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Physical Frictions and Digital Banking Adoption*

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Abstract

The 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

The 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 showed that such nudges can have long-lasting effects. In health science, Thorndike et al. (2012) and Vandenbroele et al. (2021) showed 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 study, we examine the impact of such choice architecture in influencing digital banking adoption.

The small friction 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 very close by. Might such small frictions be sufficient to induce digital banking adoption and other spillover effects of financial technology (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 if the lockdowns are severe.[1] 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.

We use a novel data set 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

[1] It would still be extremely interesting to study digital banking adoption motivated by lockdowns during the Covid-19 period even though there are confounding and concurrent economic and health effects. While our sample does not cover this period, frictions associated with major lockdowns are likely to be large. Minor lockdowns would be more similar to our setting of small frictions. Fu and Mishra (2022) document an increase in financial services app downloads during the pandemic period and show that such increases were related to the stringency of lockdowns.

closures indeed face a small friction—their ATM usage distance increases by about 100 meters, and their ATM activity declines marginally. For an affected customer, this closure-induced friction increases their usage of the bank's digital platform relative to other customers who did not experience such closures. For example, for a 100m increase in usage distance, the number and dollar amount of digital transactions increases by 2.4% and 3.9%, respectively, compared to non-treated customers.[2] This shock also affects other dimensions of banking technology adoption—point-of-sale (POS) transactions increase, electronic funds transfer transactions increase, automatic bill payments increase, and automatic savings transactions 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 changes in other related financial behavior.

Studying the determinants of the adoption of digital banking has been an important agenda in recent years for policy makers. 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.[3] But it is not easy to change financial behavior. As documented in the literature, 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, Ghosh, Li, Huang, and Ruan (2022a) and Chopra, Prabhala, and Tantri (2023) show that the 2016 large-scale removal of cash in India forced customers to move to digital means of banking. Our

[2] All our results include year-month fixed effects and customer fixed effects, which control for the increasing adoption of digital banking over time and customer heterogeneity. Our results are also robust to alternative measures of distance (by incorporating the approximate workplace location) and alternative estimation procedures.

[3] Philippon (2019) argues that new financial technology 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., Beck, Pamuk, Ramrattan, and Uras (2018); Agarwal, Qian, Yeung, and Zou (2019); Hau, Huang, Shan, Sheng, and Wei (2022); and Higgins (2023)), attentiveness to accounts (e.g., Carlin, Olafsson, and Pagel (2023)), and the potential of using digital footprints to improve access to credit (e.g., Berg, Burg, Gombovi, and Puri (2020)).

study focuses on ATM closures, which we argue are quasi-exogenous to the customer and can be considered a small push factor.

Keil and Ongena (2023) show that the recent decrease in the number of bank branches in the US is mostly driven, surprisingly, by bank fragility and industry consolidation, and not by technological advancement as popularly believed. In fact, they show that banks more exposed to technological change are not less inclined to open more branches. In the period that we study, the bank was not aggressively closing ATMs as the total number of ATM locations did not decrease. The closures we examine are hence more associated with reshuffling and 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 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 increase in digital banking usage hold for both permanent and temporary closures. That the post-closure increase in digital banking also holds for temporary closures implies that the effects do not all dissipate when the temporary closures reopen. This is consistent with Larcom, Rauch, and Willems (2017)'s findings that an involuntary re-optimization caused by a temporary shock can result in permanent behavior change.

We believe our study makes several contributions to the academic literature and also to industry practice. The first is the current issue of banks downsizing their physical locations. Banks frequently cite changed customer behavior to justify downsizing.[4] 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. Keil and Ongena (2023) conjecture that reductions in physical locations can move customers to digital banking. Our study shows 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 sig-

[4]For example, in the Financial Times (Storbeck, 2020), it was reported that Deutsche Bank plans to close one in five branches in Germany, offering the reason that the coronavirus pandemic has driven more customers online.

nificant substitution effect. The key source of this friction is a 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.

