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Abstract

A behavioral literature suggests that minor frictions can elicit desirable behavior without obvious coercion. Using closures of ATMs in a densely populated city as an instrument for small frictions to physical banking access, we find that customers affected by ATM closures increase their usage of the bank's digital platform. Other spillover effects of this adoption of financial technology include increases in point-of-sale (POS) transactions, electronic funds transfers, automatic bill payments and savings, and a reduction in cash usage. Our results show that minor frictions can help overcome the status-quo bias and facilitate significant behavior change.

Keywords: Frictions; Digital Banking; FinTech; Geography; Household Finance; Financial Inclusion

JEL Classification Codes: D12, D14, G21, G40, O33

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1. Introduction

A literature in behavioral science proposes that small modifications to a person's choice set can significantly alter behavior without obvious coercion. For example, how a set of investment choices are offered can have a large impact on an investor's decision making (Benartzi and Thaler (2001); Madrian and Shea (2001); and Thaler and Benartzi (2004)). Cronqvist, Thaler, and Yu (2018)) recently show that such nudges can have long-lasting effects. In health science, Thorndike et al. (2012) and Vandenbroele et al. (2021) show that minor changes to physical accessibility can help consumers unknowingly make healthier food choices. The key idea is that small changes to the landscape have the potential to encourage desirable behavior.

In this paper, we examine the impact of such choice architecture in influencing digital banking adoption. Traditional banks, now competing with new entrants, have transformed their business strategy—adding digital means to deliver banking services. Digital banking is cheaper and can enable greater financial inclusion beyond the usual geographical reach of physical locations. Philippon (2016) argues that new financial technology (FinTech) gives incumbents an opportunity to reduce historically high financial intermediation costs. Recent studies also attest to the benefits of FinTech, such as increasing savings (e.g., Bachas, Gertler, Higgins, and Seira (2020)), business growth (e.g., Higgins (2019); Agarwal, Qian, Yeung, and Zou (2019); Beck, Pamuk, Ramrattan, and Uras (2018); and Hau, Huang, Shan, and Sheng (2017)), attentiveness to accounts (e.g., Carlin, Olafsson, and Pagel (2019)), and the potential of using digital footprints to improve access to credit (e.g., Berg, Burg, Gombovi, and Puri (2020)).

As documented in the literature, desirable behavioral change can arise from pull or push factors. For pull factors, Cole, Sampson, and Zia (2011) find that very small subsidies can greatly increase the demand for financial services, and Cookson (2018) shows that adding a lottery feature into savings accounts can significantly influence savings behavior. For push factors, Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru (2017) and Chopra, Prabhala, and Tantri (2018) show that the 2016 large-scale removal of cash in India forced customers to move to digital means of banking. Larcom, Rauch, and Willems (2017) describe how a London Underground strike in 2014 pushed commuters to experiment with new routes and this led to lasting change in behavior and improvements in route selection.

Our paper focuses on how push factors related to physical architecture can elicit behavioral change. The small push that we examine is an ATM closure. In a densely populated city, an ATM closure imposes only a minor physical friction as the next available ATM could be less than 100 meters away. Might such small frictions be sufficient to induce digital banking adoption and other spillover effects of FinTech? Obviously, if there is some pandemic-induced lockdown that completely removes physical banking access, customers will be forced to do their banking online. Our paper is not about such shutdowns, which might achieve the desirable side effect of technology adoption but will be associated with many other negative consequences. The main contribution of our paper is to examine the impact that *minor* physical frictions have in inducing both substitution and spillover effects in the consumer banking industry.

To answer this question, we use a novel dataset of 500,000 randomly selected retail customers of DBS Bank, the largest bank in Singapore, from 2015–2017. We show that customers who experience ATM closures indeed face a small friction—their ATM usage distance increases by about 100 meters and their ATM activity declines marginally. We show that for an affected customer, this closure-induced friction increases their use of the bank's digital platform relative to other customers who did not experience such closures. For example, for every 1 km increase in distance, the number and dollar amount of digital transactions increase by 27% and 38% respectively, compared to non-treated customers.[1] This substitution effect is larger for younger customers. This shock also affects other important and interesting dimensions of banking technology adoption—point-of-sale transactions increase, electronic funds transfer transactions increase, automatic bill payments increase, and automatic savings transactions

[1]This means that for a 100-meter increase in distance the increase in digital banking transactions is about 3–4%. All our results include customer fixed effects and year-month fixed effects, which control for customer heterogeneity and the increasing adoption of digital banking over time. Our results are also robust to alternative measures of distance (by incorporating the approximate workplace location), and a propensity score-matching procedure.

increase, and cash usage declines. Overall, the small friction provided by not finding a formerly used ATM results not only in more engagement with the bank's digital banking platform, but also induces positive spillover to other financial behavior.

The ATM closures that we examine in our paper can occur for two reasons, either an operations optimization decision by the bank, or a quasi-exogenous temporary closure likely due to renovations in the facility (e.g., mall) where the ATM is located. We show that for both types of closures, there is little decline in activity at the ATM just before its closure, indicating that the closure is indeed a shock for the affected customers. Importantly, our findings on the increased in digital banking usage hold for both permanent and temporary closures. The effects are also long lasting—i.e. they do not dissipate even when the temporary closures are reopened. This is consistent with Larcom et al. (2017)'s findings that an involuntary re-optimization caused by a temporary shock can result in permanent behavior change.

We believe these results speak to the current issue of banks downsizing their physical locations. Banks frequently cite changed customer behavior to justify downsizing. For example, Deutsche Bank plans to close one in five branches in Germany offering the reason that the coronavirus pandemic has driven more customers online.[2] Our study provides the first scientific evidence that the causality might also run in the opposite direction—that reductions in physical access can encourage customers towards digital banking. And more importantly, that even an innocuous and slight reduction in physical access like an ATM closure in a high ATM-density city is sufficient to induce an economically significant substitution effect.

Second, our findings add to the literature describing the benefits of FinTech adoption. As some of ATM closures in our sample are quasi-exogenous, their spillover effects can be interpreted as stemming from a somewhat random event. Such "involuntary" adoption should be classified differently from FinTech adoption that is driven by large-scale roll outs. Unsurprisingly, at-scale initiatives have been associated with widespread effects/benefits. For example, Higgins (2019) and Bachas, Gertler, Higgins, and Seira (2020) document the spillover bene-

[2]https://www.ft.com/content/fc1988d2-213f-491e-9194-5e2e91f8ea67, Deutsche Bank plans to close 1 in 5 branches in Germany. German lender responds as coronavirus pandemic drives more customers online.

fits of a policy-driven debit card distribution program, Agarwal, Qian, Ren, Tsai, and Yeung (2020b) show the impact on business growth by the introduction of a new mobile payments technology, and Agarwal, Ghosh, Li, Huang, and Ruan (2020a) show the impact of India's 2016 demonetization on FinTech use and consumption. The FinTech adoption documented by our study are driven not by such large-scale initiatives but instead by the small friction associated with ATM closures. And surprisingly, they also produce significant technology adoption and spillovers to desirable financial behavior such as more efficient movement of funds between accounts.

Third, our findings relate to the importance of geography in financial markets. Geography is important in many areas of finance.[3] In corporate banking, proximity to a banking location is related to corporate loan pricing due to information asymmetry (e.g., Bonfim, Nogueira, and Ongena (2021); Herpfer, Mjos, and Schmidt (2018); Agarwal and Hauswald (2010); and Degryse and Ongena (2005)). In consumer banking, Lippi and Secchi (2009) model the role for the density of bank branches and ATM networks on an agent's cash holding choices, and Bachas et al. (2018) describe physical distance as a transaction cost in consumer banking. Our key finding is that shocks to the ease of accessing ATM services (in the form of a disappearance of an often-used ATM) can produce spillover effects to banking behavior. The key source of this friction is an agent's geographical preference for closer distances compared to longer distances. Given that our evidence is based on a densely populated city, we believe that the magnitude of such impact is likely a lower bound when it is extrapolated to less dense cities.

Fourth, our findings are related to the literature on nudge economics, to the extent that ATM closures can be considered a minor friction to physical banking access rather than a complete forbidding of physical banking. Kahneman, Knetsch, and Thaler (1991) show that investors exhibit the status quo bias and even the simple switch to make a default option slightly more inconvenient to select, can have a large effect on the eventual action chosen.

[3]For example, the home or familiarity bias of investment (Grinblatt and Keloharju (2001) and Coval and Moskowitz (1999)), accuracy of sell-side research (Malloy (2005)), dividend policy (John, Knyazeva, and Knyazeva (2011)), and even financial misconduct (Parsons, Sulaeman, and Titman (2018).)

In a city where ATMs are readily available in adjacent locations, we show that even a slight increase in the distance to the nearest physical banking access point can increase digital banking usage.

The rest of the paper is organized as follows. Section 2 describes the data and sample, Section 3 reports summary statistics, Section 4 presents the main empirical results, Section 5 reports additional results and robustness tests, and Section 6 concludes.

2. Data and Sample

2.1. Retail Banking in Singapore

Before describing the data, we provide some background on the banking landscape in Singapore. Singapore is a developed city-country with 5.5 million residents in our sample period of 2015–2017. Its banking industry is dominated by three local banks. Although foreign banks can take retail deposits, they face restrictions on their total number of physical locations. In contrast, using network sharing, each local bank provides a large network of ATMs. A typical local bank customer has access to about 1,000 ATMs in the country's small land area of 721.5 square km.[4] Figure 1 shows a Singapore map where dots indicate ATM locations for DBS, the bank that provided our sample. Banking customers are also well served by bank branches, with each local bank having more than fifty branches in this period.

