Online Appendix

Mobile Wallet and Entrepreneurial Growth

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1. Mobile payment in Singapore

Singapore possesses a strong banking and payment system. It is among the world's first to launch the FAST (Fast and Secure Transfers) payment system, which supports 24/7 fund transfers in real time. On the other hand, most consumer payments are still completed via cash. Among the 2.2 billion non-SVF (Stored Value Facilities) consumer transactions in 2015, 60 percent are still paid in cash, followed by 27 percent of card payment (including credit and debit card), 12 percent funds transfer, and 1 percent cheque payment.[1] The preference towards cash, however, is not unique for Singapore. By 2010s, the value of currency in circulation for developed regions is around 10 percent of the GDP (Rogoff, 2015); around 60 percent of North America consumers pick cash as (one of) the most frequently used payment instrument in 2016 and expect to be frequent cash users in the future (Accenture, 2016). The paper-based payments (including cash and cheques) cost around 0.52 percent of Singapore GDP per year. (KPMG, 2016)

According to a survey by KPMG in 2015, e-payments in Singapore are primarily accepted for online shopping or paying bills, while paper-based payments prevail for offline consumption, especially for small merchants like hawker center/food court, small shops, and convenient stores. Among the surveyed businesses, the acceptance of cash is nearly universal (84 percent), while less than half of them accept card payments; and cash is the preferred payment instrument for 54 percent of the businesses, especially the retailers. The slow settlement of payment, high transaction and management cost, and concerns for fraud and security are the top challenges prevent merchants from accepting cashless payments.

Starting from 2017, Singapore has been working hard to move towards a cashless society, and the fast development in mobile payments plays a critical role. 13th April 2017 marks the first date of the introduction of QR (Quick Response) code payment in the city state, which allows users to make transactions by generating their own QR code. Buyers and sellers of goods and services can complete transactions by displaying or scanning QR codes on their mobile phones, which reduces the transaction costs especially for small and new businesses. Based on the machine-readable image of QR code, which can hold 300 times more information than a standard barcode,

[1] The SVFs (Stored Value Facilities) need top-ups before using, and are used mostly for public transportation (eg., the EZ-link card in Singapore).

the QR code payment technology provides a reliable method of payment by allowing for immediate settlement, lower transaction costs, and enhanced security. On 10th July 2017, the Association of Banks in Singapore announced a unified peer-to-peer (P2P) fund transfer service called PayNow, allowing customers of the seven participating banks to make real-time FAST transfers for free.

The transaction value of mobile POS payments in Singapore has more than doubled from 218 million US dollars in 2016 to 470 million by the end of 2017 (Statista, 2018). According to a survey conducted by VISA in July 2017, 67 percent of Singapore respondents have made device-initiated payments (including both mobile payments and card payments such as Visa contactless payments); additionally, 68 percent of them are confident to go cashless for a whole day, and 42 percent are comfortable without cash for 3 days (Visa, 2018).

2. Data

We base our study on a large panel of dataset containing a variety of bank activities for 250,000 Singapore consumers from a leading local bank during 2016:01 to 2017:12. This bank covers over 80 percent of the entire Singapore population; our sample comprises randomly drawn individuals from the bank's customer base. In this dataset, we can observe the transactions for the mobile wallet developed by the bank which allows for QR code payment. Additionally, we have all the debit card, credit card, and ATM transactions information in this bank for the same set of individuals (see detailed description on the bank data in Agarwal and Qian, 2014, 2017).

The bank's mobile wallet was first launched in May 2014. Before the availability of QR code payment, this mobile wallet is mainly used for person-to-person (P2P) fund transfers within the bank's customers; whereas after 13th April 2017 all the mobile wallet users, including customers without this bank's account, can receive and make payments by generating QR codes. In 2017, this mobile wallet is Singapore's fastest growing personal mobile wallet, with more than 785,000 users, and processes over 15,000 P2P transactions a day. In our sample, we have every transaction from the randomly chosen customers. For each transaction, we are able to observe the transaction amount and transaction time. We aggregate all the mobile wallet transaction amount and count of transactions in 2017 at weekly and monthly frequency, to directly check the effect of QR code payment technology. The ATM withdrawals, on the other hand, are also aggregated into monthly frequency and used as a benchmark.

