>10</sup> Specifically, industries targeted by the promotion campaign include retail sale via stalls and markets; fast food outlets, food courts, and food kiosks; stalls selling cooked food and prepared drinks.

consumers who did not sign up for mobile payment as of the event time as the control group. Specifically, we estimate the following regression model:

$$Y_{it} = \beta \times Treatment_i \times Post_t + \alpha_i + \delta_t + \epsilon_{it} \quad (3)$$

Where  $Y_{it}$  is the logarithm of spending in different categories (i.e., mobile payment, cash withdrawal, credit card spending, debit card spending, or bill payment) for consumer  $i$  in month  $t$ .  $Treatment_i$  is a dummy variable equal to 1 for consumers who had already signed up for mobile payment before the introduction of QR code, and 0 for the remaining consumers.  $\alpha_i$  represents a vector of individual fixed effects. Standard errors are clustered at the individual level.

Before we proceed to the regression analysis, in Table 5, we tabulate the summary statistics of the consumers from the treatment and control group. As shown in Panel A, the treated and control consumers show observable differences in multiple dimensions. For a cleaner identification, we conduct a propensity-score matching to control for the observable differences between the two groups. Specifically, we calculate the propensity scores using a logistic regression that controls for the individual's latest updated pre-event information of age, income, bank account balance, gender, nationality, marital status, ethnicity, and tenure with our bank (see Table A4 for the logistic regression result). We then conduct a one-to-one nearest-neighbor matching without replacement. As shown in Panel B of Table 5, after matching, the differences in observables between the two groups become statistically and economically indistinguishable from zero.

Consistent with our hypothesis, the treated consumers are indeed more receptive to the newly-introduced mobile payment technology than the control consumers. As shown in Table 6 Panel A Column 1, the treated consumers increased their mobile payment amount by 25.4% after the introduction of QR-code payment, relative to the control consumers. Given the average pre-event monthly mobile payment amount of SGD 10 for the treatment group (Table 5 Panel C), the introduction of QR-code payment technology increased the mobile payment amount of the treated consumers by SGD 2.5 per month. Since 35.6% of the consumers are treated in our sample (Table 5 Panel A), it follows that the total increase in mobile payment for the consumers in our sample is SGD 222,500 per month. Since our sample accounts for about 5% of the population of the local retail consumers in our bank (250,000 out of 5 million), our estimate implies that the aggregate increase in mobile payment as a response of the QR-code payment technology is SGD 4.5 million per month, which is economically large. Note that this number is likely to be a lower bound, since a significant proportion (18%) of consumers in the control group also adopted mobile payment within the 12 months after the QR-code payment introduction. In Column 2 and Column 3, we decompose mobile payment into “payment to business” and “P2P transfer” and find the increase in mobile payment is mainly driven by the “P2P transfer” component.

At the same time, mobile payment technology induced consumers to decrease their cash usage. As shown in Table 6 Panel B Column 1, the treated consumers significantly decreased their cash withdrawal amount by 2.7% after the event. In Column 2 and Column 3, we decompose total cash withdrawal into “ATM cash withdrawal” and “over-the-counter cash withdrawal”. The decrease



in cash withdrawal is entirely driven by ATM cash withdrawal, while over-the-counter cash withdrawal shows no response after the technology shock.

### 5.6 ATM closure response

With the prevalence of mobile payment, consumers are moving from ATM cash withdrawal to cashless payment. Accordingly, ATMs at the bank closed at an increasing rate after the QR payment introduction: the number of ATM closed increased from 11.9 per month during the pre-event period to 16.6 per month after the introduction of QR-code payment. More importantly, if operating efficiently, banks are supposed to close ATMs in areas with a larger increase in mobile payment usage, which are also likely to be areas that exhibit a more pronounced increase in small business creation. Based on our ATM data, in this section, we empirically examine this hypothesis.

We start by applying the geographical heterogeneity analysis in section 5.3 on the probability of an ATM being closed after the introduction of mobile payment. Specifically, at the ATM level, we estimate the following cross-sectional regression:

$$Closure\_after\_event_i = \alpha + \beta \times Region_i + \epsilon_i \quad (4)$$

The sample is restricted to the 1,188 ATMs that had already been existing at the beginning of our sample period (January 2016).  $Closure\_after\_event_i$  is a dummy equal to 1 if ATM  $i$  is closed after the introduction of QR-code payment.  $Region_i$  is a dummy indicating whether ATM  $i$  falls into a specific region group (i.e., HDB versus non-HDB areas, high versus low house price areas, or prime versus non-prime areas, as defined in section 5.3). As shown in Panel A of Table 7, ATMs located in HDB areas (Column 1), low-house-price areas (Column 2) and non-prime areas (Column 3) are more likely to be closed after the introduction of mobile payment, with the estimates statistically significant for the HDB-area dummy and low-house-price-areas dummy.

By the same token, we investigate the geographical heterogeneity in ATM opening after the introduction of mobile payment, conditional on the 111 ATMs opened after the first month of our sample period (January 2016). As shown in Panel B of Table 7, across different areas, we find no significant difference in the ATM opening after the introduction of QR-code payment.

We then examine whether areas that exhibit a larger treatment effect of small business creation also show a more pronounced acceleration in ATM closure after the launch of QR-code payment. At the planning area level, we estimate the following cross-sectional regression:<sup>11</sup>

$$\Delta ATM\_closure\%_i = \alpha + \beta \times \Delta Treated\_firm\_growth\%_i + \epsilon_i \quad (5)$$

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<sup>11</sup> Planning areas are the main urban planning and census divisions of Singapore. There are 55 planning areas in total.

Where,  $\Delta ATM\_closure\%_i$  is the increase in the average monthly ATM closure rate during the post-event period relative to the pre-event average in planning area  $i$ ;  $\Delta Treated\_firm\_growth\%_i$  is the growth rate of the average monthly small business creation per treated industry during the post-event period relative to the pre-event period, net of the growth rate for the control industries, in planning area  $i$ . Standard errors are derived based on 1,000 bootstrap replications.

As shown in Table 7 Panel C, there is a significantly positive correlation between the speedup of ATM closure rate and the treatment effect of small business creation across planning areas. Given that the standard deviation of  $\Delta ATM\_closure\%$  and  $\Delta Treated\_firm\_growth\%$  are respectively 1.4% and 31.3%, the coefficient estimate (0.013) suggests that one-standard-deviation increase in the growth rate of small business creation can explain 0.29 standard deviation of the increase of monthly ATM closure rate, suggesting an economically meaningful impact.

In Figure 4, we plot a pair of heatmaps that respectively visualize the geographic distribution of  $\Delta ATM\_closure\%$  and  $\Delta Treated\_firm\_growth\%$ . Consistent with the regression result, areas that experienced a higher acceleration of ATM closure coincide with those that witnessed a larger increase in small business creation.

### *5.7 Consumers' spending response*

As discussed earlier, QR-code payment offers convenience to consumers, which can stimulate consumers' demand and further benefit merchants. Using the bank data, in this section, we examine consumers' spending response to the mobile payment technology introduction.

The results are shown in Table 8. Based on the matched sample and the regression specification shown in Equation (3), we find that the treated consumers increased their total spending by 4.2% after the introduction of mobile payment technology (Table 8 Column 1). Given the average pre-event monthly total spending amount of SGD 4,100 for the treatment group (Table 5 Panel C), the mobile payment technology shock increased the spending of the treated consumers by SGD 172.

In Column 2-6, we take a closer inspection of the spending response in different categories. In addition to a decrease in cash withdrawal and an increase in mobile payment, we also find a significant increase in card spending, which is mainly driven the increase in credit card spending (by 3.3%). Bill payment shows no change.

The fact that consumers' credit card spending increases together with their mobile payment usage is intriguing. One may expect that mobile payment should serve as a substitute for card spending. Nevertheless, consumers may still want to enjoy credit cards' liquidity provision as well as promotion benefits. Banks also have a strong incentive to maintain the market share of the credit card business lines given their high profit margin. As a result, banks may increase their credit provision in response to the mobile payment technology shock.

Consistent with bank's response channel, consumers show a significant credit response to the mobile payment technology. With all the consumers in our dataset included, in Table 9 Column 1, we find consumers with prior experience of mobile payment usage exhibit an increase in the probability of becoming a credit card holder by 1.6% after the introduction of QR-code. Column 2 shows that the number of credit cards owned by the existing cardholders in the treatment group increased by 0.09 after the event, equivalent to a 3.1% increase relative to their pre-event mean. These results show a wider usage of credit cards by consumers after the introduction. Moreover, conditional on having a credit card account, treated consumers also experience an increase in credit card limit by 4.7% after the technology shock, as shown in Column 3.<sup>12</sup>

### *5.8 Change in income and spending of the self-employed*

So far, we mainly focus on business creation to evaluate how mobile payment technology stimulate small business growth. In the last section of the empirical analysis, we use our bank data to assess the business performance aspect by studying the income and spending change of entrepreneurs after the introduction of mobile payment technology.

According to the occupation information in our bank data, 3.7% of the consumers are "self-employed", who are likely to be an owner of a small business. As shown in Table A5 of the Internet Appendix, self-employed consumers increased their bank account inflows by 6.9% after the introduction of mobile payment technology, compared to the non self-employed consumers. This suggests an increase in their income. They also exhibit a significant increase in their total spending by 3% after the technology shock.

## **VI. Model**

Our empirical results show that QR-code technology affects multiple sectors (i.e., consumers, merchants, and banks) in the economy. To link these empirical findings, we develop a model that rationalizes each sector's response. The model further helps us understand the key structural parameters that drive the effects of mobile payment technology in these different sectors.

In the model, consumers choose a payment method for the transaction. Merchants make an entry decision based on their expected profit from entering. The profit-maximizing bank decides the number of ATMs and credit supply. Both merchants and the bank have different profit margins for each payment method. We start with the model of consumers.

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<sup>12</sup> In Singapore, interest rate on credit cards are constant across consumers or cards, making it an unlikely venue for the bank to respond. We also consider other potential margins of adjustment such as cashback on credit cards and find no change in the post-QR period.