The primary reason for a customer to visit a branch or an ATM is cash related. Debit and credit cards are available as payment methods for the majority of merchants but some small businesses still use cash as the only means of payment so as to avoid the fees associated with electronic payments. Checks are still a common payment method for individuals and businesses, even though electronic payment of bills and electronic funds transfer services can

[4] The three local banks are DBS, UOB, and OCBC. DBS has its own unshared network of about 1,000 ATMs. The other two banks' customers are allowed to use each other's ATMs and in aggregate also have access to about 1,000 ATMs in their shared network. Singapore's central bank estimates that the majority of the population has access to an ATM within 1 km of their residence. http://www.mas.gov.sg/News-and-Publications/Parliamentary-Replies/2017/Reply-to-parliamentary-question-on-accessibility-of-ATMs.aspx

be done without fees. Overall, while the infrastructure for digital banking is mostly in place, there is a variation in digital banking usage across different customers. In our random sample of customers, two-thirds use the bank's digital platform at least once. This is comparable to the fraction of digital banking users reported in the US in a similar period.[5]

2.2. Sample Description

Our data is from DBS bank from January 2015 to December 2017. Known as a leading financial services company in Asia, DBS is headquartered and listed in Singapore and has a large retail market share in Singapore.[6] Our unique proprietary dataset contain transaction-level banking activity for 500,000 randomly sampled (using the cross-section of customers in 2016) retail customers from the bank's customer base in Singapore.

The detailed data used in this study can be categorized into three parts. First, we have the transaction-by-transaction data of a customer's savings and checking accounts with the bank. Second, we have all of the customer's ATM transactions, specifying the ATM location, amount associated with the transaction if any, type of usage (withdrawal, deposit, fund transfer, balance enquiry, etc.), and the date and time of usage. Finally, we have a dataset containing all of the customer's activity on the bank's Internet platform or mobile banking app. This activity can be classified as either financial-related activity, which we define as transactions associated with non-zero dollar amounts (e.g., funds transfers or bill payments), or non-financial activity (e.g., log-ins, account summary views, transaction enquiries, or requests for SMS passcodes).

Besides banking data, we have demographics information, such as race, marital status, gender, and age. For the purpose of our study, we need the mailing address of the customer. To adhere to privacy regulations, the bank provided addresses only at the postal code level and anonymized all customers' original national identifiers with pseudo identifiers. Unlike in the U.S., where a ZIP code identifies a sizable area within a city, a Singapore postal code identifies an exact building. But because about 90% of Singapore residents live in high-rise

[5]For example, see, https://www.wsj.com/articles/u-s-unbanked-population-continues-to-fall-1540316543.
[6]Please see https://www.dbs.com/about-us/ for more information on DBS.

apartments, this sufficiently masks customer identities within a building.[7]

The bank provided three January snapshots of the customer's mailing postal code. In Singapore, physical mail is still important and customers typically change their mailing address immediately after moving as mail forwarding service is costly. For movers, since we do not observe the actual month of move, there is noise in the assumed customer location in the non-January months. As customer moves are infrequent in our sample (4% of the customers), we believe that this noise is minimal and does not bias our results.[8]

Since the bank serves a large fraction of the population in Singapore and provides comprehensive banking services, this random sample is likely to be representative of a customer's overall retail banking activity. But we cannot rule out the possibility that a customer maintains accounts with other banks. Hence, to be more certain that the customers we use for our tests use this bank as their main bank, we focus only on customers in the sample period who have either 1) at least one salary credit, *or* 2) auto-debit transactions totaling at least S$20 in at least six of the months in the sample. A salary credit shows a customer is actively using the bank as they elect for this bank to receive an important source of regular income.[9] The presence of auto-debit transactions shows that the account is actively being used for regular payments and can also capture customers who might have regular income not flagged as a salary credit, e.g., freelancing income, landlord income, or retirement-related income.

We also exclude customers who hold joint-named accounts. Multiple single-named accounts are fine as the variables in each account can be aggregated to the customer level. But joint-named accounts are tricky because we cannot tell which of the joint-account holders

[7]As an additional safeguard, the bank excluded customers associated with postal codes where it had fewer than 50 customers. This screen will exclude landed houses from our sample. Only 5% of Singapore households reside in such non-high rise locations.

[8]Our robustness tests will include an alternative cluster-based distance measure that estimates a customer's alternative location anchors such as a new address that was not declared in a timely manner to the bank. We obtain similar results with this cluster-based distance measure. Our results also remain similar when we drop all movers from the sample.

[9]This screen is sufficient to identify customers who regularly credit their salary because the mean (median) number of months with a salary credit for those who satisfy this screen is 25 (30) in our 36-month sample. In unreported tests, we show that our results also hold if we do not use the second (auto-debit) screen and restrict the sample only to customers who have at least one salary credit in the sample period.

invoked the auto-debits or received the salary credits, although we can observe ATM and digital activity at the individual level. After these screens, our final sample consists of 197,028 customers. The drop in sample size from the original 500,000 comes from the salary credit, auto-debit, and non-joint account screens. The large drop shows the important of screening to focus only on active customers because a large fraction of customers who maintain accounts might not be active. This final sample is about 3% of total population in Singapore in 2015.

3. Summary Statistics

3.1. Demographics, ATM Usage Distance, and Banking Activity

Table 1 reports summary statistics for our final sample of about 6 million customer-month observations from January 2015 to December 2017. Panel A reports demographic characteristics of age, monthly salary, and the beginning-month account balance. The average customer age is 42.18. The average monthly salary of customers is 2,270 Singapore dollars (S$).[10] The average beginning-month balance, summed across all of the customer's accounts, is S$19,090. During our sample period the mean exchange rate is 0.73 US dollars per Singapore dollar.

We define (*Distance to ATM*) as the mean usage distance of a customer to an ATM. To compute this, for each ATM transaction, we obtain the GPS distance between the customer's postal code and the ATM location postal code.[11] The customer's average ATM usage distance each month is weighted by the number of transactions at each ATM. If we cannot measure the distance for a customer due to no ATM usage in a month, we replace it with the most

[10]The salary statistics in Table 1 are computed by assuming that the salary is zero when there is no salary credit for a customer-month. If we focus on only non-missing salary-months, we can compare our sample's salary statistics to the country's salary statistics so as to ascertain whether our salaried customers look like those in the population. The median gross monthly salary (excluding employer pension contributions) reported by the Ministry of Manpower is S$3,467, S$3,500, and S$3,749 from 2015 to 2017 respectively. In Singapore, the salary that gets credited into a bank account will further exclude the employee's own pension contribution which is 20% of the gross salary for most. The median non-zero monthly salary credits in our sample from 2015 to 2017 are S$2,692, S$2,754, and S$2,835 respectively. These are close to 80% of the nationally reported medians, and show that our sample is fairly representative of the population.

[11]Postal codes are converted to latitudes and longitudes using www.gps-coordinates.net or Google Maps.

recent distance of the customer when available (13% of customer-months contain such filled distance measures). The average *Distance to ATM* for a customer-month is 5.08 km.

How do we interpret this mean distance? While customers always have an ATM located close to their homes, they can also use ATMs when they are at other locations such as at a shopping mall or a transport hub. Our average weighs the importance of each location to a customer using the number of transactions.[12] A disadvantage of this home-address based distance measure is that customers could also cluster their activity not just around their home, but around their workplace or some alternative location such as a favorite mall. Unfortunately the customer is not required to register such alternative locations to the bank. To address this issue, while our baseline tests use the home-based distance measure, we also compute a cluster-based distance measure in robustness tests. We proxy for alternative clusters by choosing the top three geographical centers of a customer's clusters of ATM transactions (we impose a maximum of five clusters in the estimation). With these three cluster centers as alternative locations of the customer, we can have up to four addresses (inclusive of the home) for each customer. The alternative measure, *Distance to ATM (Clustered)* is the minimum distance between the used ATM location and any of these four locations. The last row of Panel A shows that this variable averages 1.96 km—unsurprisingly lower than the 5 km average obtained when distance is measured relative to only the customer-provided (home) address.

Panel B reports statistics of various customer banking activity. For ATM activity, we report the total number of transactions, the number of non-financial transactions, and the average dollar amount of an ATM transaction. On average, a customer does 8.26 total ATM transactions per month. Non-financial ATM transactions, i.e. balance enquiry or password change, occur 1.26 times per month. A financial transaction at an ATM, defined as one associated with a non-zero dollar amount, has a mean amount of S$372 (the median cash transacted is S$200).

[12] We obtain similar average distances if we weigh the importance of each location with the absolute dollar amount transacted instead. The disadvantage of using dollar weights is that we would not be able to include transactions that do not have dollar amounts associated with them, such as a balance enquiry.

For digital activity, we report the total number of transactions, number of financial transactions, and the sum of dollars transacted in a month. On average, a customer does 26.87 digital transactions per month, which includes 2.5 financial transactions (defined by transactions that are associated with non-zero amounts). Total summed dollar amount of financial digital transactions done in a month is S$2,036 per month on average. Note that the averages are computed by setting non-digital users' usage activity and amounts to zero.

We report the total number account-level transactions as a proxy for their overall banking activity with the bank. This counts the total number of transactions across the customer's savings and checking accounts. Savings accounts form the majority (more than 90%) of account activity. The average number of account-level transactions is 27.54 per month.

We also report the descriptive statistics of other outcome variables. Note that the variables take a value of zero if there are no transactions for that variable. The amounts associated are the sum of dollars transacted in a month. The average number of point-of-sale (POS) transactions is 8.76 for a customer-month and the average total POS amount in a month is S$816.94. The average number of regular funds transfers made by a customer is 2.54 and the average total amount transferred in a month is S$1,825.53. Because a regular funds transfer takes 2–3 days to clear, a new method known as Fast And Secure Transfers (FAST) that enables customers to transfer funds from one bank to another almost instantaneously was introduced in 2014. The average number of such FAST transfers made is 0.75 per month in our sample period and the average total amount transferred in a month is S$878.45.

Next, we report the number and mean of auto-debit transactions, which are known as General Interbank Recurring Order (GIRO) transactions. This allows customers to make regular bill payments directly from their bank account to avoid the inconvenience of having to make recurring bill payments manually. We see that the average number of GIRO transactions is 0.70 per month and the average total amount in a month is S$933.

We also proxy for a person's propensity to save using the bank's automatic savings plan called the "Save as You Earn" (SAYE) scheme, where the customer chooses a monthly amount to be deposited to a SAYE account and additional interest is given if there is no withdrawal is made for some specified time period.[13] The average number of SAYE transactions each month is 0.17 and the average total amount saved in a month S$73.54.[14] The last item in Panel B is the sum of total cash withdrawals in a month, which is S$1,717.

3.2. Visualizing the ATM Usage Distance

Because our main analysis uses distance as the friction proxy, this section provides visual evidence on how customers access proximate versus distant ATMs.