The information we mainly rely on in investigating the spillover effect of QR code payment technology on business growth is the debit and credit card transactions from the same group of bank customers. For each card transaction, besides the information on transaction amount, transaction time, we can also observe the merchant name where the transaction is completed, plus the Merchant Category Code (MCC) for each merchant. Moreover, the data provides (masked) card holder information so that we are able to identify for each merchant, who are making the purchases, and which region do the customers come from (i.e., the 2-digit postal sector).[2] Debit and credit cards together are the dominant cashless payment instruments for disposable consumption of Singapore households, accounting for nearly 30 percent of aggregate consumption in the country (Agarwal and Qian, 2014).[3] Therefore the card transaction information particularly fits our study which aims to investigate the spillover effect of a new mobile wallet payment technology on consumption. We aggregate all the card sales for each merchant at monthly frequency.

The proprietary dataset offers several key advantages for our study. First, digital payment, which contributed 80 percent of the global FinTech transaction in 2017 (Statista, 2018), is reshaping the world's payment system and households' consumption behaviors. The real-time mobile wallet transactions give us the opportunity to directly check the effect of a payment technology shock. Second, our high-frequency administrative dataset records (card) consumption with little measurement error, compared with the traditional survey-based datasets in the United States such as the Survey of Consumer Finance (SCF), Consumer Expenditure Survey (CEX), or Consumer Payment Choice (CPC) survey. Moreover, we can track the sales to each merchant through the transaction record, which is crucial for our study. Relative to earlier studies utilizing consumer shopping diary or scanner data (Klee, 2008; Cohen and Rysman, 2013; Wang and Wolman, 2016;

[2] A 6-digit postal code in Singapore represents a very small neighborhood of one building. The first two digit from the 6-digit postal code represents the postal sector of a building, and there are 81 postal sectors in total. One to six postal sectors constitute one postal district, and there are 28 postal districts in total.

[3] The remaining 70 percent of consumption is transacted via checks, direct transfers, and cash. Consumers with recurring payments like mortgages payment, rent payments, and auto loans payments use instruments such as checks and direct deposit. We confirm this using our credit and debit transaction-level data; looking through the transaction category codes, merchant names, transaction types, we do not find a *single* transaction for mortgage, rent, and auto loan payments in over 35 million debit card and credit card transactions. Hence, we conclude that these reoccurring payments are through checks and direct deposits.

Wakamori and Welte, 2016; Agarwal et al., 2018), we are able to study a long time series (two-year) of sales from large scale of offline merchants (over 16,000 merchants in final sample) in different categories. This enables us to make more generalizable inferences on the entrepreneur growth. Finally, compared to existing studies that use micro-level credit card data (e.g. Gross and Souleles 2002, Agarwal, Liu, and Souleles, 2007, Aaronson, Agarwal, and French, 2012; Agarwal, Qian, and Zou, 2018), our card transaction dataset provides more comprehensive consumption information. For example, rather than observing a single credit card account, we have information on every credit card and debit card that each customer has with the bank. In addition, we also observe individuals' other bank activities such as the ATM withdrawals, and rich demographic information such as the 2-digit postal sector of their residence.

One limitation of our data is that we do not have information for the card consumption from other banks, therefore we cannot fully capture all the card sales for each merchant. Nevertheless, similar to Agarwal, Qian, and Zou (2018a), our identification strategy does not require a complete account of all card spending by customers. To the extent that the choice of card is plausibly exogenous to the merchant's size (i.e., customers do not use cards from the financial institution in our sample to only purchase goods from small merchants), spending aggregated from our dataset is an unbiased indicator of the card sales of the merchants. Additionally, given the market share of the bank (also as a card issuer), it is likely that we are picking up a majority proportion of the (card) sale for merchants in sample.