## 6.1 Consumers

Consumer  $i$  chooses a payment method  $j$  from among the following options: cash, credit card, mobile payment, debit card, or an outside option (i.e., no transaction).<sup>13</sup> We define consumer  $i$ 's utility at time  $t$  associated with each payment method as follows.

$$U_{ijt} = \begin{cases} -\text{TXNCost}_{cash} + \theta \log(ATM)_t + \varepsilon_{it,cash} & \text{if } j = \text{cash}, \\ -\text{TXNCost}_{credit} + \beta \log(CL)_t + \varepsilon_{it,credit} & \text{if } j = \text{credit}, \\ -\text{TXNCost}_{mobile,t} + \varepsilon_{it,mobile} & \text{if } j = \text{mobile}, \\ -\text{TXNCost}_{debit} + \beta_s \log(CL)_t + \varepsilon_{it,debit} & \text{if } j = \text{debit}, \\ \varepsilon_{it,outside} - \rho \text{Entry\_B2C}_t & \text{if } j = \text{outside}, \end{cases} \quad (6)$$

where  $\text{TXNCost}_j$  is the time-invariant transaction cost for payment method  $j$ .  $ATM$  is the number of ATMs. Cash becomes more preferable for consumers when there are more ATMs; parameter  $\theta$  measures how sensitive the consumer's use of cash is to the number of ATMs.  $CL$  is the credit supply from the bank (i.e., credit limit). A higher credit limit increases the consumer's use of credit cards; parameter  $\beta$  measures how sensitive the consumer's use of cash is to the number of ATMs. We also leave room for the possibility of interaction between two different card options (i.e., credit cards and debit cards); we model this by allowing  $\beta_s$  to measure the preference for debit cards depending on the average credit limit. Finally,  $\varepsilon$  is a random variable that captures the unobserved preference heterogeneity for each payment method.

Since the presence of more firms may increase the consumer's probability of a transaction, we model this channel as the average probability of entries across firms,  $\text{Entry\_B2C}$ , expecting it to decrease consumers' value of the outside option (i.e., no transaction).<sup>14</sup> The variable  $\rho$  measures the effect of firm entries on the probability of making a transaction.

We also seek to model the effect of QR-code technology on reducing the transaction cost of a mobile payment, but this cost depends on whether the technology has been introduced (i.e., whether the transaction is after April 2017). Specifically, we parametrize  $\text{TXNCost}_{mobile,t}$  as follows:

$$\text{TXNCost}_{mobile,t} = \alpha_0 - (\alpha_1 + \alpha_2 m_t) \text{Post}_t. \quad (7)$$

$\text{Post}_t$  indicates whether the period is after the introduction of QR-code payment technology (i.e., April 2017).  $m_t$  indicates that period  $t$  is  $m$  months after April 2017. The variable  $\alpha_0$  is the baseline parameter for the transaction cost of mobile payment;  $\alpha_1$  captures the average effect of mobile payment adoption after the introduction of QR-code payment technology. The parameter  $\alpha_2$

<sup>13</sup> We model the choice of payment methods given a transaction amount (i.e., extensive margin). A consumer may change the transaction amount depending on payment methods (i.e., intensive margin). The model will predict more or fewer transactions to approximate the change in the intensive margin.

<sup>14</sup>  $\text{Entry\_B2C}_t = E_m[\text{Entry\_B2C}_{mt}]$  denotes the average entry probability across merchants.

captures a differential time trend after the introduction of QR-code technology. We assume  $\alpha_2 > 0$  to rationalize the increasing number of mobile payment transactions after the introduction.

Such an empirical pattern could be due to the externalities in adoption. That is, the transaction cost of mobile payment could be lower later on, when more consumers have adopted mobile payment (Crouzet et al. 2019). We model the externalities in reduced form as the change in consumer preference over time, which is modeled via a positive time trend for the transaction cost of mobile payment in Equation (7). The time trend changes the utility of mobile payment relative to other payment methods and shows that consumer preference for mobile payment becomes stronger in the later period.<sup>15</sup>

## 6.2 Merchants

For a business-to-consumer merchant  $m$ , its average profit associated with each payment method  $j$  follows

$$y_{B2C_{jt}} = \begin{cases} \tau_{cash} + \delta_t & \text{if } j = \text{cash}, \\ \tau_{credit} + \delta_t & \text{if } j = \text{credit}, \\ \tau_{mobile} + \delta_t & \text{if } j = \text{mobile}, \\ \tau_{debit} + \delta_t & \text{if } j = \text{debit}, \\ 0 & \text{if } j = \text{outside}, \end{cases}$$

where  $\tau$  is the average profit received by a business-to-consumer merchant relative to a business-to-business merchant. The profits are different across payment methods because of the cash-handling cost and credit card interchange fees. The average profit of a merchant in business-to-business industries is  $\delta_t$ ; the profit is unaffected by a consumer's choice of payment method. In other words,  $\delta_t$  represents year-month fixed effects, which control the time-specific cost fluctuations that determine the entry decisions for merchants in business-to-consumer as well as business-to-business industries. That is,

$$y_{B2B_{jt}} = \delta_t.$$

The merchant chooses to enter as long as the expected profit is greater than the profit of not entering. The average profit of not entering is normalized as zero. Therefore,

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<sup>15</sup> One limitation of the reduced-form approach to modeling externalities is that the model does not capture the demand feedback from externalities. This may further change the endogenous response of merchants and the bank. Considering the feedback, the estimates of profit margins would become less dispersed, since demand would be more responsive. In the counterfactual analysis, the bank's equilibrium response would be smaller than the current model prediction but qualitatively similar.

$$\text{Entry\_B2C}_{mt}(ATM_t, CL_t) = \begin{cases} 1, & \text{if } \sum_j y_{B2C} \times \text{Frac}_{jt}(ATM_t, CL_t) + \omega_{m1} \geq \omega_{m0}, \\ 0, & \text{otherwise,} \end{cases} \quad (8)$$

$$\text{Entry\_B2B}_{mt}(ATM_t, CL_t) = \begin{cases} 1, & \text{if } \delta_t + \omega_{m1} \geq \omega_{m0}, \\ 0, & \text{otherwise,} \end{cases}$$

where  $\omega_m$  is a random variable that captures the unobserved heterogeneity that determines a merchant's entry decision (e.g., a higher profit or a lower cost of entry).  $\text{Frac}_{jt}$  denotes the fraction of consumers choosing payment method  $j$ .  $\text{Expect}_{y_{mt}}(ATM_t, CL_t)$  denotes the average profit of a merchant in business-to-consumer industries conditional on entering.

Note that here we do not explicitly model a merchant's entry cost (i.e., an upfront fixed cost when merchant enters). Rather, the entry cost is embedded in the profit function; a higher entry cost will decrease the average profit and probability of entry.

Since we find different entry patterns for small and large merchants, we allow small and large merchants to have different profit margins, costs of handling cash, and credit card interchange fees in the estimation.<sup>16</sup> Since the rollout of QR codes mostly pushes small merchants to accept mobile payments, we assume that small and large merchants differ in the payment methods they offer to consumers. Small merchants accept mobile payments but not credit cards. Large merchants accept credit cards but not mobile payments.

To simplify the model, we only allow consumers to decide which payment method to use. A consumer's choice to visit a small or large merchant is embedded in their payment decisions. In other words, consumers visit small merchants when they choose to pay via mobile payment. If consumers decide to use cash, they have an equal probability of visiting a small merchant or a large one.

### 6.3 Bank

A profit-maximizing bank chooses the number of ATMs and the credit supply to maximize its profit. The bank's profit function for each transaction is

$$\Pi_t(ATM_t, CL_t) = -f_\gamma(ATM_t) - f_\lambda(CL_t) + \sum_j \pi_j \times \text{Frac}_{jt}(ATM_t, CL_t),$$

where  $f_\gamma$  is the cost function of maintaining ATMs,  $f_\lambda$  is the cost function of providing a given credit limit. The cost may come from the high risk associated with a higher credit limit. The credit card company weighs the marginal cost of maintaining an ATM (i.e., direct periodic maintenance costs and substitution of other payment methods with higher profit for the bank) and the marginal benefit of maintaining an ATM (i.e., more cash transactions). Similarly, providing a higher credit

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<sup>16</sup> We calibrate the fractions of small merchants and large merchants (0.46 and 0.54, respectively) using business registry data.

limit is costly to the company, but it helps retain card customers. The variable  $\pi_j$  is the average bank's profit margin of a dollar transaction for payment method  $j$ .

The first-order conditions associated with the bank's optimization problem are

$$\begin{aligned}\frac{\partial \Pi_t(ATM_t, CL_t)}{\partial ATM} &= -\frac{\partial f_\gamma(ATM)}{\partial ATM} + \frac{\partial \sum_j \pi_j \times \text{Frac}_{jt}(ATM_t, CL_t)}{\partial ATM} = 0, \\ \frac{\partial \Pi_t(ATM_t, CL_t)}{\partial CL} &= -\frac{\partial f_\lambda(CL)}{\partial CL} + \frac{\partial \sum_j \pi_j \times \text{Frac}_{jt}(ATM_t, CL_t)}{\partial CL} = 0.\end{aligned}\quad (9)$$

The bank's model highlights the importance of the role of the bank in equilibrium outcomes; we find that the bank closed more ATMs after the advent of QR-code technology. This could be due to a resulting decrease in consumers' demand for cash.

At the same time, the relevance of the credit card business influences the bank's decision. To the extent that credit cards command a higher profit margin than mobile payments, the bank would increase its credit supply to retain consumers in the credit card business after the introduction of QR-code technology.

## 6.4 Identification and Estimation

We estimate the model parameters using the administrative business registry and consumer financial transaction data from DBS. For the consumer side, we use the fraction of transactions for each payment method and the time-varying number of ATMs and credit supply to identify consumer preference. We use merchants' entry decisions to identify their profit margins. Finally, we find parameters for the bank's profit margins that fit the number of ATMs and credit supply in the data.