Figure 2 plots the time-series of the average *Distance to ATM*. We split ATM transactions into three groups: 1) weekday working hours (defined as 8AM–6PM on non public-holiday weekdays), 2) weekday non-working hours, and 3) weekends and public holidays. If the measure correctly captures a customer's physical distance from home to the near-home banking services, the distance should be similar during weekday non-working hours and during weekends/public holidays, both of which are times when the customer is more likely to be at home. In contrast, the distance should be longer during weekday working hours as the customer is more likely to be at work and hence is more likely to use banking services close to their work location. We indeed find that usage distance is longer during working hours. The remarkable similarity between the other two lines plotting the *Distance to ATM* during non-working hours and weekends gives us confidence that the measure correctly picks up the proximity of the customer from their home to their typical banking location.

Although the average distance is 5 km, this obviously does not mean that a customer prefers ATMs that are exactly at this distance. To see this, we plot a histogram of the probability that a typical customer uses an ATM that is x km away from their postal address. The top chart of Figure 3 shows this plot, where red bars denote the fraction of amounts that a typical customer transacts at ATMs at a particular km. We can see that 40% of a customer's

[13] https://www.posb.com.sg/personal/deposits/savings-accounts/saye

[14] This amount seems small because the majority of customers do not have such accounts. For non-zero SAYE transactions, the average monthly amount contributed is S$688.31.

ATM transaction amounts are done at ATMs within the first km from their postal address. The second km is much less important, where the usage fraction declines to less than 10%. This fraction declines further the farther away the ATMs are.[15] To make sure this skewness is not driven by the distribution of ATMs, we plot (with blue bars) as a benchmark the fraction of ATMs that are within x km of a typical customer. One can see that only about 1% of the ATMs in the city are within 1 km of a typical customer but they use these proximate ATMs with a 40% likelihood. This shows the importance of nearness to an ATM.

To visualize the usage pattern of an individual customer with reference to their provided address, we plot in Figure 4 an ATM usage heatmap by distance. We randomly pick 1,000 customers and arrange them from left to right in the chart in order of increasing mean distance. Each column represents one customer and each cell in a column depicts the probability that the customer uses ATMs at that particular distance, with the red intensity representing a higher usage probability at that particular km. One can see immediately that the lowest-distance customers rely almost exclusively on ATMs within the first km of their address. Second, even the median customer transacts about half of their dollar amounts at ATMs in the first km. Finally, even for far-away customers, the first km retains some importance. Overall, the heatmap shows that customers rely heavily on closer ATMs.

We have assumed so far that the postal address is the home location. The provided postal codes are indeed associated with residential buildings 90% of the time, with the rest associated with commercial buildings.[16] For customers with commercial addresses, which is likely to be their work location, we plot the histogram of their ATM usage in increasing distance from this address in the second chart in Figure 3. We find that the distribution is less skewed compared to the first chart. Although such customers are still more likely to use ATMs close to their

[15]To match this histogram with the 5 km mean we report in the prior figure, one can take the weighted average of the km value in each bin using the fraction of usage as the weights and this would recover an average of about 5 km. Hence, while the average distance of a typical customer is about 5 km, the most frequently used ATM is the one within the first km. Also note that the longest distance in this histogram is 30+ km which represents a customer with an address at one end of the island (e.g., Tuas at the extreme West of the island) using an ATM at the airport (at the extreme East).

[16]The address category is determined by searching for the postal code with an "(S) " prefix in streetdirectory.com.

work addresses, the strong reliance on the closest ATMs is not as stark. We conclude that the home compared to the work location is a more reliable anchor when customers access ATMs. Also, this means that the distance measure computed from commercial addresses is a noisier proxy for the friction faced by a customer.[17]

3.3. ATM Closure Measures

To establish a more causal relation between the *Distance to ATM* and customers' digital banking activity, we need an instrument that changes distance without changing digital banking activity except through changes in distance. In this paper, we use ATM closure events as a quasi-exogenous shock to distance. A closure is defined as an ATM postal code where no more ATM transactions occur at the postal code for at least 30 days in our sample. Defining ATM closures at the postal code (building) rather than a specific ATM machine avoids the problem that in a building such as a mall, an ATM is closed on one floor but there is an ATM on another floor. We have 109 closures of ATMs at the postal code level in our sample period.[18] These closures are spread out as shown by the red markers in Figure 1.

These closure events might not be fully exogenous because the closure of an ATMs is unlikely to be completely random. However, because the density of ATMs is so high in the city, we believe that ATM closures are still useful for studying the impact of minor frictions. From a single affected customer's point of view, the customer uses an ATM because of convenience. When the ATM closes for this frequent user, this might be akin to a random shock for the customer.[19] Second, some of the ATM closures in our sample are not strictly a result of the bank's optimization decisions but due to renovations at the facility where the ATM is located. For example, Compass One is a mall located in the sub-urban town of Sengkang and the mall

[17]This also motivates the use of our alternative cluster-based distance measure as a robustness test that can help detect the other locations that such customers anchor on.

[18]We do not include the closures of temporary ATMs set up to cater to seasonal demand such as ATMs for Chinese New Year or for the Formula One race event. Usage at such temporary ATMs are also not included when computing the distance measure.

[19]Banks do not inform customers individually of an ATM closure but they place a notice at the ATM's location to announce the closure and describe the nearest alternative ATM locations.

closed for renovation in late October 2015 and re-opened on September 1, 2016. Due to this renovation, the ATM in the mall closed from September 22, 2015 to September 24, 2016. In such cases, the closure serves as a quasi-exogenous shock to the users of the ATMs at that location. Hence, temporary closures are more likely to satisfy the exclusion restriction. While our baseline tests combines both types of closures, we will examine temporary and permanent closures separately in a later section.

Panel C of Table 1 reports the summary statistics of the two dummy variables used to identify customers affected by ATM closures. The first treatment group consists of customers whose favorite (i.e. most used) ATM closes. For this definition, to be certain that that these ATM users are active, we require that the favorite ATM be used at least six times by the customer in the prior three calendar months (i.e. an average of twice a month). Customers in this treatment group are actually reliant on the ATM before its closure and are fairly active ATM users in general. The second treatment group consists of customers whose postal address is the nearest to the closed ATM *regardless* of whether they used the ATM prior to its closure. While this second definition of a treatment group might overlap with the first definition, it identifies affected customers more generally as those who might *potentially* be inconvenienced by the closure. For example, while one might not have used the ATM nearest to them recently, the removal of the option for them to use it could have an effect on their behavior.

Denoting the first treatment group, *Post Closure (Favorite ATM)* equals 1 for [0,+] months from the ATM closure event for customers who use this ATM as their favorite, and 0 otherwise. That is, for such customers, all months starting from the month of the ATM closure up to the end of the sample period in December 2017 take the value of one. About 3% of our sample is defined as treated using this approach. Denoting the second treatment group, *Post Closure (Nearest ATM)* equals one for [0,+] months from the ATM closure event for customers who are nearest to the ATM, and zero otherwise. Because this measure considers only proximity and does not explicitly require usage, a larger fraction (about 5%) of our sample is defined as treated compared to the first measure.

4. Main Empirical Results

4.1. First Stage: Impact of Closures on ATM Usage

We have shown that customers are more likely to use banking services very close to where they are located. One can hence view distance as a friction. In a city where ATM density is high, the unavailability of ATMs at one location might induce only a small friction as there are multiple ATMs in the vicinity of the closed ATM. Our goal is to examine whether this minor increase in friction, as proxied by changes to ATM usage induced by the closure, can increase digital banking activity.

In the first stage tests, we examine the effect of ATM closures on friction as proxied by *Distance to ATM* using panel regressions reported in Table 2. The dependent variable is *Distance to ATM* and the independent variables are the two measures of closure shock—*Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. We include control variables, namely, the beginning-month account balance in thousands (Beginning Balance), the monthly salary in thousands, year-month fixed effects, and customer fixed effects. Standard errors are clustered at the customer level for this regression and all the other regressions in the paper.

In column (1), We find that if a customer's favorite ATM closes, the post-closure ATM usage distance of the customer increases by 108 meters. In column (2), we see that the closure of the customer's nearest ATM increases their post-closure ATM usage distance by 128 meters. In column (3), when we put both closure measures in the estimation, the coefficients from both types of closures show statistical significance. A favorite ATM closure, controlling for the other type of closure, increases the ATM usage distance by 74 meters (about 1.5% of the mean *Distance to ATM*). The closure of the customer's nearest ATM, controlling for the other type of closure, increases the customer's post-closure ATM usage distance by 117 meters (about 2.3% of the mean *Distance to ATM*). This increase in friction is not large, around a hundred meters, and is due to the high density of ATMs (see Figure 1) in the country.

In columns (4) to (6), instead of using *Distance to ATM*, we regress a direct measure of

ATM usage on the ATM closure dummies. In other words, the proxy for friction is no longer *Distance to ATM*, but the actual reduction in ATM usage. This is useful if the distance variable is measured with noise because the friction proxy is now ATM activity itself—if ATM activity declines due to a closure regardless of the distance, it must be that the customer now has more difficulty assessing an ATM.

The dependent variable is the log of 1+ the total number of ATM transactions. We find a significant reduction in the total number of ATM transactions when the favorite ATM closes, or when the nearest ATM closes. But in column (6) when both types of closures enter the regression, the effect from the nearest ATM closure becomes insignificant. But the effect from the favorite ATM closure remains robust, with a coefficient of –0.058, which is equivalent to a decrease of half a transaction.[20] In a robustness test section, we will use the ATM usage decrease in response to the closure of the favorite ATM as the friction proxy.

Overall, in this section of first stage regressions, we find that ATM closures impact the manner which customers access ATM services. The ATM usage distance increases and the total number of ATM transactions also declines. Because the ATM usage distance is more robustly related to both types of closures that we examine, we use distance as our main proxy for frictions.

4.2. Impact of Distance on Customers' Digital Banking Activity

In the second stage, we use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* to estimate an instrumental variable (IV) regression to examine if closure-induced frictions can push customers towards digital banking. This is the main question we examine in this paper—will a minor increase in physical frictions lead to an increase in digital banking activity?