3. Card Sales Response: By Transaction Size

Previous studies have documented that consumers tend to use cash for small-size payments, and cashless instruments for large-size transactions (Cohen and Rysman, 2013; Wang and Wolman, 2016). The QR code payment technology makes small transactions easier and may raise consumers' willingness and capability to make more small-size payments. The dramatic increase of small-size mobile wallet transactions in Figure 2 is consistent with the postulation. We therefore examine in this sub-section whether the positive spillover on card payments stemming from adopting QR code payment technology is also more pronounced in small-size transactions. Following the results in Table 1, we expect to see the spillover effect on card sales with small merchants driven by the ones featuring small-size transactions.

To investigate, we further divide the small merchants into two sub-groups according to their median transaction size per purchase in 2016. Specifically, we define the small merchants with median transaction size in 2016 below the 50th-percentile as the small transaction size type and expect them to exhibit the strongest increase in card sales. Results reported in Table A2 are consistent with our expectation. The change in log sales amount after the technology shock is indistinguishable between large merchants and small merchants with large transaction size (coefficient=-0.011, *p* value=0.538). In contrast, the small merchants with small transaction size register 8.5 percent increase (= exp(0.082)-1) in card sales amount than their counterparties with large transaction size, and the difference is statistically significant at the 1 percent level. Similar result is found for the card transaction counts: only the small merchants with small transaction size exhibit a significant increase in card sales count of 6.7 percent (= exp(0.072-0.007)-1) relative to large merchants.

4. Heterogeneity by Goods Sold

In this section, we examine the extent of spillover effect on different types of merchant defined by their goods sold. As validated above that card sales increase mainly works through new small merchant and in small-size transactions, it is unlikely that the sales of visible goods (used to signal status), which are typically expensive from well established brands, will be affected to a large extent. Following the definitions in Agarwal, Qian, and Zou (2018b), we group the merchants as visible goods sellers and non-visible goods sellers, and separately check their sales response.[4] As reported in Panel A of Table A3 (columns (1)-(2)), the small merchants, relative to the large merchants, selling non-visible goods register significantly more increase in card sales amount (coefficient=0.073, *p* value<0.001), while the difference in card sales growth between small and large merchants selling visible goods are statistically indistinguishable from zero (coefficient=-0.023, *p* value=0.255). Chi-test suggests the difference between visible goods sellers and non-visible goods sellers are statistically significant at 1 percent level.

We also examined whether there’s difference between merchants selling discretionary goods versus non-discretionary goods. We define merchants mainly selling goods in “local conveyance

[4] Specifically, we classify merchants mainly selling the following types of goods as visible goods sellers: specialty retail, automotive-related, rental, apparel, department stores, watches & jewelry, home/office furnishing & appliances, electronic and computer, music, entertainment & recreational, dining, associations/memberships, pets.

& taxi”, “supermarkets”, and “food & beverage stores” as non-discretionary goods sellers, and the rest as discretionary goods sellers. In columns (3)-(4) of Panel A, Table A3, we find that the small merchants selling discretionary goods register a significant 3.9 percent increase in card sales amount relative to their large counterparties; this effect is an insignificant 2 percent for the non-discretionary sellers. Chi-test suggests that the difference is insignificant (Chi-test statistic=0.08, *p* value=0.773).

Besides classifying merchants into broad binary types, we further classify merchants into six categories: supermarket, apparel, dining entertainment, travel, and personal care. As reported in Panel B of Table A3, card sales for dining merchants benefit most from the enhanced payment efficiency: small merchants exhibit 12.6 percent more increase in total card sales amount than large merchants.