### 6.4.1 Estimation—Consumers

We assume that the random variable follows a type-I extreme value distribution. Given the utility function in Equation (6), the relative fraction of consumers choosing cash and card payments to mobile payment is a closed-form solution in the following:

$$\begin{aligned}\ln(\text{Frac}_{j=cash,t}(ATM_t, CL_t)) - \ln(\text{Frac}_{j=outside,t}(ATM_t, CL_t)) &= -\text{TXNCost}_{cash} + \theta ATM_t, \\ \ln(\text{Frac}_{j=credit,t}(ATM_t, CL_t)) - \ln(\text{Frac}_{j=outside,t}(ATM_t, CL_t)) &= -\text{TXNCost}_{credit} + \beta CL_t, \\ \ln(\text{Frac}_{j=mobile,t}(ATM_t, CL_t)) - \ln(\text{Frac}_{j=outside,t}(ATM_t, CL_t)) &= -\text{TXNCost}_{mobile}, \\ \ln(\text{Frac}_{j=debit,t}(ATM_t, CL_t)) - \ln(\text{Frac}_{j=outside,t}(ATM_t, CL_t)) &= -\text{TXNCost}_{debit}.\end{aligned}$$

The transaction cost parameters for cash and card payments are time-invariant. The transaction cost for mobile payment only changes in two periods (i.e., before and after the introduction of QR-

code technology). We use the monthly variations in the number of ATMs and credit supply, as well as the corresponding payment method choice over time, to identify consumers' sensitivity to ATM and credit supply. We assume a fixed and sufficiently large market size and calculate the fraction of the outside option.<sup>17</sup>

We estimate parameters regarding consumer preference by minimizing the distance between observed and predicted shares of payment methods. The share of payment methods is calculated using consumers' share of the transaction amount for each payment method. In practice, we estimate the parameters using the predicted number of ATMs,  $\widehat{ATM}$ , which we obtain using the number of ATMs in the previous month as the instrument. We use the predicted credit supply,  $\widehat{CL}$ , similarly, which we obtain using the credit supply in the previous month as the instrument.

#### 6.4.2 Estimation—Merchants

Recall that we allow merchant size to be heterogeneous. Each merchant can be either small (i.e.,  $type = small$ ) or large (i.e.,  $type = large$ ), separately.

The administrative business registry data provide the number of entries for different types of businesses. The data show the number of entries (i.e., the number of newly created firms) for business-to-consumer industries (i.e.,  $N\_B2C_{type,t}$ ) and business-to-business industries (i.e.,  $N\_B2B_t$ ) over time. We assume  $\omega$  is an error distributed by the type-I extreme value distribution. We also assume a *sufficient* number of potential entrants (i.e.,  $MS\_B2C$  and  $MS\_B2B$  for business-to-consumer industries and business-to-business industries, respectively).<sup>18</sup> Equation (7) implies that the probability of entry for a business is

$$\begin{aligned} Entry\_B2C_{type,t} &= \frac{N\_B2C_{type,t}}{MS\_B2C_{type} - N\_B2C_{type,t}} = e^{\sum_j y\_B2C \times Frac_{jt}(ATM_t, CL_t)}, \\ Entry\_B2B_t &= \frac{N\_B2B_t}{MS\_B2B_{type} - N\_B2B_t} = e^{\delta_t}. \end{aligned} \tag{10}$$

Given the estimates for consumer preference in Section 6.4.1, the  $Frac_{jt}$  is known. We estimate the profit margins using the following equation implied by Equation (10):

$$\begin{aligned} &\log(Entry\_B2C_{type,t}) - \log(Entry\_B2B_t) \\ &= \tau_{cash}^{type} \times Frac_{j=cash,t} + \tau_{credit}^{type} \times Frac_{j=credit,t} + \tau_{mobile}^{type} \times Frac_{j=mobile,t} \\ &+ \tau_{debit}^{type} \times Frac_{j=debit,t}. \end{aligned}$$

The variations in  $Frac_{jt}$  over time and the corresponding change in the number of entrants for business-to-consumer industries relative to business-to-business industries identify merchants'

<sup>17</sup> In practice, we assume the market size equals 200% of the largest transactions observed.

<sup>18</sup> We assume the size of potential entrants equals 150% of the largest number of entered businesses observed in a month.



parameters. We then estimate parameters regarding profit margins (i.e.,  $\tau$ ) by minimizing the distance between the observed and predicted merchant's share of entry.

### 6.4.3 Estimation—Bank

We impose a convex functional form on the cost functions of maintaining ATMs and providing credit:

$$\begin{aligned} f_\gamma(ATM) &= c_\gamma ATM^\gamma \\ f_\lambda(CL) &= c_\lambda CL^\lambda \end{aligned}$$

According to the bank's first-order condition in Equation (9), the cost parameters of maintaining ATMs and providing credit (i.e.,  $c_\gamma$  and  $c_\lambda$ ) satisfy the following for a given  $t=T$ :

$$\begin{aligned} c_\gamma &= -\frac{\partial \sum_j \pi_j \times \text{Frac}_{jT}(ATM_T, CL_T)}{\partial ATM} \times (\gamma ATM^{\gamma-1})^{-1}, \\ c_\lambda &= \frac{\partial \sum_j \pi_j \times \text{Frac}_{jT}(ATM_T, CL_T)}{\partial CL} \times (\lambda CL^{\lambda-1})^{-1}. \end{aligned}$$

The estimations in Sections 6.4.1 and 6.3.2 give  $\text{Prob}_{jt}$  and  $y_{mt}$ . The parameters to be estimated are banks' profit margins associated with each payment method and the cost function  $\gamma$  and  $\lambda$ . The bank uses ATM closures and the credit supply to try to steer consumers toward payment methods with a higher profit margin. The extent of that steering depends on the relative size of each profit margin.

For a given vector of the profit margins  $\pi_j$ , our model predicts equilibrium ATM quantity  $\widehat{ATM}_t$  and equilibrium credit supply  $\widehat{CL}_t$ . We find values for  $\pi_j$  to fit the number of ATMs and credit supply over time in the data. In practice, we use the following moment conditions:

$$E_t \begin{bmatrix} \widehat{ATM}_t(\pi_j, \gamma, \lambda) - ATM_t \\ \widehat{CL}_t(\pi_j, \gamma, \lambda) - CL_t \end{bmatrix} = 0. \quad (11)$$

We iterate the parameters (i.e.,  $\pi_j, \gamma, \lambda$ ) that minimize the moment conditions in Equation (11).

### 6.5 Parameter Estimates

We estimate the structural parameters as outlined in Section 6.4. Standard errors are calculated using delta methods. Table 10 shows the parameters that best fit the data. We discuss the key parameters below.

We find that consumers' preference for credit cards increases with the credit supply, and consumers' preference for cash increases with the number of ATMs. The parameter, "Post," rationalizes the decrease in the transaction cost of mobile payment (i.e., the increase in mobile payment transactions) after the introduction of QR-code technology; the estimate suggests that the technology diminishes the transaction cost of mobile payments by about 12.53%.

Merchants' profit associated with each payment method rationalizes their entry decisions. We estimate the profit margins for small and large merchants separately. We find that small merchants' profit margin for mobile payment is larger than cash. Therefore, the introduction of mobile payment technology increases small merchants' profit as more consumers switch from cash to mobile payment. On the other hand, the estimated profit margin is larger for small merchants compared to large merchants, implying a greater effect of mobile payment introduction on small business creation, all else equal.

Finally, the key parameters that drive the bank's supply of credit and ATMs are the respective differences in the profit margin for each payment method. Our estimates rationalize the empirical finding that the bank offered fewer ATMs and a greater credit supply after the advent of QR-code technology. The model estimates indicate that the profit margin for credit cards is much larger relative to all other payment methods; the bank's profit margin for credit cards is about 3.7 times that of the profit margin for cash. On the other hand, the bank's profit margin for mobile payment is higher than that of cash by about 7.94 percent. The parameters in the cost functions  $c_\gamma$  and  $c_\lambda$  implied by the estimated model are  $1.832 \times 10^{-17}$  and 0.017, respectively.

## *6.6 Model Prediction*

We evaluate the model's fit by comparing the share of transactions for all payment methods (See Table A6 of the Internet Appendix). The model captures the changes in payment methods over time—the share of mobile payment increases after the introduction of QR-code technology. Our model tracks reasonably well the changes in business entries after that point.

Also, we compare the predicted number of ATMs and the predicted credit supply with the data. Our model rationalizes the decrease in ATMs and the increase in credit supply after the advent of QR-code technology. Since the estimated profit margin for credit cards is higher, the bank has an incentive to increase the credit supply to retain consumers. On the other hand, the estimated profit margin for cash is lower relative to other payment methods, so the bank does not increase the number of ATMs to retain consumers in this sector.

In addition, the model allows heterogeneous impacts of QR-code technology for small and large merchants (See Table A7 of the Internet Appendix). The model predicts that small merchants see an increased demand for mobile payment after the QR-code technology. The increase is partially offset by the decrease in demand for cash transactions. On the other hand, large merchants also experience an increase in consumer demand. The increase is mainly from the credit card sector due to the increased credit supply.

Overall, our model incorporates the equilibrium responses from consumers, merchants, and banks. The model is able to capture the key changes in the data following the introduction of QR-code technology. The key structural parameters that rationalize the empirical findings are consumer preference and the difference in the payment methods' profit margins for both merchants and banks.

### *6.7 Counterfactual Analysis*

We perform a series of counterfactuals and compare the results with context gleaned from other countries, seeking external validity. In countries outside Singapore, we notice different (anecdotal) patterns when mobile payment technology was introduced. For the case of the United States, the bank has a higher profit for credit cards. One source of higher profit is the higher interest revenue from credit card borrowers, as US consumers are more likely to borrow from credit cards (Badarinza, Campbell, and Ramadorai, 2016). Moreover, a larger fraction of consumers already used credit cards before the mobile payment was introduced. Therefore, the introduction of mobile payment had a less visible effect. For the case of China, the bank earns a higher profit from mobile payment compared to Singapore because consumers typically link their credit cards and debit cards to their mobile wallet. Besides, most transactions were in cash before the mobile payment option became available.