Table 3 reports the IV regression estimates of the effect of the *Distance to ATM* on digital banking activity. The dependent variable in column (1) is the natural log of 1+ the total

[20] From the Table 2 reported average of 8.26 ATM transactions a month, we get exp[(log(1+8.26)–0.058]–1=7.74 which is 0.52 transactions less than 8.26, or 6% fewer transactions.

number of digital banking transactions.[21] The main independent variable is the *Distance to ATM* instrumented by both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. As in Table 2, we also include the beginning balance, monthly salary, year-month fixed effects, and customer fixed effects as controls so that we estimate the changes within a customer and control for any time trend. Standard errors are clustered at the customer level.

We find that customers indeed do more digital banking after an ATM closure shock increases their *Distance to ATM*. In column (1) we find an increase in the number digital transactions by consumers due to the increase in distance due to ATM closures—a 1 km increase in *Distance to ATM* increases the dependent variable by 0.232. Since the average of the number of digital transactions is 26.87, it is an increase of 7.27 transactions (exp(log(1+26.87)+0.232)–1=34.14; 34.14–26.87=7.27) and this is about 27% of the average.

Column (2) uses the log of 1+ the total number of digital financial transactions as the dependent variable. Financial-related transactions are defined those associated with dollar amounts. We find that a 1 km increase in *Distance to ATM* increases financial digital transactions by 0.121. Since the average of the number of digital transactions is 2.50, this is an increase of 0.45 transactions (exp(log(1+2.5)+0.121)–1=2.95; 2.95–2.50=0.45) and is about 18% of the average.

Column (3) uses the log of 1+ the total dollar amount of digital transactions as the dependent variable. We find that a 1 km increase in *Distance to ATM* increases total dollar amount of digital transactions by 0.381. This implies that the total amount of digital transactions went up by about 38%.[22] The effect on the transacted amount seems larger than the number of transactions indicating that the amount per transaction also went up.

Column (4) reports the results on the total number of transactions in the savings and

[21]We take the natural log to deal with potential nonlinearity in the banking transaction variables so as to prevent the results from being driven by outlier observations. Because some observations for these variables can have a value zero, we add 1 before taking the log to avoid undefined variable values. Our results are robust when we use the raw value of the variables instead of their log-transformed versions.

[22]Since the dollar amounts are larger when compared to the counts of the number of transactions, the adding of one to the amount before the taking of logs does not have much of an impact. So we can use the variable's coefficient as an estimate for the economic significance.

checking accounts associated with the customer, i.e. the number of entries in their account statements. This is not the same as the sum of ATM and digital transactions as not every ATM or digital transaction is reflected as an entry in the bank account statement. Using the same closure instruments, we show there is no significant impact on the total number of banking transactions in the customer's accounts. Assuming that the total number of banking transactions can proxy the degree of financial inclusion, this suggests there is no significant change in financial inclusion or account activeness. Hence, there is no evidence that such ATM closures cause the customer to disengage with the bank. Or another way to view this might be that the reduction in ATM transactions and the increase in digital transactions offset each other.

Overall, this section illustrates our key results. An ATM closure causes only a slight inconvenience to an affected customer as their distance to ATM increases by about 0.1 km. This magnitude is not large considering that this is a city with a high density of ATMs. Interestingly, we find evidence of a substitution effect as a corresponding increase in digital banking activity occurs in the post-closure period. This is evidence that an ATM closure serves as a small friction to induce the customer towards more usage of the bank's digital platform. This is consistent with a literature in behavioral economics which shows that small changes to the choice architecture can have a significant impact on behavior.

5. Additional Results and Robustness Tests

In this section, we document several additional results. We first investigate how our main results look for permanent versus temporary ATM closures. Second, we investigate the impact of closures on other variables associated with desirable outcomes that relate to financial or digital inclusion. Third, we divide the sample according to age groups. Fourth, instead of distance, we use the reduction in ATM activity as the closure-induced friction to investigate its impact on digital banking usage. Finally, to determine robustness, we consider a few alternative methodologies for some of our measures and estimations.

5.1. Temporary and Permanent Closures

Our results have thus far treated all ATM closures at the 109 postal-code locations as one group. However, some closures are temporary and some are permanent. We can proxy for temporary closures by checking whether ATM activity resumes subsequently at the particular postal code after it ceased. With this method we mark 34 out of the 109 closures as temporary. Note that this is a lower bound on the number of temporary closures because we cannot observe whether end-2017 closures reopened subsequently as our data from the bank ends in 2017. Of the 34 closures determined as temporary, the average number of days closed is 111, and the shortest closure duration is 34 days.

Temporary closures in our sample are likely to be motivated by some remodelling of the building or facility. Such closures are likely more exogenous to the bank and to the customer than are permanent closures. The concern for permanent closures is that they occur for ATMs which face declining customer traffic and the bank closes these ATMs when the customers using those ATMs are more ready to migrate online. To investigate this, we plot in Figure 5 the average number of transactions at a permanent versus a temporary ATM closure location around the closure month.

We see three interesting trends. First, ATMs affected by temporary closures are at busier locations with higher on-average traffic (about 4,500 transactions in the month prior to closure), compared to ATMs affected by permanent closures (about 2,500 transactions in the month prior to closure). This is not surprising since the temporary closures are more likely to be associated with mall renovations and ATMs at such locations likely see more traffic than a typical ATM location. Second, we do not see much evidence that permanent closures are associated with a greater pre-closure decline in ATM activity. Since closures occur in event-month 0, if a permanent closure is preceded by a greater decline in ATM activity, there should be a sharper decline in ATM activity from event month –6 to month –1 for permanent closures compared to temporary closures. However, while there is some decline in ATM activity in this period, this decline appears small in magnitude and does not seem to be different between permanent and temporary closures.

The third trend is that for temporary closures, activity in the ATM starts to bounce back after month 0. And within 4 to 5 months, ATM activity recovers but it does not go back up to the initial pre-closure levels. This is a useful fact to square up with our main result showing that digital banking activity increases without reversal in the post-shock period. If these results also hold for temporary closures, this would mean that a returning ATM does not move the customer back to traditional banking.

Table 4 reports the results of our main analysis estimated separately for permanent and temporary closures. To prevent the control group from containing customers affected by the other type of closures, when examining the impact of temporary closures in Panel A we remove from the non-treated group all customers who were in the sample period affected by permanent closures; and vice versa when we examine the impact of permanent closures in Panel B.

The dependent variable in column (1) is the log of 1+ the total number of digital transactions. We find an increase in digital transactions by customers in both types of closures. column (2) uses the log of 1+ the total number of digital financial transactions as the dependent variable and column (3) uses the log of 1+ the total dollar amount of digital transactions as the dependent variable. These results both indicate that the effects from temporary and permanent closures on digital banking activity are similar.

Overall, we do not find evidence in this section that permanent ATM closures are driving our main results.[23] The results for temporary closures are similar to those on permanent closures. This shows that customers who increase digital banking after temporary closures do

[23] Agarwal et al. (2020b) who also use data from DBS suggest that some ATMs were closed in 2017 in response to the introduction of mobile payments technology for merchants in the vicinity. However, their definition of ATM closures is based on the number of machines at the district (large area) level while we identify closures as all machines closing at a particular postal code (i.e. one building). Our closures are more likely to be renovation motivated rather than due to slight adjustments by the bank at postal codes with multiple ATMs. In addition, our results are robust when we drop 2017 from our sample. Second, there is no evidence of large scale ATM reductions during our sample period as the total number of postal codes with ATMs actually increased from 700 in January 2015 to 756 in December 2017.

not move back to traditional means when the closed ATM reopens. This evidence is consistent with Larcom et al. (2017) who show that an exogenous shock-motivated change that results in more optimal behavior does not reverse in the long term.

5.2. Spillover Effect to Other Banking Activity

Thus far, we have shown that the closure-induced increased distance to ATM increases the customer's use of the bank's digital platform. We now examine outcome variables that are related to an adoption of a specific technology in the digital banking. The richness of our banking transactions data allows us to identify various types of financial behavior that can be classified as desirable and related to technology adoption.

We examine the following financial activity as new outcome variables: 1) POS transactions which have been shown (e.g., in Bachas et al. (2020)) to have many positive spillover benefits; 2) Regular funds transfers, which provide a more efficient and less costly method of moving funds compared to using checks or cash; 3) FAST transfers, which provides an instantaneous transfer of funds to another bank without waiting for the 2-3 days that regular fund transfers require; 4) GIRO auto-debit transactions, which make bill payments more efficient; 5) SAYE automatic savings transactions, a proxy for disciplined savings which a desirable financial behavior (see, e.g., Cronqvist and Siegel (2015)); and 6) Total cash withdrawn in a month, where a reduction here is a proxy for better digital savviness.

Table 5 reports the results of second-stage regressions, using the fitted distance's effect on these new outcome variables. As before, we take the natural log of 1+ each measure, for the number of transactions for that measure, as well as the total dollar amount used in a month. The first two columns show that the usage of POS transactions goes up both in its number as well as the total dollar amount used. Inferring the economic magnitude from the dollar amount, we find that the dollar amount of POS transactions increases by 17.3% for a 1 km increase in *Distance to ATM*.

The next set of columns use the number and dollar amount of Regular Funds Transfer transactions as the dependent variables. We find that the usage of Funds Transfer transactions significantly increases. The dollar amount of Transfer transactions increases by 27.6% for a 1 km increase in *Distance to ATM.*

Next we examine a more efficient type of transfers—FAST transfers. Customers are also increasing their number of FAST transactions in response to the distance friction. Using the dollar amount of FAST transactions as the dependent variable. We find that a 1 km increase in *Distance to ATM* increases the amounts of FAST transaction usage by 23.4%.

We then examine the number of GIRO transactions and the dollar amount of GIRO transactions as dependent variables. We find that usage of GIRO transactions increases but we have statistical significance only for the number of GIRO transactions.

The next set of columns use the number and total amount of SAYE transactions as the dependent variables. We find that the number of SAYE transactions increases and the dollar amount of SAYE transactions increases by 7.4% for a 1 km increase in *Distance to ATM.*

Finally, column (11) uses the total amount of cash transacted at an ATM in a month as the dependent variable. We find that the cash usage decreases. The dollar amount of cash transacted at at ATM reduces by 8% for a 1 km increase in *Distance to ATM.*

Overall, we find in this section that the distance friction brings about a significant change in eliciting desirable financial behavior from the affected customers. The small push from an ATM closure not only increases digital banking activity in general, but this spills over positively to other useful FinTech-related outcome variables like POS transactions, funds transfer services, automatic saving plan contributions, and a reduction in cash usage.