A. Log (Sales Amount) **B. Log (Sales Count)**

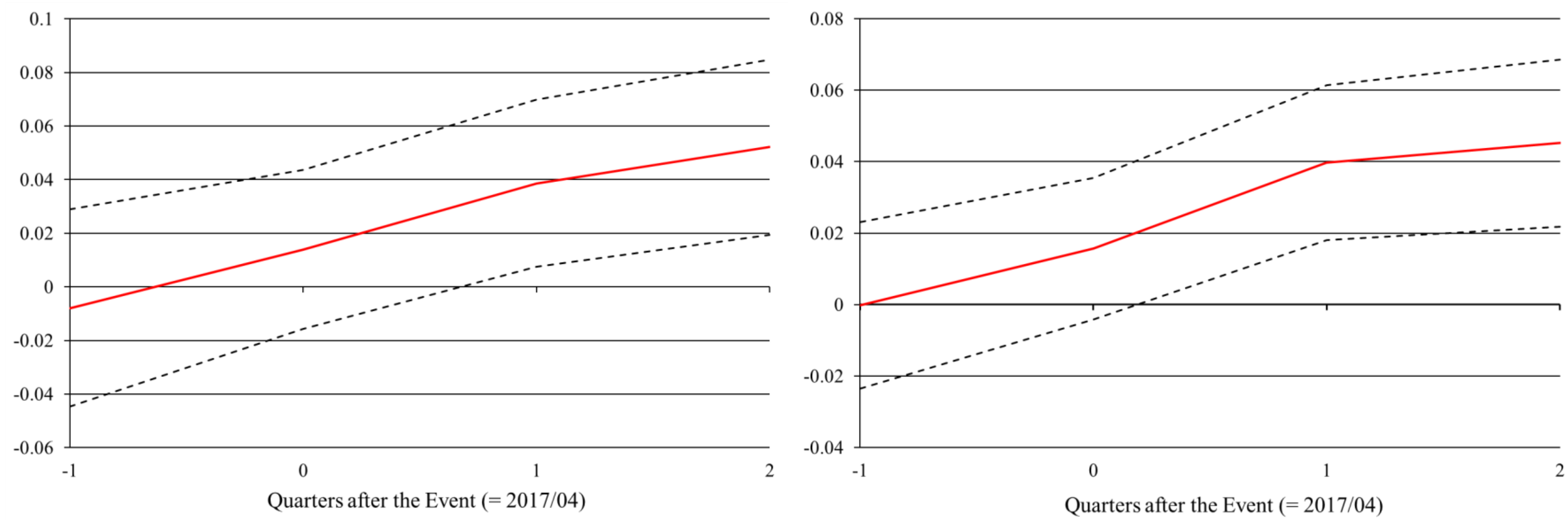

FIGURE A1. *DYNAMIC RESPONSE OF LOG SALES*

Note: This figure plots the dynamic response of log card sales, for the one month before and three quarters on and after the first introduction of QR code payment technology. The x-axis denotes the qth quarter after the first QR code payment introduction, and the y-axis shows the response of log sales amount in Panel A, and log sales count in Panel B.

	[-1,-14 week] window	[1,37 week] window	Difference in means (2)-(1)
	(1)	(2)	(3)
Panel A. All Mobile Wallet Transactions			
Transaction amount (SGD)	130,502	243,856	113,353***
Transaction count (#)	1,260	2,623	1,363***
Panel B. Small-size vs. Large-size Mobile Wallet Transactions			
Transaction amount (SGD)			
Small-size transactions	39,645	74,424	34,779***
Large-size transactions	90,858	169,461	78,574***
Difference in means: small-large	-51,213***	-95,008***	-43,795
Transaction count (#)			
Small-size transactions	962	2,063	1,101***
Large-size transactions	297	560	262***
Difference in means: small-large	665***	1,503***	838
Number of weeks	14	37	