In the first set of counterfactuals, we perturb the bank's profit margin for each payment method to understand the role of financial intermediaries on the impact of QR-code technology. In the second set of counterfactuals, we perturb the transaction cost of each payment method to understand how the equilibrium might change depending on consumer preference.<sup>19</sup>

Table 11 presents the counterfactuals when the bank's profit margin for each payment method increases by 1 percent. Column 1 of Table 11 shows that when the profit margin for credit card payment increases, the bank offers a higher credit limit and fewer ATMs so that more consumers use credit cards, diluting the effect of mobile payment technology on the mobile payment adoption. Consequently, the introduction of mobile payment technology has a smaller effect on small business creation relative to the baseline. Similarly, Column 2 of Table 11 shows the equilibrium when the bank's profit margin for mobile payments increases and equals 50 percent of the profit margin for credit cards. In this case, the bank provides a lower credit limit than the baseline as the mobile payment becomes more profitable. Accordingly, more consumers adopt mobile payments as the credit supply decreases (i.e., the incentives to use credit cards decrease). The introduction of mobile payment technology has a larger effect on small business creation relative to the baseline.

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<sup>19</sup> The counterfactual equilibrium may have zero number of ATMs or zero credit supply when a parameter becomes large enough. However, this equilibrium may not be realistic since there has to be a minimum number of ATMs (or credit limit) in order for consumers to withdraw (or spend). Therefore, we impose a minimum number of ATMs and a minimum credit supply for the counterfactual equilibrium. The minimum number of ATMs and the minimum credit supply are assumed to be 600 units and \$100 million, respectively.

Panel A in Figure 5 plots the change in mobile payment adoption along with the change in the number of ATMs when we perturb the bank's credit card margin. The adoption in mobile payment decreases as the number of ATMs decreases in the equilibrium. Panel B in Figure 5 plots the change in mobile payment adoption along with the fraction of credit card transactions when we perturb the bank's credit card margin. The adoption in mobile payment decreases as the fraction of credit card transactions increases in the equilibrium. Figure 5 shows the importance of a financial intermediary (i.e., banks) in adopting financial technology. That intermediary's endogenous response could influence the equilibrium outcomes, which depend on the extent of the bank's incentive to promote credit cards.

Table 12 presents the counterfactuals when the transaction costs of credit cards and cash decrease by 3 percent, respectively. Column 1 of Table 12 shows that, when the transaction cost of credit cards is lower, more consumers prefer to use them. The substitution effect from credit cards to mobile payment becomes smaller. Therefore, the introduction of mobile payment technology has a smaller effect on mobile payment transactions compared to the baseline. Column 2 of Table 12 shows that when the transaction cost of cash is lower (i.e., there is more demand for cash), the equilibrium number of ATMs is higher and the credit limit falls. The switch from credit cards to mobile payments increases and the switch from cash to mobile payment decreases. The former substitution effect dominates the latter, therefore the introduction of mobile payment technology has a larger effect on mobile payment transactions compared to the baseline. We also find a large business creation effect in this case.

The counterfactual exercises are consistent with the evidence as casually observed in other countries, which extend our results beyond the context in Singapore. The impact of mobile payment hinges on the prevalence and profitability of other (cashless) payment methods. Mobile technology has less of an effect when more consumers already have credit cards when the mobile payment option is introduced, and the bank also has a higher margin for credit cards. On the other hand, mobile technology has a large effect in the counterfactual where more consumers use cash before the introduction of mobile payment technology and the bank has a higher margin for mobile payment.

## **VII. Conclusion**

We utilize the introduction of QR-code payment technology by the largest bank in Singapore, which allows consumers to make transactions or transfer funds by displaying or scanning QR codes on their mobile phones, to study how mobile payment technology reshapes economic activities and stimulates business creation. This newly introduced mobile payment technology significantly lowered the cost of mobile payment and boosted mobile payment usage: in the first year subsequent to the QR code introduction, the number of consumers who signed up (used) mobile payment increased by 53.8% (304%).

Our difference-in-differences analysis shows that after the introduction, business-to-consumer industries witnessed a higher growth rate of business creation by 8.9% per month relative to business-to-business industries, with the effect entirely driven by small merchants. The effect is also more pronounced among industries characterized by a higher cost of cash handling. Underlying this pattern is a strong adoption of mobile payment and a large decline in cash ATM withdrawals among consumers during the post-shock period, associated with a significant closure of ATMs by the bank.

The reduced transaction cost also allows consumers to increase their spending capacity and further fosters business growth. Due to this added convenience for consumers' transactions, consumers show a significant increase in their total spending by 4.2% of the QR-code payment introduction. Interestingly, part of the increased consumer demand is captured by credit card spending, which likely reflects consumers' continued preference for other cashless payment and the bank's endogenous response to maintain its credit card business. Consistently, mobile users exhibit an increase in credit card limits after the technology shock. Since credit cards are less prevalent among small merchants, the effect of increased demand on small business creation may be diluted due to banks' endogenous response.

To extend the empirical results, we estimate a model that rationalizes the responses in the multiple sectors (i.e., consumers, merchants, banks). The counterfactual analysis highlights the importance of banks' endogenous response to the impact of mobile payment technology. The key structural parameters that drive banks' endogenous response are banks' profit margins for credit cards and mobile payment. The difference in these structural parameters can partially explain the different patterns when mobile payment technology was introduced in other countries, such as the United States and China.

## Reference

Agarwal, Sumit, Pulak Ghosh, Jing Li, and Tianyue Ruan. 2019. "Digital Payments Induce Over-Spending: Evidence from the 2016 Demonetization in India." *Working paper*.

Agarwal, Sumit, and Wenlan Qian. 2014. "Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore." *American Economic Review*, 104(12), 4205-30.

Agarwal, Sumit, and Wenlan Qian. 2017. "Access to home equity and consumption: Evidence from a policy experiment." *Review of Economics and Statistics*, 99(1), 40-52.

Agarwal, Sumit, Wenlan Qian, Bernard Y. Yeung, and Xin Zou. 2019. "Mobile wallet and entrepreneurial growth." *AEA Papers and Proceedings*, 109, 48-53.

Association of Certified Fraud Examiners (ACFE). 2014. "2014 Report to the Nation on Occupational Fraud and Abuse."

Arango, Carlos and Varya Taylor, Merchant Acceptance. 2008. "Costs and Perceptions of Retail Payments: A Canadian Survey." *Bank of Canada Discussion Paper*, 2008-12.

Badarinza, C., Campbell, J.Y. and Ramadorai, T., 2016. "International Comparative Household Finance." *Annual Review of Economics*, 8, 111-144.

Carlin, Bruce, Arna Olafsson, and Michaela Pagel. 2019. "Generational Differences in Managing Personal Finances." *AEA Papers and Proceedings*, 109, 54-59.

Chava, Sudheer, Alex Oetl, Manpreet Singh, and Linghang Zeng. 2018. "The Dark Side of Technological Progress? Impact of E-Commerce on Employees at Brick-and-Mortar Retailers." *Working paper*.

Chen, Tao, Yi Huang, Chen Lin, and Zixia Sheng. 2019. "Finance and Firm Volatility: Evidence from Alibaba FinTech Credit in China." *Working paper*.

Chen, Haiqiang, and Wenlan Qian. 2019. "Does E-commerce Crowd Out Consumer Spending Offline?." *Working paper*.

Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti. (2019) "Shocks and Technology Adoption: Evidence from Electronic Payment Systems." *Working paper*.

D'Acunto, Francesco, Alberto Rossi, and Michael Weber. 2019. "Crowdsourcing Financial Information to Change Spending Behavior." *Working paper*.

D'Acunto, Francesco, Thomas Rauter, Christoph Scheuch, and Michael Weber. 2019. "Perceived Precautionary Savings Motives: Evidence from FinTech." *Working paper*.

Economists Incorporated. 2014. "Retailer Payment Systems: Relative Merits of Cash and Payment Cards."

Fan, Jingting, Lixin Tang, Weiming Zhu, and Ben Zou. 2018. "The Alibaba effect: Spatial consumption inequality and the welfare gains from e-commerce." *Journal of International Economics*, 114, 203-220.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther. 2018. "Predictably Unequal? The Effects of Machine Learning on Credit Markets." *Working paper*.

Gupta, Apoorv, Jacopo Ponticelli, and Andrea Tesei. 2019. "Technology Adoption and Access to Credit Via Mobile Phones." *Working paper*.

Hau, Harald, Yi Huang, Hongzhe Shan, and Zixia Sheng. 2018. "FinTech credit and entrepreneurial growth." *Working paper*.

Hause, John C., and Gunnar Du Rietz. 1984. "Entry, industry growth, and the microdynamics of industry supply." *Journal of Political Economy*, 92(4), 733-757.

Huang, Yi, Chen Lin, Zixia Sheng, and Lai Wei. 2019. "Digital Finance and Customer Capital Development." *Working paper*.

Kennedy, Jay P. 2014. "A View from the Top: Managers' Perspectives on the Problem of Employee Theft in Small Businesses." *Working paper*.

Klapper, Leora, Luc Laeven, and Raghuram Rajan. 2006. "Entry regulation as a barrier to entrepreneurship." *Journal of Financial Economics*, 82(3), 591-629.

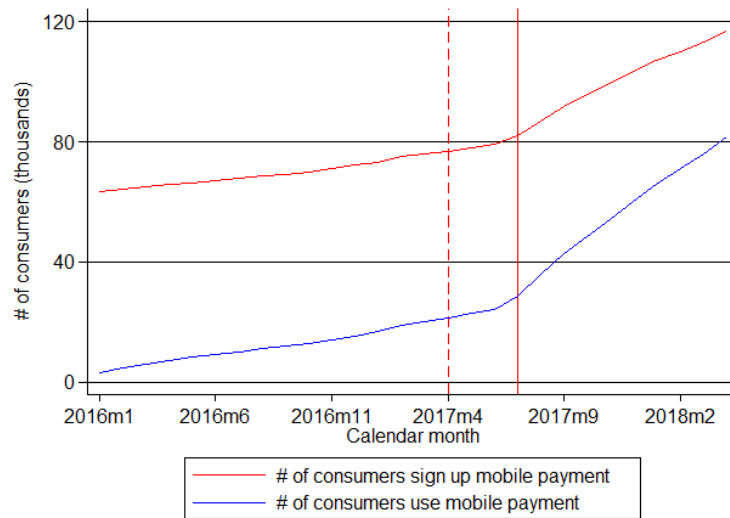
Mihet, Roxana. 2019. "Who Benefits from Innovations in Financial Technology?" *Working paper*.