5.3. Subsamples by Age Group

In Table 6, we estimate the results for different age groups. We split our sample into age terciles so that we have an equal number of customers in each group. The first tercile (indicated by 1/3) represents customers under the age of 33 with an average age of 26. The second group (2/3) has customers from ages 34 to 47 with an average age of 40. The third group (3/3) consist of customers above 48 and their average age is 58.

In columns (1)–(9), we find that the increase in the number and the amount of digital transactions as a result of the distance friction are the largest in the youngest group (1/3) followed by the middle group (2/3). The oldest group (3/3) also shows an increase in digital transaction but the effects are the weaker compared to the magnitude of the coefficients in the other two groups. These results show that the small push towards digital banking is more effective for the younger age groups compared to the the oldest age group.

For the other outcome variables, most show that the effects are stronger for the younger age groups, although there are a few mixed results. For example, we find that the increase in FAST transactions is the largest among older groups while the increase of POS transactions shows the opposite ordering. However, the increase in Transfer transactions, GIRO transactions, and SAYE transactions are larger in the youngest group compared to the oldest group. The reduction in cash withdrawal is largest in the middle group while the youngest group and the oldest group show no effect.

We conclude that the substitution from physical to digital facilitated by an ATM-closure appears to affect younger customers more than older customers. It could be that the costs of switching is lower for younger and more tech-savvy customers so that a minor friction is sufficient to induce a substitution effect.

5.4. Using ATM Usage Decline as an Alternative Proxy for Friction to ATM Access

The baseline results use distance as a proxy for the friction faced by customers due to ATM closures. We now use an alternative proxy for the friction—the decline in ATM activity as the channel by which the substitution to digital channels occurs. This means a first stage estimation where we regress ATM activity on the ATM closure dummies (already reported in the second set of columns in Table 2), and then use the fitted value of the ATM activity in the second stage to relate to digital banking-related outcome variables. This measures whether the reduction in the use of an old financial technology (ATMs) induced by a closure of an ATM, can lead to spillover effects onto other types of desirable financial behavior. In other words, the proxy for friction is no longer distance, but the actual reduction in usage of the older technology is used to proxy for "friction". Such an analysis could also be useful if the distance variable is measured with noise because the friction proxy is now ATM activity itself—if ATM activity declines due to a closure regardless of the distance, it must be that the customer now has more difficulty assessing an ATM.

We report the IV regression estimates in Table 7. The key independent variable is the log of 1+ the number of total ATM transactions, instrumented by *Post Closure (Favorite ATM)*. We exclude *Post Closure (Nearest ATM)* as an instrument because its coefficient in the first stage reported in Table 2 is insignificant. The dependent variable for column (1) is the log of 1+ the total number of digital transactions. We see that this significantly increases when the total number of ATM transactions decreases. Because both the dependent and independent variables are in logs, the coefficient can be interpreted as the percentage change in the total number of digital transactions when the total number of ATM transactions changes by 1%. A negative coefficient indicates a substitution effect, i.e., a 1% reduction in the total number of ATM transaction leads to a 0.69% increase in the total number of digital transactions.

Column (2) uses the log of 1+ the total number of digital financial transactions and column (3) uses the log of 1+ the total dollar amount of digital transactions as the dependent variables. We find that a 1% reduction in the total number of ATM transactions leads to a 0.36% increase in the number of digital financial transactions and a 1.00% increase in the dollar amount of digital transactions.

In column (4), we use the log of 1+ the total number of account-level transactions as the dependent variable and we find a significant increase. This implies that the positive spillover to digital banking as a result of the ATM closure more than compensates for the reduction in ATM activity so that the total banking activity as proxied by the number of entries in their banking accounts goes up.

Hence, this section provides additional evidence of the substitution effect using an alternative proxy for frictions. Customers who face ATM closures reduce their ATM activity. This involuntary reduction of ATM activity then provides the push for the substitution of physical banking services by an increase in digital banking activity.

5.5. A Cluster-Based Distance Measure

Our main results are based on the *Distance to ATM* measure which is defined as the average usage distance between the customer's reported address to the bank and the used ATMs. This ignores the possibility that a customer might anchor not only on their reported address (which we assume to be their home), but also on their workplace or a favorite mall. As described in Section 3, we compute an alternative distance measure which includes up to three new "addresses" for each customer by clustering their ATM usage and choosing the top three (based on frequency) cluster centers as additional location anchors. These three new addresses will very likely include their workplace and an additional two other favorite locations. The new *Distance to ATM (Clustered)* measure which relies on the minimum distance between the ATM and any of these three new anchors or the home address has a mean of of 2 km (reported in Table 1) instead of a mean of 5 km of the original *Distance to ATM* measure.

In unreported results, when we regress this new clustered distance measure on both ATM closure shocks, we get a coefficient of 0.084 for the *Post Closure (Favorite ATM)* dummy, and a coefficient of 0.069 for the *Post Closure (Nearest ATM)* dummy. It is not surprising that the increase in the distance, 69–84 meters, is smaller than what it was for the baseline distance measure because we are allowing more location anchors for the customer.

Importantly, when we use this new distance measure for our tests, our results (unreported) are still robust—showing that digital banking activity and other financial outcome variables go up because of the distance friction induced by the closure of the ATM. Hence, we believe our results are not sensitive to the lack of a workplace address in our baseline sample.

5.6. Using a Propensity-Score Matched Control Sample

Our main tests use the full panel of customers as the control group and we add customer fixed effects to control for any heterogeneity in observable customer characteristics or unobservable demographics. We believe that using the full panel provides the most power for our tests and the use of fixed effects adequately controls for any observable or unobservable customer characteristics. However, we now explore another way to form the control sample which is to use a targeted group matched on certain characteristics.

We form a propensity-score matched sample by using five lagged-month variables, namely, distance to ATM, number of ATM transactions, number of digital banking transactions, number of account-level transactions, and monthly salary. In the month before closure for each treated customer (i.e. a customer-closure observation associated with either a favorite or a nearest closure shock), we identify another customer who was not affected by any closure but had the closest predicted probability of facing a closure based on these five characteristics. We find similar results (unreported) when the regressions are estimated using only this control sample alongside the treated observations in the resulting smaller panel.

6. Conclusion

We use novel consumer banking data to examine whether small physical frictions can help move customers towards digital banking. Our data comes from a large bank in Singapore from 2015–2017, where we show that ATM closures induce only a small friction to bank customers—increasing their ATM usage distance by about 100 meters. Interestingly, this minor friction is sufficient to nudge affected customers towards more digital banking activity.

The usage of new banking technology has the potential to help customers manage their finances better and potentially make better financial decisions. We show that the substitution from physical to digital banking facilitates several important spillover outcomes associated with desirable financial behavior. Treated customers who reduce their usage of ATMs, increase their point-of-sale payments, regular funds transfers, instantaneous funds transfers, and automatic bill payments/savings schemes, and they reduce their cash usage. In terms of cross-sectional differences, these effects are generally stronger for younger age groups. These results add to the literature which shows that new financial technology can have real benefits.

We believe that our study also speaks to the literature on choice architecture, showing that minor modifications to a person's choice set can elicit desirable behavioral change. The friction here is the physical distance to banking. That minor changes in distances can have such impact shows that physical distance remains an important friction for customers and shocking these distances in a minor way can have significant impact. These results also reveal that the preference of customers to have easier physical access to banking locations can be substituted by digital access to banking, which could provide other spillover benefits.

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Table 1: Summary Statistics

We report summary statistics of the variables for our analysis. Our sample includes customer-month observations from January 2015 to December 2017. Panel A reports the demographic details of our sample's customers, namely their age, monthly salary in S$ thousands, and monthly account beginning balance in S$ thousands. We also report summary statistics for *Distance to ATM* a transaction-weighted distance to their used ATMs from the provided customer address. The clustered distance uses three additional address anchors—the top three cluster centers from the customer's ATM activity. Panel B reports the customers' banking activity. For their monthly ATM activity, we report the total number of ATM transactions, the number of non-financial transactions, and the mean dollar transaction amount. For their monthly digital banking activity, we report the total number of digital transactions, the total number of financial transactions, and sum dollar amount of monthly transactions. We also report the total number of account-level transactions recorded in the customer's savings and checking accounts. For the monthly total of other banking transactions, we report the number and amount of Point-of-Sale (POS) transactions, Transfer (regular funds transfers) transactions, FAST transactions (instant funds transfers), General Interbank Recurring Order (GIRO) transactions (which are auto bill payments), Save-As-You-Earn (SAYE) automatic savings transactions, and the total amount of cash withdrawn. In Panel C, *Post Closure (Favorite)* equals to 1 from the ATM closure event when the closed ATM is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address.