TABLE A1. MOBILE WALLET TRANSACTIONS BEFORE AND AFTER QR CODE PAYMENT INTRODUCTION

Note: This table compares the amount and count of Mobile Wallet transactions in 14 weeks before and 37 weeks after the first QR code payment introduction in week 15 of 2017. Panel A pools all transactions, while Panel B separates small-size transactions (i.e., transaction size <SGD100) and large-size transactions (i.e., transaction size ≥SGD100). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(Total Sales Amount)	Log(Total Sales Count)
	(1)	(2)
Small Merchant × Pre$_1$	-0.008	-0.001
	(0.44)	(0.06)
Small Merchant × Post	-0.011	-0.007
	(0.62)	(0.62)
Small Merchant × Small Transaction Size	0.082***	0.072***
× Post	(4.33)	(5.51)
Constant	6.885***	1.899***
	(889.30)	(366.70)
Fixed Effects	Merchant, year-month	
Observations	148,460	148,460
R-squared	0.81	0.91

TABLE A2. HETEROGENEITY BY TRANSACTION SIZE

Note: This table reports the heterogeneity in average card sale response by the size of card transaction. *Small Merchant* is a binary variable equal to one for the small merchants, which is defined as merchants with median monthly sales lower than the 50th-percentile within each MCC in 2016. *Small Transaction Size* is a dummy variable equal to one for the merchants with median transaction size per purchase lower than 50th-percentile among the small merchants in 2016. *Pre$_1$* is a binary variable equal to one for the one month before the first QR code payment introduction (i.e., 2017:03). *Post* is a binary variable equal to one for the nine months on and after the first QR code payment introduction (i.e., 2017:04 - 2017:12). *Total Sales Amount* is computed by adding all monthly card sales amount for each merchant. *Total Sales Count* is computed by counting monthly count of card purchases for each merchant. Merchant and year-month fixed effects are included, and standard errors are clustered at the merchant level. T-statistics are reported in parentheses under the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	Log(Total Sales Amount)			
	Merchants sell			
	Visible vs. non-visible goods		Discretionary vs. non-discretionary goods	
	Visible	Non-visible	Discretionary	Non-discretionary
	(1)	(2)	(3)	(4)
Small Merchant × Post	-0.023	0.073***	0.038***	0.020
	(1.14)	(5.02)	(3.13)	(0.32)
Constant	6.808***	6.932***	6.886***	6.819***
	(504.78)	(745.60)	(876.13)	(154.66)
Fixed Effects	Merchant, year-month			
Observations	56,931	91,529	143,656	4,804
R-squared	0.78	0.83	0.81	0.90

Panel B

	Supermarket	Apparel	Dining	Entertainment	Travel	Personal care
	(1)	(2)	(3)	(4)	(5)	(6)
Small Merchant × Post	0.020	-0.027	0.119***	0.008	-0.020	-0.059
	(0.32)	(0.85)	(6.62)	(0.17)	(0.34)	(1.57)
Constant	6.819***	6.832***	6.911***	6.594***	7.435***	6.625***
	(154.66)	(327.03)	(622.35)	(216.95)	(201.27)	(263.11)
Fixed Effects	Merchant, year-month					
Observations	4,804	21,469	45,089	10,634	9,169	15,651
R-squared	0.90	0.81	0.86	0.80	0.85	0.71

TABLE A3. HETEROGENEITY BY GOODS SOLD

Note: This table reports the heterogeneity in average card sales amount response by type of goods sold by merchants. Panel A divides all merchants into binary groups by the visibility of goods sold in columns (1)-(2), or the sale of discretionary versus non-discretionary goods in columns (3)-(4). Please refer to Section 4.6 for detailed classifications. Panel B further checks the average sales amount response for merchants selling six categories of goods: supermarket goods, apparel, dining, entertainment, travel, and personal care. *Small Merchant* is a binary variable equal to one for the small merchants, which is defined as merchants with median monthly sales lower than the 50th-percentile within each MCC in 2016. *Post* is a binary variable equal to one for the nine months on and after the first QR code payment introduction (i.e., 2017:04 - 2017:12). *Total Sales Amount* is computed by adding all monthly card sales amount for each merchant. Merchant and year-month fixed effects are included, and standard errors are clustered at the merchant level. T-statistics are reported in parentheses under the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.