Monetary Authority of Singapore. 2016. "Singapore Payments Roadmap Report August 2016".

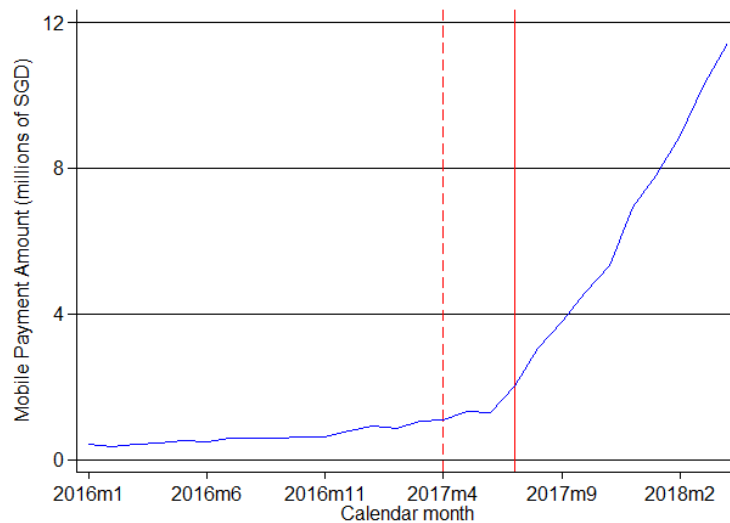
Philippon, Thomas. 2019. "On Fintech and Financial Inclusion." *NBER Working Paper No. W23598*.

**FIGURE 1. USAGE OF MOBILE PAYMENT AROUND THE QR CODE INTRODUCTION**

Panel A: number of consumers who sign up (use) mobile payment



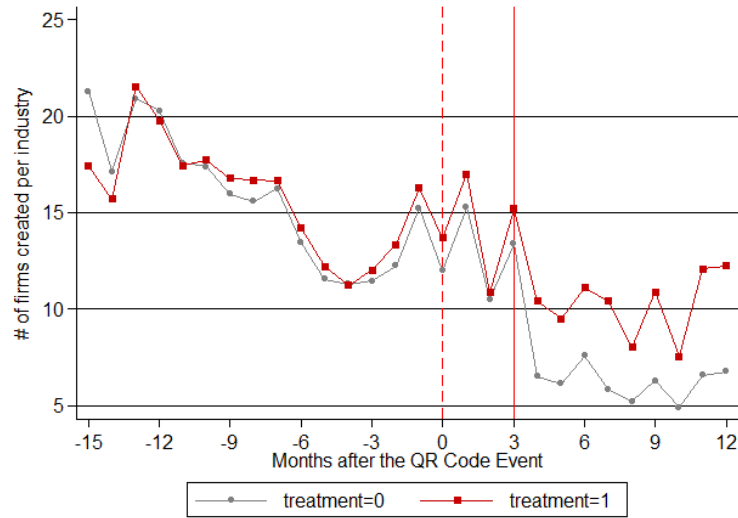
Panel B: Mobile payment transaction amount



This figure shows the time trend of mobile payment usage around the launch of QR code payment technology, based on a random, representative sample of our bank's retail customers composed of 250,000 individuals. The dotted vertical red line indicates the introduction of QR-code payment (i.e., April 2017) and the solid vertical red line indicates the introduction of mobile interbank fund transfer (i.e., July 2017). In Panel A, we respectively plot the number of consumers who sign up (use) mobile payment in a given month. In Panel B, we plot the total dollar amount of mobile payment transactions in a given month.

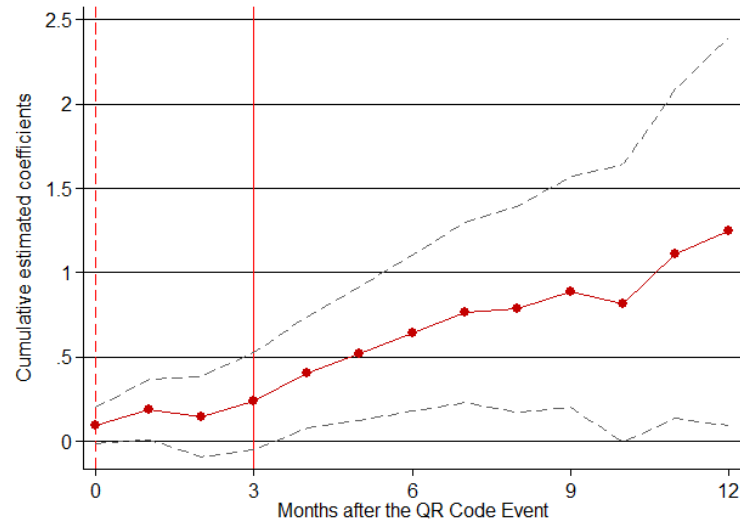


**FIGURE 2. UNCONDITIONAL MEAN OF NUMBER OF BUSINESSES CREATED**



This figure shows the unconditional means of the number of businesses created per industry during the period of January 2016–April 2018, for the treatment group and the control group respectively. The dotted vertical red line indicates the introduction of QR-code payment (i.e., April 2017) and the solid vertical red line indicates the introduction of mobile interbank fund transfer (i.e., July 2017). The  $x$ -axis denotes the  $s^{\text{th}}$  month after the QR code payment introduction.

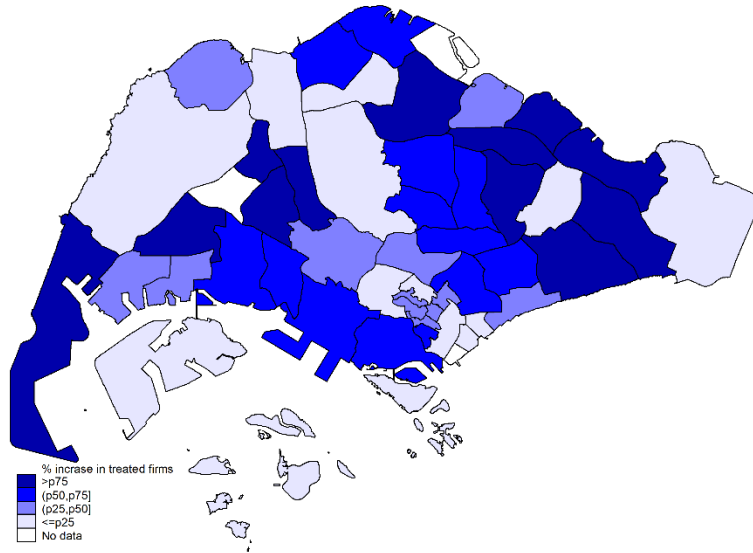
**FIGURE 3. DYNAMIC PLOT OF CUMULATIVE ESTIMATED COEFFICIENTS**



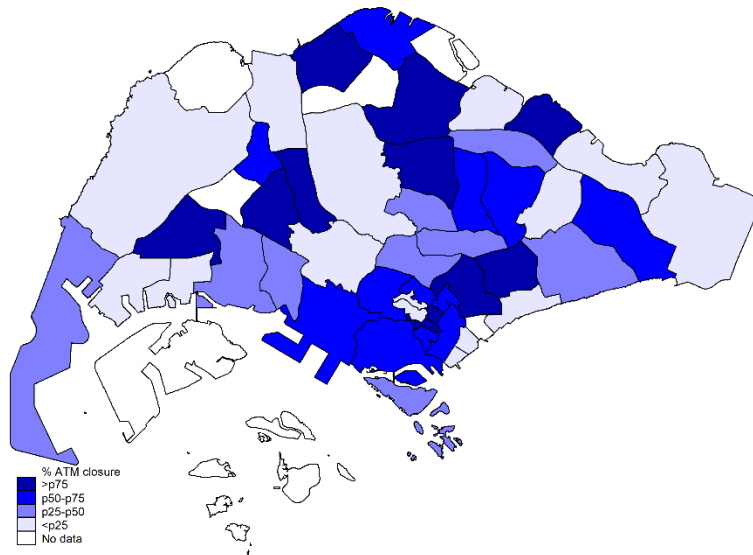
This figure shows the dynamics of the cumulative estimated coefficients as estimated from Equation (2). Each point of the red line shows the cumulative coefficient of treatment effect  $b_s$ . The black dashed lines show the corresponding 95% confidence intervals. The dotted vertical red line indicates the introduction of QR-code payment (i.e., April 2017) and the solid vertical red line indicates the introduction of mobile interbank fund transfer (i.e., July 2017).

## FIGURE 4. SMALL BUSINESS CREATION AND ATM CLOSURE

Panel A: Growth rate of small business creation in treated industries, planning-area level



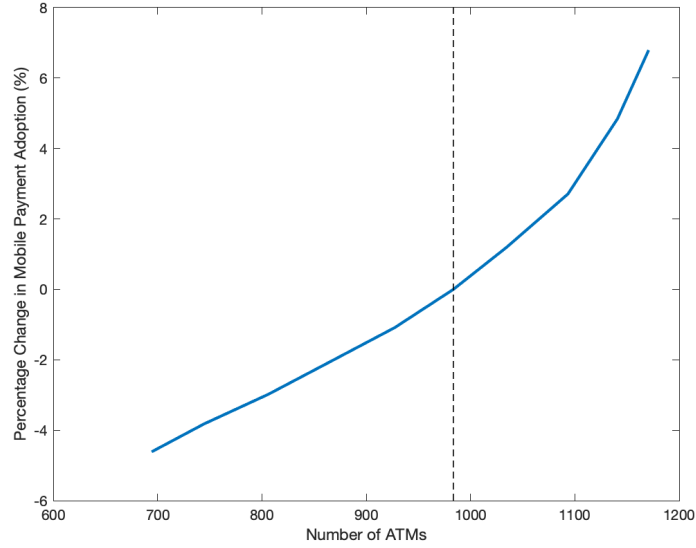
Panel B: Increase in ATM closure rate, planning-area level



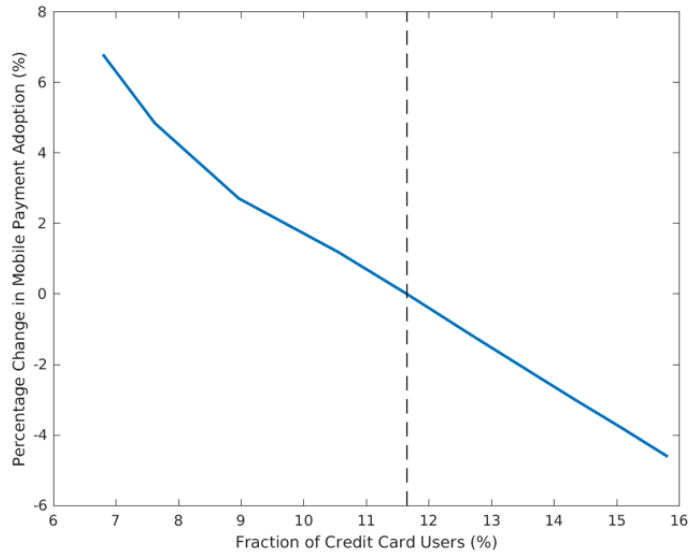
This figure shows the geographic distribution of the growth rate of small business creation in treated industries (Panel A), and the distribution of the increase in ATM closure (Panel B). Specifically, in Panel A, for each planning area, we calculate the growth rate of the average number of monthly non-company business creation per treated industry after the mobile payment introduction relative to the pre-event period, net of the growth rate among the control industries; in Panel B, for each planning area, we calculate the increase of average monthly ATM closure rate after the QR-code payment introduction relative to the pre-event period.