Variables		Obs	Mean	Std. Dev.	10th	25th	50th	75th	90th
Panel A: Customer Demographics									
Age		5,994,130	42.18	14.49	24	30	41	53	63
Monthly Salary (S$'000)		5,994,130	2.27	5.89	0	0	0.75	3	5.67
Begining Balance (S$'000)		5,994,130	19.09	71.85	0.05	0.5	2.5	11.88	44.1
Distance to ATM		5,994,130	5.08	4.59	0.44	1.36	3.87	7.49	11.54
Distance to ATM (Clustered)		5,994,130	1.96	2.15	0.17	0.49	1.27	2.66	4.66
Panel B: Customers' Banking Activity									
ATM Transactions	Total #	5,994,130	8.26	8.47	1	3	6	11	17
	non-Financial #	5,994,130	1.26	3.5	0	0	0	1	4
	Average S$ per txn	5,994,130	372	1236	50	100	200	416	800
Digital Transactions	Total #	5,994,130	26.87	48.4	0	0	6	38	78
	Financial #	5,994,130	2.5	6.53	0	0	0	3	8
	Monthly Total S$	5,994,130	2036	14068	0	0	0	1140	4539
Total # of Account-level Transactions		5,994,130	27.54	22.03	8	13	23	36	52
Other Transactions (Monthly Total)									
	# of POS Transactions	5,994,130	8.76	11.21	0	2	5	12	22
	S$ of POS Transactions	5,994,130	817	2185	0	58	337	979	2080
	# of Transfer Transactions	5,994,130	2.54	7.26	0	0	1	3	7
	S$ of Transfer Transactions	5,994,130	1825	14613	0	0	2.5	976	3570
	# of FAST Transactions	5,994,130	0.75	2.48	0	0	0	0	2
	S$ of FAST Transactions	5,994,130	878	5978	0	0	0	0	1600
	# of GIRO Transactions	5,994,130	0.7	0.46	0	0	1	1	1
	S$ of GIRO Transactions	5,994,130	933	6328	0	0	168	613	1836
	# of SAYE Transactions	5,994,130	0.17	0.59	0	0	0	0	0
	S$ of SAYE Transactions	5,994,130	73	428	0	0	0	0	0
	S$ of Cash Withdrawal	5,994,130	1717	4045	160	400	1000	2000	3480
Panel C: ATM Closure Shock									
Post Closure (Favorite ATM)		5,994,130	0.03	0.16	0	0	0	0	0
Post Closure (Nearest ATM)		5,994,130	0.05	0.22	0	0	0	0	0

Table 2: The Effect of ATM Closures on the Distance to ATM and ATM Usage

We report panel regression estimates of the effect of an ATM Closure Shock on a customer's usage distance to an ATM and a customer's ATM usage. The dependent variable in columns (1)–(3) is the *Distance to ATM*, a transaction-weighted distance to their used ATMs from the provided customer address. In column (1), we use the *Post Closure (Favorite ATM)* as the main independent variable. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. In column (2), we use the *Post Closure (Nearest ATM)* as the main independent variable. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address whether or not the customers used the ATM before its closure. In column (3), we use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the main independent variables. The dependent variable for columns (4)–(6) is the natural log of 1+ the Total Number of ATM Transactions. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Distance to ATM			log (1+# of ATM Total Txns)		
Post Closure (Favorite ATM)	0.108***		0.074***	-0.059***		-0.058***
	(4.67)		(3.12)	(-16.57)		(-16.12)
Post Closure (Nearest ATM)		0.128***	0.117***		-0.009***	-0.001
		(7.83)	(6.94)		(-4.08)	(-0.56)
Beginning Balance	0.0002***	0.0002***	0.0002***	0.0001***	0.0001***	0.0001***
	(3.57)	(3.57)	(3.56)	(8.64)	(8.58)	(8.64)
Monthly Salary	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(7.86)	(7.85)	(7.85)	(10.77)	(10.76)	(10.77)
Observations	5,994,130	5,994,130	5,994,130	5,994,130	5,994,130	5,994,130
R^2	0.573	0.573	0.573	0.654	0.654	0.654
F-Statistics	30.67	43.84	36.01	150.02	62.90	112.62
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Using Closure-Induced Changes in ATM Usage Distance to Predict Digital Banking Activity (IV regression)

We report Instrumental Variable (IV) regression estimates of the effect of ATM usage distance on customers' Digital Banking Activity using ATM Closure Shocks as instrumental variables. The main independent variable is *Distance to ATM*, a transaction-weighted usage distance to ATMs from the provided customer address, instrumented by the ATM Closure Shocks. We use *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. The dependent variable for column (1) is the log of 1+ the Total Number of Digital Transactions, for column (2) is the log of 1+ the Total Number of Digital Financial Transactions, for column (3) is the log of 1+ the Total S$ Amount of Digital Transactions, and for column (4) is the log of 1+ the Total Number of Account-level Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) log(1+# of Digital Total Txns)	(2) log(1+# of Digital Financial Txns)	(3) log(1+S$ of Digital Txns)	(4) log(1+# of Account Txns)
$\widehat{\text{Distance to}}$ ATM	0.232***	0.121***	0.381***	-0.0107
	(4.60)	(4.64)	(4.12)	(-0.63)
Beginning Balance	0.0002***	0.0002***	0.001***	0.0004***
	(5.01)	(7.42)	(8.80)	(9.81)
Monthly Salary	0.004***	0.003***	0.013***	0.005***
	(10.01)	(10.17)	(10.83)	(11.04)
Observations	5,994,130	5,994,130	5,994,130	5,994,130
R^2	0.709	0.646	0.690	0.734
Year-Month FE	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes

Table 4: Temporary and Permanent ATM Closures (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' Digital Banking activities using temporary and permanent ATM Closure Shocks as an IV. The main independent variable is *Distance to ATM*, a transaction-weighted distance to ATMs used from the customer-provided address, instrumented by temporary or permanent ATM Closure Shocks. Panel A reports the regression results for temporary closures excluding customers who experienced any permanent closures of their favorite or nearest ATM. Panel B reports the regression results for permanent closures excluding customers who experienced any temporary closures of their favorite or nearest ATM. We use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. The dependent variable for column (1) is the log of 1+ the Total Number of Digital Transactions, for column (2) is the log of 1+ the Total Number of Financial Digital Transactions, and for column (3) is the log of 1+ the Total Amount of Digital Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Panel A: Temporary ATM Closures

	(1)	(2)	(3)
	log (1+# of Digital Txns)		log (1+S$ of
Variables	Total	Financial	Digital Txns)
$\widehat{\text{Distance to}}$ ATM	0.228**	0.115**	0.402**
	(2.38)	(2.35)	(2.23)
Beginning Balance	0.0002***	0.0002***	0.001***
	(4.41)	(7.21)	(8.94)
Monthly Salary	0.004***	0.003***	0.012***
	(8.29)	(8.89)	(9.63)
Observations	5,367,297	5,367,297	5,367,297
R^2	0.713	0.661	0.679
Year-Month FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes

Panel B: Permanent ATM Closures

	(1)	(2)	(3)
	log (1+# of Digital Txns)		log (1+S$ of
Variables	Total	Financial	Digital Txns)
$\widehat{\text{Distance to}}$ ATM	0.201***	0.115***	0.366***
	(3.76)	(4.03)	(3.62)
Beginning Balance	0.0002***	0.0002***	0.001***
	(5.03)	(7.08)	(8.40)
Monthly Salary	0.004***	0.003***	0.013***
	(9.68)	(9.71)	(10.36)
Observations	5,609,306	5,609,306	5,609,306
R^2	0.742	0.659	0.696
Year-Month FE	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes

Table 5: Using Other Banking Activity as Outcome Variables (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to ATM on customers' other tech-adoption related banking activity using ATM Closure Shocks as an IV. Columns (1) and (2) use the monthly number and total S$ amount of POS transactions respectively as the dependent variable. Columns (3) and (4) use the number and S$ amount of Regular Transfer transactions respectively as the dependent variable. Columns (5) and (6) use the number and S$ amount of FAST transactions (instantaneous transfers) respectively as the dependent variable. Columns (7) and (8) use the number and S$ amount of GIRO transactions (auto-debit bill payments) respectively as the dependent variable. Columns (9) and (10) use the number and S$ amount of SAYE transactions (automatic savings transactions) respectively as the dependent variable. And column (11) uses the total S$ cash amount transacted as the dependent variable. For all outcome measures, we add 1 before taking the natural log. The main independent variable is *Distance to ATM*, a transaction-weighted distance to ATMs used from the provided customer address, instrumented by the ATM Closure Shock. We use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IV. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. *Post Closure (Nearest ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. For brevity, the coefficients of the control variables are not reported. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels.

Variables	(1) log(1+# of POS Txns)	(2) log(1+S$ of POS Txns)	(3) log(1+# of Transfer Txns)	(4) log(1+S$ of Transfer Txns)
$\widehat{\text{Distance to}}$ ATM	0.096*** (3.56)	0.173*** (2.97)	0.099*** (3.94)	0.276*** (3.05)

Variables	(5) log(1+# of FAST Txns)	(6) log(1+S$ of FAST Txns)	(7) log(1+# of GIRO Txns)	(8) log(1+S$ of GIRO Txns)
$\widehat{\text{Distance to}}$ ATM	0.058*** (2.86)	0.234** (2.55)	0.016* (1.70)	0.126 (1.59)

Variables	(9) log(1+# of SAYE Txns)	(10) log(1+S$ of SAYE Txns)	(11) log(1+S$ of Cash Withdrawal)
$\widehat{\text{Distance to}}$ ATM	0.013** (2.11)	0.074** (2.09)	-0.080*** (-2.58)

Table 6: Results according to Age Groups (IV using ATM Closure Shock)

We report Instrumental Variable (IV) regression estimates of the effect of distance to Digital Banking activity, and other Banking Activity using ATM Closure Shocks as an IV in age group terciles subsamples. In columns (1)–(3), the dependent variable is the log of 1+ the number of total digital transactions. Column (1) reports the result of youngest tercile group (1/3), Column (2) reports the result of middle tercile group (2/3), and Column (3) reports the result of oldest tercile group (3/3). The main independent variable is the *Distance to ATM*, instrumented by *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. For brevity, the coefficients of the control variables are not reported. Other dependent variables are the log of 1+ the number of financial digital transactions (columns (4)–(6)), the log of 1+ the S$ amount of digital transactions (columns (7)–(9)), the log of 1+ the number of POS transactions (columns (10)–(12)), the log of 1+ the number of Transfer transactions (columns (13)–(15)), the log of 1+ the number of FAST transactions (columns (16)–(18)), the log of 1+ the number of GIRO transactions (Columns (19)-(21)), the log of 1+ the number of SAYE transactions (columns (22)–(24)), and the log of 1+ the S$ amount of total monthly cash transacted at an ATM (columns (25)–(27)). Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+# of Total Digital Txns)			log(1+# of Fin Digital Txns)			log(1+S$ of Digital Txns)		
$\widehat{\text{Distance to ATM}}$	0.434***	0.300***	0.113**	0.256***	0.153***	0.036	0.715***	0.524**	0.148
	(3.46)	(2.80)	(2.03)	(3.63)	(2.72)	(1.51)	(3.30)	(2.57)	(1.56)

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+# of POS Txns)			log(1+# of Transfer Txns)			log(1+# of FAST Txns)		
$\widehat{\text{Distance to ATM}}$	0.161***	0.112**	0.080**	0.201***	0.134**	0.040	0.026	0.111**	0.052**
	(0.74)	(2.42)	(2.03)	(2.82)	(2.14)	(2.35)	(3.27)	(2.55)	(1.46)

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
Age Groups	1/3	2/3	3/3	1/3	2/3	3/3	1/3	2/3	3/3
Variables	log(1+# of GIRO Txns)			log(1+# of SAYE Txns)			log(1+S$ of Cash Withdrawal)		
$\widehat{\text{Distance to ATM}}$	0.041**	0.028	0.009	0.026**	0.014	0.004	-0.026	-0.130*	-0.045
	(2.08)	(1.61)	(0.74)	(2.02)	(1.06)	(0.69)	(-0.52)	(-1.94)	(-1.04)

Table 7: Alternative Proxy for Frictions - Using Closure-Induced Changes in ATM Usage to Predict Digital Banking Activity

We report IV regression estimates of the effect of customers' total number of ATM transactions on digital banking activities using ATM closure shocks as an IV. The main independent variable is the log of 1+ the number of total ATM transactions, instrumented by *Post Closure (Favorite ATM)*. *Post Closure (Favorite ATM)* equals to 1 from the ATM closure event when the closed ATM is the one that is the customer's favorite ATM based on the number of times used in the prior three calendar months. The dependent variable for column (1) is the log of 1+ the Total Number of Digital Transactions, for column (2) is the log of 1+ the Total Number of Financial Digital Transactions, for column (3) is the log of 1+ the Total S$ Amount of Digital Transactions, and for column (4) is the log of 1+ the Total Number of Account-level Transactions. Other controls include monthly beginning account balance in thousands (Beginning Balance), Monthly Salary in thousands, year-month fixed effects, and customer fixed effects. Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered at the customer level, with ***, **, and * respectively denoting statistical significance at the 1%, 5%, and 10% levels

	(1)	(2)	(3)	(4)
	log(1+# of Digital Txns)		log(1+S$ of	log(1+# of
Variables	Total	Financial	Digital Txns)	Account Txns)
log(1+ # of $\widehat{\text{Total}}$ ATM Txns)	-0.693***	-0.361***	-1.003***	0.253***
	(-4.66)	(-4.69)	(-3.65)	(5.22)
Beginning Balance	0.0003***	0.0002***	0.001***	0.0003***
	(7.18)	(8.28)	(9.01)	(9.58)
Monthly Salary	0.006***	0.004***	0.017***	0.004***
	(9.12)	(9.51)	(10.04)	(10.44)
Observations	5,994,130	5,994,130	5,994,130	5,994,130
R^2	0.815	0.763	0.766	0.801
Year-Month FE	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes

Figure 1: ATM Network in Singapore

We mark DBS bank's ATM network in Singapore for the 2015–2017 sample period. Blue dots represent building locations (postal codes) that have at least one ATM. Red dots are the 109 locations associated with ATM location closures in the sample period.

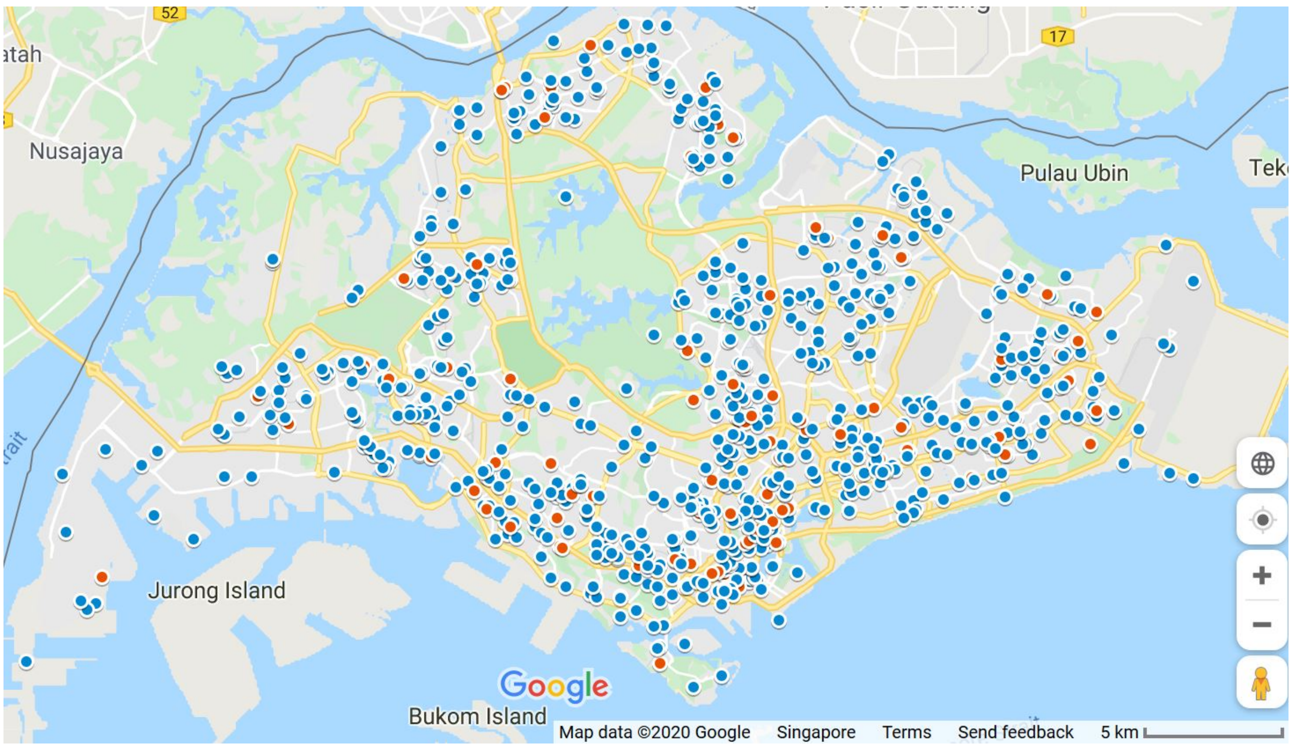


Figure 2: Distance to ATM by the Time of Usage

We report the time-series of the average *Distance to ATM* by the time of usage. We use the *Distance to ATM* which is a transaction-weighted distance to ATMs used from the provided customer address. The red dashed line represents the mean *Distance to ATM* during working hours. Working hours are defined as 8am to 6pm on non public-holiday weekdays. The blue solid line represents the average *Distance t ATM* during non-working hours on weekdays. The green long-dashed line represents the average *Distance to ATM* during weekends and public holidays. The distance averages are computed as follows. For each ATM transaction, we first compute a GPS distance between customer's address and ATM location. Using the total number of ATM transactions as the weight, we compute the weighted average distance per customer for each month. The sample is based on customers who had at least one salary credit or at least 6 months with auto-debit transactions in the 2015–2017 sample.

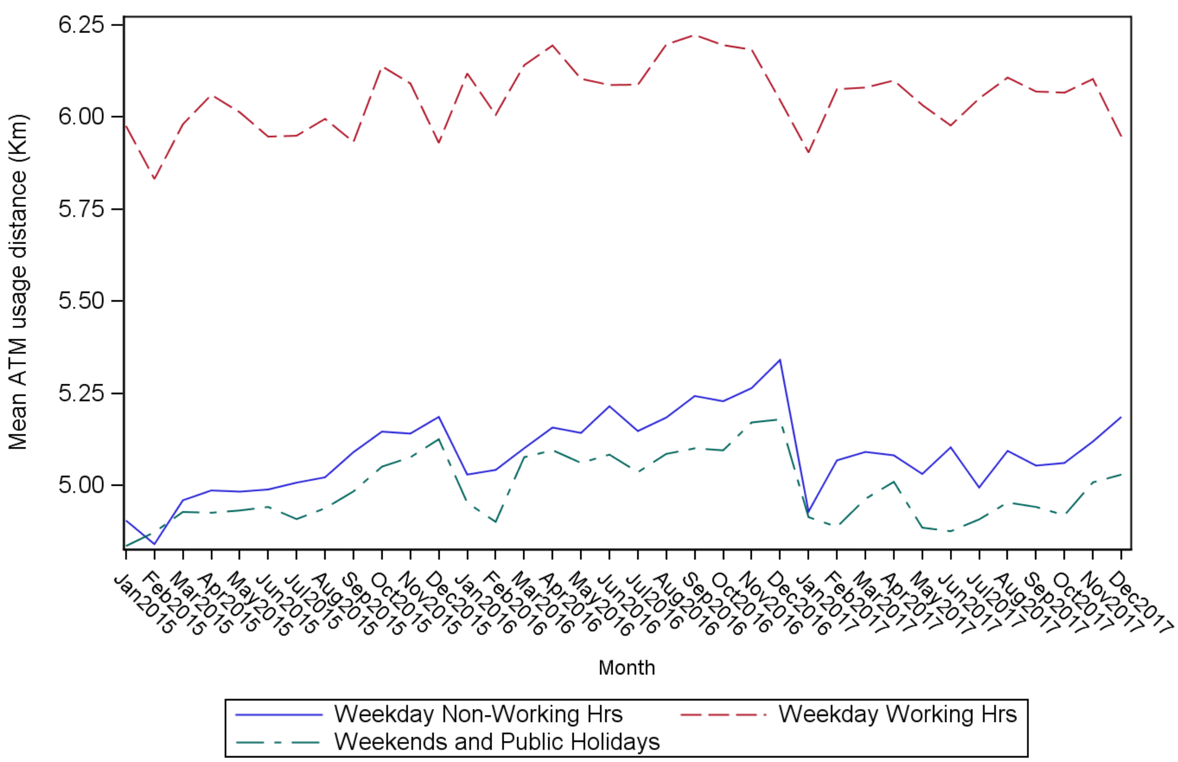
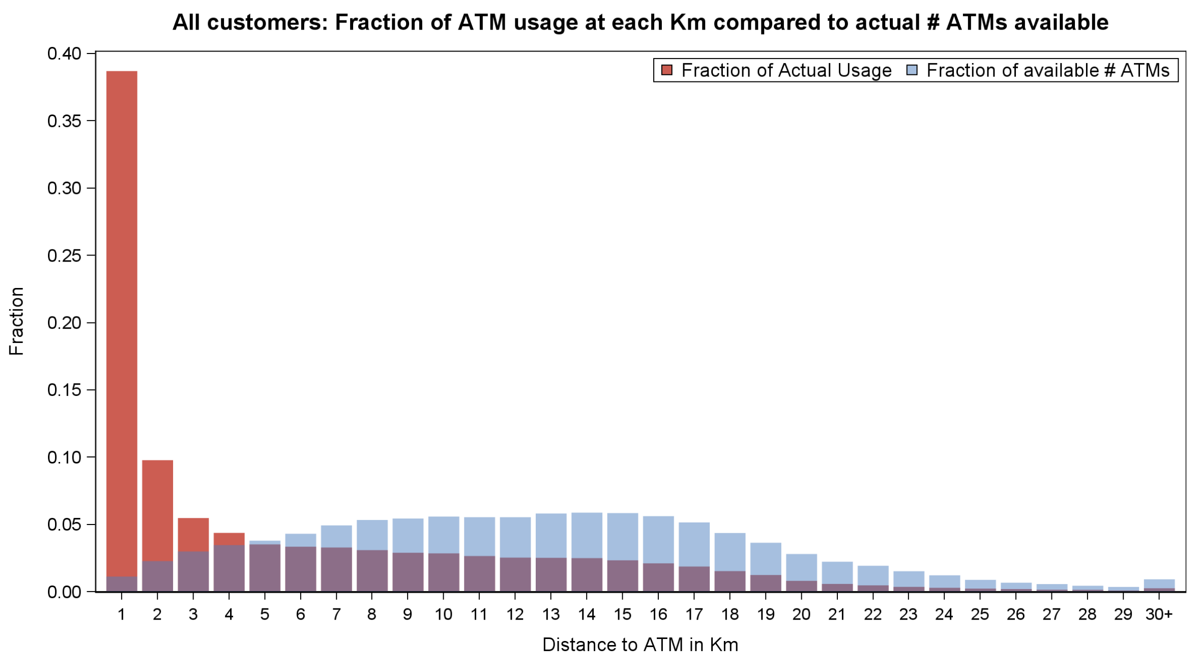