### FIGURE 5.—PROFIT MARGIN OF CREDIT CARDS

Panel A: Number of ATMs and Mobile Payment Adoption



Panel B: Credit Card Transactions and Mobile Payment Adoption



This figure plots the change in mobile payment transactions (before and after the introduction of mobile payment technology) along with the number of ATMs in the post-period in Panel A, and along with the fraction of credit card users in Panel B. The change in equilibrium is when the bank's profit margin for credit cards changes by  $-0.1$  to  $0.1$  from the estimate. The vertical line indicates the baseline equilibrium. The y-axis indicates the percentage change in mobile payment adoption relative to the change in mobile payment adoption of the baseline equilibrium.

**TABLE 1. —SUMMARY STATISTICS: ACRA DATA**

	Treated industry		Control industry	
	Mean	SD	Mean	SD
Monthly # of creation	18.5	50.2	10.6	47.6
% Non-company firms	45.1	49.8	36.4	48.1
% HDB area	77.1	42.0	72.5	44.6
% prime district	20.0	40.0	28.1	44.9
% high house-price district	36.3	48.1	40.8	49.1
# of industries	95		244	

This table reports the industry-level summary statistics for all new firms created during the pre-event window (2016:01-2017:03). The treated industries are the business-to-consumer industries; the control industries are business-to-business industries. We tabulate the distribution of firms created in different organization types (sole proprietorship/partnership or corporation) and in different areas. At the 2-digit postal sector level, we define an area to be a low-house-price area if its average residential property transaction price during the pre-event window (January 2016 to March 2017) is below the median of all postal sectors. The prime districts include postal districts 1, 2, 6, 9, 10 or 11. HDB areas are those within a 500-meter radius of an HDB building.

**TABLE 2. —MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION: AVERAGE EFFECT**

	(1)	(2)	(3)	(4)	(5)
	Dependent Var. = Log(1+# of new businesses)				
	Full sample	Non-company		Company	
Treated*Pre		0.024 (0.80)		-0.033 (-1.09)	
Treated*Post	0.089*** (2.60)	0.111** (2.58)	0.123*** (3.25)	0.094* (1.96)	-0.065 (-1.12)
Fixed effects	Industry, year-month, Industry-division×year				
Observations	9,226	9,226	9,226	9,226	9,226
Adj $R^2$	0.898	0.898	0.861	0.862	0.836

This table shows the average effect of mobile payment technology introduction on business creation. The sample period runs from January 2016 to April 2018. “*Treated*” is a dummy equal to 1 for business-to-consumer (B2C) industries, and 0 for business-to-business (B2B) industries. “*Post*” is a dummy equal to 1 for the months after QR-code payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 3. —MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION: HETEROGENEOUS EFFECT ACROSS DIFFERENT REGIONS**

Dependent Var. = Log(1+# of non-company new businesses)		
<b>Panel A: High versus low house price areas</b>		
	(1)	(2)
	Low house price areas	High house price areas
Treated*Post	0.128*** (3.42)	0.061** (2.26)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	9,226	9,226
Adj $R^2$	0.844	0.668
<b>Panel B: Prime versus non-prime districts</b>		
	(1)	(2)
	Non-prime districts	Prime districts
Treated*Post	0.125*** (3.18)	0.043** (2.15)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	9,226	9,226
Adj $R^2$	0.844	0.652
<b>Panel C: HDB versus non-HDB</b>		
	(1)	(2)
	HDB area	Non-HDB area
Treated*Post	0.121*** (3.36)	0.054** (2.19)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	9,226	9,226
Adj $R^2$	0.844	0.668

This table shows the heterogeneous treatment effect among businesses created in different regions. The sample period runs from January 2016 to April 2018. In Panel A, at the 2-digit postal sector level, we define an area to be a low-house-price area if its average residential property transaction price during the pre-event window (January 2016 to March 2017) is below the median of all postal sectors; in Column 1 (2), the dependent variable is the number of non-company business creation per industry per month in low-house-price (high-house-price) areas. In Panel B, the prime districts include postal districts 1, 2, 6, 9, 10 or 11; in Column 1 (2), the dependent variable is the number of non-company business creation per industry per month in non-prime (prime) areas. In Panel C, HDB areas are those within a 500-meter radius of an HDB building; in Column 1 (2), the dependent variable is the number of non-company business creation per industry per month in HDB (non-HDB) areas. Refer to Table 2 for definitions of variables. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 4. —MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION: HIGH CASH-TRANSACTION COST VERSUS LOW CASH-TRANSACTION COST INDUSTRIES**

	(1)	(2)
	Dependent Var. = Log(1+# of non-company new businesses)	
	High cash-transaction cost industries	Low cash-transaction cost industries
Treated*Post	0.437*** (3.40)	0.113 (1.58)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	6,856	7,256
Adj $R^2$	0.859	0.855

This table shows the heterogeneous treatment effect among high-cash-transaction-cost retail and food industries (in Column 1) and among low-cash-transaction-cost retail and food industries (in Column 2). The sample period runs from January 2016 to April 2018. In Column 1, the sample includes high-cash-transaction-cost retail and food industries (i.e., food/grocery stores, gas stations, and miscellaneous retailers) as the treatment group, and non-company businesses created in all B2B industries as the control group. In Column 2, the sample includes non-company businesses created in the retail and food industry divisions excluding the food/grocery stores, gas stations, and miscellaneous retail industries (i.e., low-cash-transaction-cost retail and food industries) as the treatment group, and non-company businesses created in all B2B industries as the control group. Refer to Table 2 for definitions of variables. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.



**TABLE 5.—SUMMARY STATISTICS: BANK DATA**

<b>Panel A: Before matching comparison, demographic information</b>					
	Treatment group		Control group		Diff (Control-treatment)
	Mean	SD	Mean	SD	
Age	41.6	10.2	45.8	11.2	4.2***
Monthly income	6618.4	5908.2	6884.9	6237.7	266.5***
Bank account balance	41182.1	89362.4	50069.6	99187.0	8887.4***
%Female	41.9%	49.3%	40.8%	49.2%	-1.1%***
Ethnicity					
%Chinese	78.4%	41.1%	77.5%	41.7%	-0.9%***
%Malay	5.1%	22.0%	5.2%	22.3%	0.2%
%Indian	9.1%	28.8%	8.1%	27.2%	-1.1%***
%Married	49.3%	50.0%	53.8%	49.9%	4.5%***
%Foreigner	21.1%	40.8%	22.0%	41.4%	0.9%***
Tenure with the bank (years)	19.2	6.3	20.0	6.7	0.7***
N	49,268		89,180		
<b>Panel B: After matching comparison, demographic information</b>					
	Treatment group		Control group		Diff (Control-treatment)
	Mean	SD	Mean	SD	
Age	41.6	10.2	41.6	10.1	0.0
Monthly income	6618.4	5908.2	6626.7	5969.8	8.4
Checking account balance	41182.1	89362.4	41629.6	87629.4	447.5
%Female	41.9%	49.3%	41.8%	49.3%	-0.1%
Ethnicity					
%Chinese	78.4%	41.1%	78.0%	41.4%	-0.4%
%Malay	5.1%	22.0%	5.3%	22.4%	0.2%
%Indian	9.1%	28.8%	9.3%	29.0%	0.2%
%Married	49.3%	50.0%	49.2%	50.0%	0.0%
%Foreigner	21.1%	40.8%	21.0%	40.8%	-0.1%
Tenure with the bank (years)	19.2	6.3	19.2	6.3	0.0
N	49,268		49,268		
<b>Panel C: After matching comparison, financial information</b>					
	Treatment		Control		
	Mean	SD	Mean	SD	
Total spending	4100.4	4249.1	3866.8	4077.7	
Mobile payment	10.0	101.5	0.0	0.0	
Cash withdrawal	1346.9	1940.8	1442.8	2034.9	
Credit card spending	783.5	1508.2	726.4	1465.9	
Debit card spending	399.8	693.1	399.0	690.5	
Bill payment	1560.2	2708.8	1298.7	2462.6	
N	49,268		49,268		

This table reports the summary statistics of consumers' financial and demographic information during the pre-event window (2016:01-2017:03). Treated consumers are consumers who signed up for mobile payment in our bank before the event. We restrict to consumers who have both bank accounts and credit cards from our bank. We exclude inactive consumers— consumers with zero monthly spendings for at least half of the sample period as of the event time. Panel A shows the demographic information of the treatment and control group as of the month immediately before the event (i.e., 2017:03), based on the unmatched full sample; Panel B shows the demographic information as of the month immediately before the event (i.e., 2017:03), based on the matched sample; Panel C shows the financial information during the pre-event window based on the matched sample. We perform a 1-to-1 nearest matching without replacement based on the treatment and control groups' age, income, checking account balance, gender, marital status, race, foreigner status, and consumers' tenure with the bank (refer to Table A4 for the detail of the matching procedure). All the continuous variables are winsorized at the 1% and 99% level.

**TABLE 6. —MOBILE PAYMENT AND CASH USAGE RESPONSE**

<b>Panel A: mobile payment response</b>			
	(1) Log(1+Total mobile payment)	(2) Log(1+to Business payment)	(3) Log(1+P2P transfer)
Treated*Post	0.254*** (44.42)	0.028*** (22.99)	0.232*** (43.64)
Fixed effect		Individual, year-month	
Observations	2,696,557	2,696,557	2,696,557
Adj $R^2$	0.382	0.334	0.356
<b>Panel B: cash withdrawal response</b>			
	(1) Log(1+Cash withdrawal)	(2) Log(1+ATM cash withdrawal)	(3) Log(1+OTC cash withdrawal)
Treated*Post	-0.027*** (-3.39)	-0.029*** (-3.42)	0.002 (0.69)
Fixed effect		Individual, year-month	
Observations	2,696,557	2,696,557	2,696,557
Adj $R^2$	0.641	0.649	0.162

This table shows consumers' mobile payment (in Panel A) and cash usage (in Panel B) response to the launch of QR-code payment, based on the matched sample. The sample period runs from January 2016 to April 2018. “*Treated*” is a dummy equal to 1 for consumers who signed up for mobile payment in our bank before the QR-code payment introduction. “*Post*” is a dummy equal to 1 for the months after QR-code payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Individual and year-month fixed effects are included. Refer to Equation (3) for regression specification. Standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 7.—MOBILE PAYMENT TECHNOLOGY AND ATM CLOSURE/OPENING**

<b>Panel A: ATM closure</b>			
	(1) ATM Closure after event	(2) ATM Closure after event	(3) ATM Closure after event
HDB	0.126*** (5.36)		
Low house price		0.066*** (2.72)	
Non-prime district			0.017 (0.53)
Constant	0.112*** (6.00)	0.163*** (8.46)	0.193*** (6.49)
Observations	1,188	1,188	1,188
Adj $R^2$	0.017	0.006	-0.001
<b>Panel B: ATM opening</b>			
	(1) ATM Opening after event	(2) ATM Opening after event	(3) ATM Opening after event
HDB	-0.121 (-1.18)		
Low house price		-0.035 (-0.34)	
Non-prime district			-0.090 (-0.70)
Constant	0.455*** (5.20)	0.394*** (4.59)	0.444*** (3.76)
Observations	111	111	111
Adj $R^2$	0.004	0.001	-0.004
<b>Panel C: Small business creation and ATM closure</b>			
	(1) $\Delta ATM\_closure\%$		
$\Delta Treated\_firm\_growth\%$	0.013** (2.22)		
Constant	0.004 (1.18)		
Observations	46		
R-squared	0.064		

At the ATM level, Panel A and B show whether an ATM is likely to be closed (opened) after the QR-code payment introduction. Refer to Equation (4) for regression specification. In panel A, the dependent variable is a dummy equal to 1 if an ATM is closed after the introduction of mobile payment. We restrict the sample to ATMs that had already been existing at the beginning of our sample period. In panel B, the dependent variable is a dummy equal to 1 if an ATM is opened after the introduction of mobile payment. We restrict our sample to ATMs opened after the first month of our sample period. Refer to Table 1 for the definitions of the independent variables in Panel A and B. At the planning area level, Panel C shows the geographic correlation between ATM closure and small business creation,  $\Delta ATM\_closure\%$  is the increase of the average monthly ATM closure rate during the post-event period relative to the pre-event period in a planning area.  $\Delta Treated\_firm\_growth\%$  is the growth rate of the average number of monthly small business creation per treated industry after the event relative to the pre-event period, net of the growth rate among the control industries, in a planning area. Refer to Equation (5) for regression specification. Standard errors are estimated based on 1000 bootstrap replications. Sample period: 2016:01-2018:04. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 8. —SPENDING RESPONSE TO MOBILE PAYMENT TECHNOLOGY**

	(1) Log(1+Total spending)	(2) Log(1+mobile payment)	(3) Log(1+cash withdrawal)	(4) Log(1+credit card spending)	(5) Log(1+debit card spending)	(6) Log(1+bill payment)
Treated*Post	0.042*** (8.44)	0.254*** (44.37)	-0.027*** (-3.39)	0.033*** (3.55)	0.012* (1.66)	-0.002 (-0.25)
Fixed effect			Individual, year-month			
Observations	2,696,557	2,696,557	2,696,557	2,696,557	2,696,557	2,696,557
Adj $R^2$	0.608	0.382	0.641	0.686	0.611	0.754

This table shows consumers' spending response to the mobile payment technology shock, based on the matched sample. The sample period runs from January 2016 to April 2018. "*Treated*" is a dummy equal to 1 for consumers who signed up for mobile payment in our bank before the QR-code payment introduction. "*Post*" is a dummy equal to 1 for the months after QR-code payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Individual and year-month fixed effects are included. Refer to Equation (3) for regression specification. Standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 9.—CREDIT RESPONSE TO MOBILE PAYMENT TECHNOLOGY**

	(1) Having credit card	(2) # of credit cards	(3) Log(credit limit)
Treated*Post	0.016*** (19.18)	0.093*** (32.66)	0.047** (24.24)
Fixed effect		Individual, year-month	
Observations	6,623,455	4,169,090	4,169,090
Adj $R^2$	0.934	0.965	0.940

This table shows the credit response to the mobile payment technology shock. The sample period runs from January 2016 to April 2018. Column 1 includes all consumers with a bank account in our dataset; Column 2 and Column 3 includes consumers who own a credit card account with our bank. In Column 1, the dependent variable is a dummy equal to 1 if a consumer have a credit card account with our bank. In Column 2, the dependent variable is the number of credit cards held by a consumer. In Column 3, the dependent variable is the log credit card limit. “*Treated*” is a dummy equal to 1 for consumers who signed up for mobile payment in our bank before the QR-code payment introduction. “*Post*” is a dummy equal to 1 for the months after QR-code payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Individual and year-month fixed effects are included. Refer to Equation (3) for regression specification. Standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE 10.—PARAMETER ESTIMATES**

<b>Panel A: Consumer Parameters</b>		
TXNCost—Debit Cards		3.519 (0.101)
TXNCost—Credit Cards		5.775 (0.109)
TXNCost—Mobile Payment		7.267 (0.017)
TXNCost—Cash		1.814 (0.255)
$\theta$		0.084 (0.035)
$\beta$		0.691 (0.022)
$\beta_s$		0.223 (0.022)
$\alpha_1$		0.911 (0.012)
$\alpha_2$		0.165 (0.001)
$\rho_{small}$		0.077 (0.004)
$\rho_{large}$		0.167 (0.009)
<b>Panel B: Merchant Parameters</b>	Small Merchants	Large Merchants
$\tau_{cash}$	0.000 (0.000)	0.000 (0.000)
$\tau_{debit}$	(—)	0.000 (0.000)
$\tau_{credit}$	(—)	0.462 (0.067)
$\tau_{mobile}$	54.922 (2.806)	(—)
<b>Panel C: Bank Parameters</b>		
$\pi$ —Debit Cards		1.014 (0.315)
$\pi$ —Credit Cards		2.814 (0.789)
$\pi$ —Mobile Payment		0.824 (0.543)
$\pi$ —Cash		0.762 (0.156)
$\gamma$		4.516 (2.204)
$\lambda$		0.540 (0.033)

This table shows the model’s parameter estimates. “*Post*” is a dummy equal to 1 for the months after the introduction of QR-code payments (i.e., April 2017). Standard errors are reported in parentheses.

**TABLE 11.—COUNTERFACTUAL ANALYSIS: BANK’S PROFIT MARGIN**

	Baseline	$\pi_{CC} + 1\%$		$\pi_{Mobile} = 0.5 \times \pi_{CC}$	
		Level	% Change	Level	% Change
<b>Panel A: Post = 0</b>					
Prob(j = Debit)	0.076	0.080	3.558	0.076	-0.054
Prob (j = Credit)	0.100	0.116	16.447	0.100	-0.206
Prob (j = Mobile) $\times 10^2$	0.054	0.515	-2.089	0.054	0.033
Prob (j = Cash)	0.227	0.227	-2.581	0.227	0.034
Small Business Creation	1.039	1.641	-0.080	1.040	0.001
ATM	1091.800	983.615	-5.782	1091.800	0.000
Credit ( $10^7$ )	221.067	273.308	28.468	220.200	-0.305
<b>Panel B: Post = 1</b>					
Prob (j = Debit)	0.080	0.083	2.580	0.080	-0.338
Prob (j = Credit)	0.116	0.131	12.148	0.115	-1.463
Prob (j = Mobile) $\times 10^2$	0.515	0.507	-1.644	0.517	0.343
Prob (j = Cash)	0.227	0.221	-2.570	0.227	0.308
Small Business Creation	1.641	1.629	-0.752	1.644	0.169
ATM	983.615	894.846	-9.025	987.769	0.464
Credit ( $10^7$ )	273.308	330.615	20.968	265.769	-2.280
<b>Panel C: Equilibrium Changes (Panel B minus Panel A)</b>					
$\Delta$ Prob (j = Debit)	0.004	0.004	-14.948	0.004	-6.533
$\Delta$ Prob (j = Credit)	0.017	0.014	-13.695	0.015	-11.655
$\Delta$ Prob (j = Mobile) $\times 10^2$	0.461	0.454	-1.592	0.463	0.379
$\Delta$ Prob (j = Cash)	0.000	0.000	-9.228	0.000	-173.669
$\Delta$ Small Business Creation	0.602	0.590	-1.915	0.604	0.463
$\Delta$ ATM	-108.185	-133.821	23.696	-104.031	-3.104
$\Delta$ Credit ( $10^7$ )	52.241	46.615	-10.769	45.569	-14.312

This table compares the counterfactual equilibrium with the baseline (i.e., estimated model). We simulate the outcomes when the profit margin for credit cards increases by 1 percent (i.e., decrease the value by 0.01) in Column 1. We simulate the outcomes when the profit margin for mobile payment equals 50 percent of the profit margin for credit cards in Column 2. We compare the outcomes for the period when Post equals 0 and 1 in upper and lower panels, respectively. “Post” is a dummy equal to 1 for the months after the introduction of QR-code payment (i.e., April 2017). Small Business Creation indicates the share of small business entries divided by the share of business-to-business entries.