Figure 3: Distribution of ATM Usage by Distance

We report the average distribution of customers' ATM usage by the distance from customers' address. The top chart includes all customers in the sample based on customers who had at least one salary credit or at least 6 months with auto-debit transactions in the 2015–2017 sample. Red bars show the average fraction of a typical customers' ATM usage by the distance at each km. For comparison with the total number of ATMs available at each km, blue bars show the average fractions of available ATMs in Singapore by the distance from a typical customer's address. The bottom chart shows the average distribution of customers' actual ATM usage by distance for the subset of customers who provide a commercial address in the bank's record instead of a residential address. The address category is determined by searching for the postal code with an "(S) " prefix in streetdirectory.com.



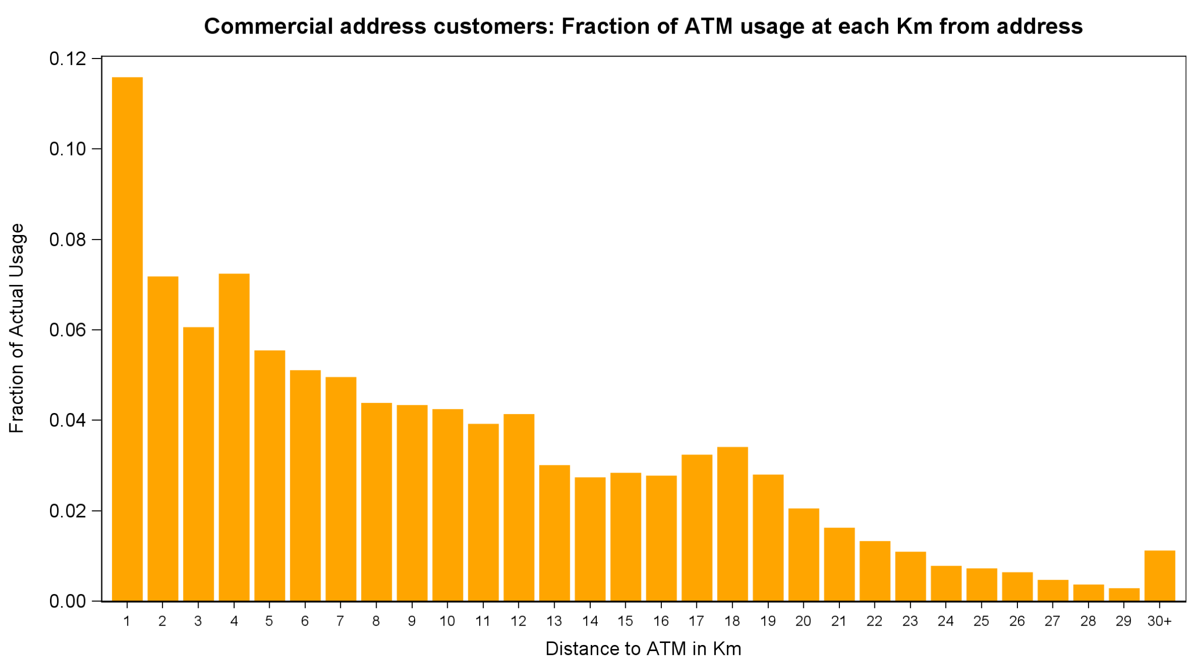


Figure 4: Customer-level Distribution of ATM Usage by Distance

We report the customer-level distribution of ATM usage by distance. We randomly select 1,000 customers who have auto-debit transactions in at least six of the sample months or at least one salary credit. They also must have at least five ATM transactions in the sample period. On the horizontal axis, the customers are arranged in increasing mean *Distance to ATM*. On the vertical axis, we report the fraction of ATM usage by distance for each customer. Each column hence represents an actual customer and the color intensity signifies the probability that the customer uses ATMs at that km from their provided address.

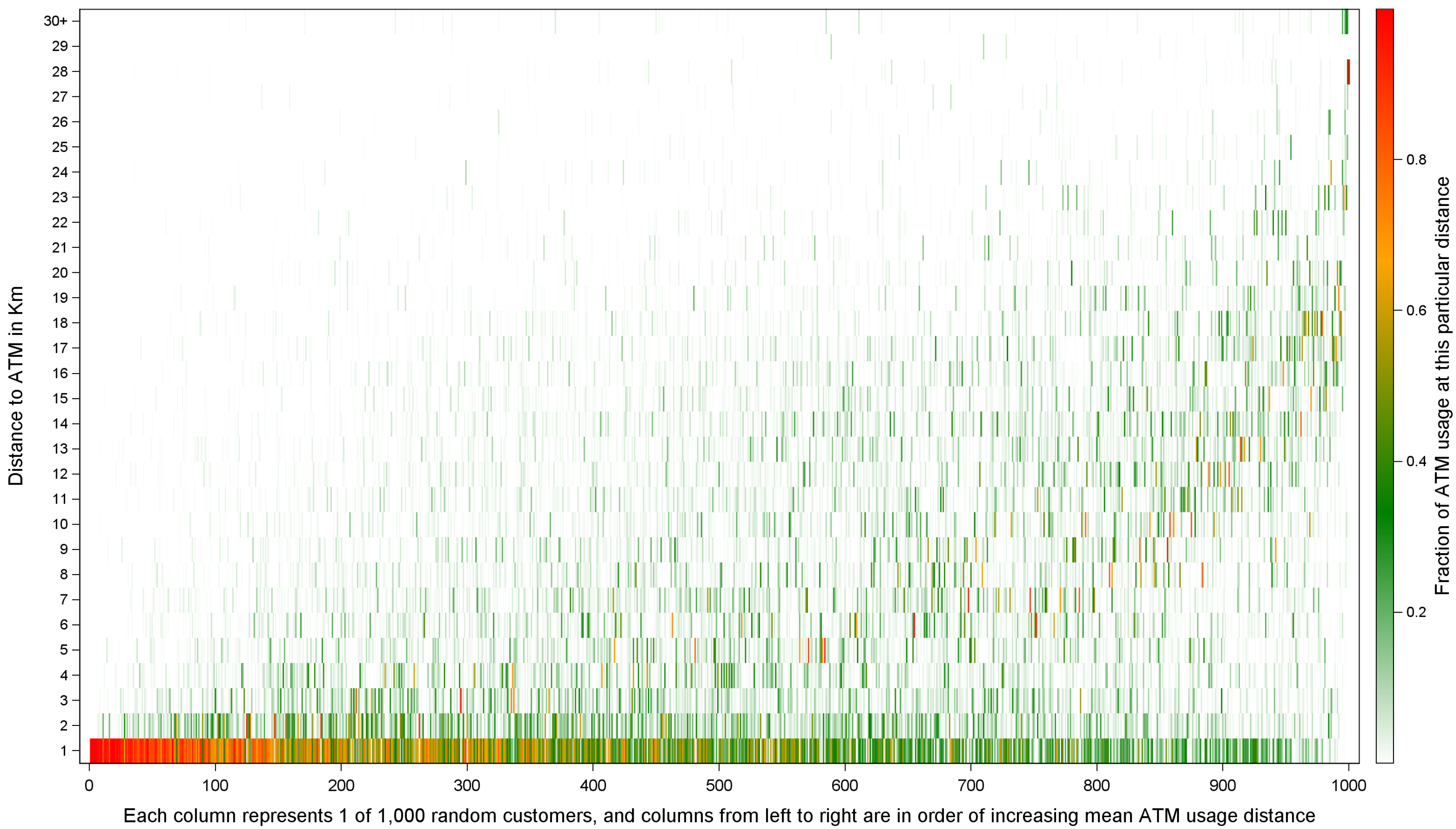


Figure 5: ATM transactions around Permanent and Temporary ATM Closures

We report the average number of ATM transactions around ATM closures by the type of ATM closures. We define an ATM closure as a temporary one if ATM activity at the postal code resumes in the subsequent months after a period of zero activity. The rest of the ATM closures are assumed to be permanent closures (i.e. those where activity at the postal code is zero from the closure date until the end of the sample period in Dec 2017). A red solid line plots the average number of ATM transactions around a permanent ATM closure. A blue dash line plots the average number of ATM transactions around a temporary ATM closure.