**TABLE 12.—COUNTERFACTUAL ANALYSIS: CONSUMER PREFERENCE**

	Baseline	TXNCost <sub>CC</sub> – 3%		TXNCost <sub>Cash</sub> – 3%	
		Level	% Change	Level	% Change
<b>Panel A: Post = 0</b>					
Prob(j = Debit)	0.076	0.080	5.477	0.071	-6.352
Prob (j = Credit)	0.100	0.132	32.225	0.078	-16.228
Prob (j = Mobile) × 10 <sup>2</sup>	0.054	0.052	-3.955	0.055	1.571
Prob (j = Cash)	0.227	0.216	-4.926	0.239	5.397
Small Business Creation	1.039	1.038	-0.151	1.043	0.313
ATM	1091.800	968.400	-11.302	1159.133	6.953
Credit (10 <sup>7</sup> )	221.067	336.000	51.990	153.267	-20.179
<b>Panel B: Post = 1</b>					
Prob (j = Debit)	0.080	0.084	3.895	0.079	-2.135
Prob (j = Credit)	0.116	0.145	24.461	0.105	-8.123
Prob (j = Mobile) × 10 <sup>2</sup>	0.515	0.499	-3.203	0.522	1.416
Prob (j = Cash)	0.227	0.215	-4.992	0.239	5.822
Small Business Creation	1.641	1.617	-1.464	1.661	1.210
ATM	983.615	814.077	-17.236	1039.538	6.870
Credit (10 <sup>7</sup> )	273.308	377.000	37.940	228.615	-11.855
<b>Panel C: Equilibrium Changes (Panel B minus Panel A)</b>					
Δ Prob (j = Debit)	0.004	0.003	-24.438	0.008	103.370
Δ Prob (j = Credit)	0.017	0.013	-22.209	0.026	74.683
Δ Prob (j = Mobile) × 10 <sup>2</sup>	0.461	0.447	-3.115	0.468	1.398
Δ Prob (j = Cash)	0.000	-0.001	34.344	0.001	-171.752
Δ Small Business Creation	0.602	0.579	-3.733	0.618	2.817
Δ ATM	-108.185	-154.323	-42.648	-119.595	-7.394
Δ Credit (10 <sup>7</sup> )	52.241	41.000	-21.518	75.349	56.360

This table compares the counterfactual equilibrium with the baseline (i.e., estimated model). For each column, we simulate the outcomes when the indicated transaction cost decreases by 3 percent (i.e., decrease the value by 0.03). We compare the outcomes for the period when Post equals 0 and 1 in upper and lower panels, respectively. “Post” is a dummy equal to 1 for the months after the introduction of QR-code payments (i.e., April 2017). Small Business Creation indicates the share of small business entries divided by the share of business-to-business entries.



# INTERNET APPENDIX

NOT INTENDED FOR PUBLICATION

**TABLE A1. —AVERAGE EFFECT MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION:  
ROBUSTNESS ANALYSIS**

	(1)	(2)	(3)	(4)	(5)
	Dependent Var. = IHS (# of new businesses)				
	Full sample	Non-company		Company	
Treated*Pre		0.034 (0.94)		-0.029 (-0.80)	
Treated*Post	0.116*** (2.78)	0.147*** (2.83)	0.150*** (3.15)	0.124** (2.07)	-0.074 (-1.04)
Fixed effects	Industry, year-month, Industry-division×year				
Observations	9,226	9,226	9,226	9,226	9,226
Adj $R^2$	0.887	0.887	0.852	0.852	0.812

This table shows the average effect of mobile payment technology introduction on business creation. The dependent variable is the inverse hyperbolic sine transformed level of the monthly number of new businesses created in an industry. The sample period runs from January 2016 to April 2018. “*Treated*” is a dummy equal to 1 for business-to-consumer (B2C) industries, and 0 for business-to-business (B2B) industries. “*Post*” is a dummy equal to 1 for the months after QR payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE A2. —MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION: TOURISM VERSUS NON-TOURISM AREAS**

	(1)	(2)
	Dependent Var. = Log(1+# of non-company new businesses)	
	Tourism areas	Non-tourism areas
Treated*Post	0.022 (1.32)	0.124*** (3.30)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	9,226	9,226
Adj $R^2$	0.456	0.851

This table shows the heterogeneous effect of QR-code payment introduction on small business creation, by tourism versus non-tourism areas. The sample period runs from January 2016 to April 2018. As per Wikipedia, tourism areas include the Sentosa island, the Orchard area, the Marina Bay area, the Raffles place area, Singapore zoo, River Safari, Botanic garden, Changi Airport, Jurong Bird Park, and Night Safari. Refer to Table 2 for definitions of variables. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE A3. — MOBILE PAYMENT TECHNOLOGY ON BUSINESS CREATION: THE ROLE OF INCENTIVIZED ADOPTION**

	(1)	(2)
	Dependent Var. = Log(1+# of non-company new businesses)	
	Industries with promotion	Industries w/o promotion
Treated*Post	0.773*** (5.60)	0.235** (2.10)
Fixed effects	Industry, year-month, Industry-division×year	
Observations	6,720	6,772
Adj $R^2$	0.842	0.853

This table shows the heterogeneous treatment effect among industries with mobile-payment promotion (in Column 1) and industries without mobile-payment promotion (in Column 2). The sample period runs from January 2016 to April 2018. In Column 1, we include industries targeted by the promotion campaign as the treated industries, and all B2B industries as the control group. In Column 2, we include high-cash-handling-cost retail and food industries that do not enjoy the promotion as the treated industries, and all B2B industries as the control group. Refer to Table 2 for definitions of variables. Industry, year-month, and industry-division×year fixed effects are included. Standard errors are clustered at the industry level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE A4. —PROPENSITY SCORE MATCHING LOGISTIC REGRESSION**

	Treatment
Age	-0.045*** (-61.15)
Checking account balance	-0.000*** (-2.76)
Income	0.000*** (6.04)
Female	-0.037*** (-3.08)
Married	0.107*** (8.60)
Chinese	0.184*** (7.66)
Malay	0.039 (1.13)
Indian	0.304*** (10.79)
Foreigner	-0.063*** (-3.21)
Tenure with the bank (years)	0.019*** (12.89)
Constant	0.780*** (21.6)
Observations	138,447
Pseudo R-squared	0.03

Note: This table shows the result of the propensity score matching logistic regression. All the continuous variables are winsorized at the 1% and 99% level. The dependent variable is equal to one for individuals in the treatment group (i.e., consumers who signed up for mobile payment before the introduction of the new mobile payment technology), and equal to zero for individuals in the control group.

**TABLE A5. —CHANGE IN INCOME AND SPENDING OF THE SELF-EMPLOYED**

	(1) Log(1+Bank account inflow)	(2) Log(1+Total spending)
Self-employed*Post	0.069*** (4.38)	0.030*** (2.62)
Fixed effects	Individual, year-month	
Observations	3,803,186	3,803,186
Adj $R^2$	0.720	0.608

This table shows entrepreneurs’ response to the mobile payment technology shock, based on the unmatched full sample. The sample period runs from January 2016 to April 2018. We use the following regression model:

$$Y_{it} = \beta \times Self_{employed_i} \times Post_t + \alpha_i + \delta_t + \epsilon_{it}$$

The dependent variable is the logarithm of bank account inflow or total spending for consumer. “*Self\_employed*” is a dummy variable equal to 1 for consumers who are self-employed in the month immediately before the event, according to our bank data. “*Post*” is a dummy equal to 1 for the months after QR-code payment introduction (i.e.,  $\geq$ April 2017). January 2016 to March 2017 are absorbed as the benchmark. Individual and year-month fixed effects are included. Standard errors are clustered at the individual level. T-statistics are reported in parentheses under the coefficient estimates. Significant at \*\*\* 1%, \*\*5%, and \*10%.

**TABLE A6.—MODEL FITS**

<i>Panel A: Post = 0</i>		
	Model	Data
Prob(j = Debit)	0.076	0.076
Prob (j = Credit)	0.100	0.099
Prob (j = Mobile) $\times 10^2$	0.054	0.052
Prob (j = Cash)	0.227	0.227
Small Business Creation	1.039	1.043
ATM	1091.800	1148.733
Credit ( $10^7$ )	221.067	225.362
<i>Panel B: Post = 1</i>		
Prob (j = Debit)	0.080	0.082
Prob (j = Credit)	0.116	0.122
Prob (j = Mobile) $\times 10^2$	0.515	0.508
Prob (j = Cash)	0.227	0.228
Small Business Creation	1.641	1.661
ATM	983.615	982.077
Credit ( $10^7$ )	273.308	286.923

This table compares the predicted share of transactions, predicted number of ATMs, and the predicted credit supply with the data. We compare the outcomes for the period when Post equals 0 and 1 in upper and lower panels, respectively. “Post” is a dummy equal to 1 for the months after the introduction of QR-code payment (i.e., April 2017). Small Business Creation indicates the share of small business entries divided by the share of business-to-business entries.

**TABLE A7.—EFFECTS FOR SMALL AND LARGE MERCHANTS**

	Small Merchants	Large Merchants
<b>Panel A: Post = 0</b>		
Prob (j = Debit)	0.000	0.141
Prob (j = Credit)	0.000	0.185
Prob (j = Mobile) $\times 10^2$	0.001	0.000
Prob (j = Cash)	0.247	0.210
<b>Panel B: Post = 1</b>		
Prob (j = Debit)	0.000	0.149
Prob (j = Credit)	0.000	0.215
Prob (j = Mobile) $\times 10^2$	0.011	0.000
Prob (j = Cash)	0.247	0.209

This table shows the model-predicted share of transactions for small and large merchants. We compare the model prediction for the period when *Post* equals 0 and 1 in upper and lower panels, respectively. “*Post*” is a dummy equal to 1 for the months after the introduction of QR-code payment (i.e., April 2017).