Second, our findings add to the literature on fintech adoption. As some of the 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 (2023) and Bachas, Gertler, Higgins, and Seira (2020) document the spillover benefits of a policy-driven debit card distribution program, Agarwal, Qian, Ren, Tsai, and Yeung (2022b) show the impact on business growth by the introduction of a new mobile payments technology, and Agarwal, Alok, Ghosh, Ghosh, Piskorski, and Seru (2023) show the impact of providing access to savings accounts through debit cards and mobile banking to millions of previously unbanked individuals in India. The fintech adoption documented by our study are driven not by such large-scale initiatives but instead by the small frictions associated with ATM closures. And surprisingly, they also produce significant technology adoption and spillovers to financial behavior such as more efficient movement of funds between accounts. With regards to savings, we do find some evidence that savings increase (although we do not observe whether customers were undersaving in the first place). In terms of negative consequences of the ATM closures, we do not find that customers are more likely to close their accounts after the closures or that they overspend as a result of greater use of digital banking.

Third, our findings relate to the importance of geography in the banking industry and the literature on ATM network effects. 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, Mjøs, and Schmidt (2023); Agarwal and Hauswald (2010); and Degryse and Ongena (2005)). In consumer banking, there is a literature on ATM network effects.

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. Knittel and Stango (2009) examine the introduction of surcharges for U.S. customers who use competitor-bank ATMs and finds that customers are willing to pay a higher price for denser ATM networks. Our paper is closely related to this work as we also examine how a customer's access to ATM services is affected by frictions. Our frictions come not from explicit surcharges but from ATM closures. Another related paper, Ferrari, Verboven, and Degryse (2010), suggest that cash withdrawal fees should be imposed at branches to encourage customers to withdraw instead from ATMs because the cost per withdrawal is higher at branches. Their focus is on the substitution between branches and ATMs, whereas our focus is on the substitution between ATMs and digital banking.

Finally, 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. 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, each local bank provides a large network of ATMs in the country's small land area of 721.5 square km.[5] Figure 1 shows a Singapore map where markers 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. One can say that the banking sector in Singapore fits the commuting-consumer banking model in Calem and Nakamura (1998) as the city-country is small, all customers are able to commute easily across the island, and competitor banks have similarly dense physical networks.

The primary reason for a customer to visit a branch or an ATM is cash related. In this period, 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 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 (e.g., see Prang and Hayashi (2018)).

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

[5]The three local banks are DBS (formerly known as Development Bank of Singapore), United Overseas Bank (UOB), and Overseas-Chinese Banking Corporation (OCBC). DBS has its own network of ATMs. DBS customers cannot use ATMs from UOB or OCBC. UOB and OCBC customers cannot use DBS ATMs but they are allowed to use each other's ATMs and the combined UOB-OCBC ATM network is comparable to the DBS ATM network. Singapore's central bank estimates that the majority of the population has access to an ATM within 1 km of their residence (https://www.mas.gov.sg/news/parliamentary-replies/2017/reply-to-pqs-on-basic-bankingaccounts-and-the-interoperability-of-automated-teller-machines).

large retail market share in Singapore.[6] Our unique proprietary data contain transaction-level banking activity for 500,000 randomly sampled 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, funds 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 apartments, this sufficiently masks customer identities within a building.[7]

The bank provided three January snapshots of the customer's mailing postal codes. 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, because 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),

[6] Please see https://www.dbs.com/about-us/ for more information on DBS.

[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.

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 that 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 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 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 no-joint account screens. The large drop shows the importance 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 4% of total population in Singapore in 2015.

[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. These results are shown in the online appendix.

[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 a test reported in the online appendix, 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.

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 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

[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 nonmissing 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 salaries (excluding employer pension contributions) reported by the Ministry of Manpower are S$3,467, S$3,500, and S$3,749 for 2015, 2016, and 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.

[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 are not able to include transactions that do not have dollar amounts associated with them, such as a balance enquiry.

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, although 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 5.08 km average obtained when distance is measured relative to only the customer-provided (home) address.

Panel B reports statistics of the main customer banking-activity variables for our analyses. 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).

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 2.50 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 dollar 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 reported 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$817. The average number of regular funds transfers (Transfers) made by a customer is 2.54 and the average total amount transferred in a month is S$1,826. Because a regular funds transfer takes 2–3 days to be processed, 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.

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]

There are three items in Panel B related to cash withdrawals in a month. The mean sum of cash transactions at ATMs in a month is S$1,717. Cash can also be withdrawn at convenience

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

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

stores and these are labelled POS withdrawals. Few customers use such services, so the mean for POS withdrawals is only S$2.50 per month (the mean for non-zero observations is S$99). Combining these two types of withdrawals, the Total withdrawal is S$1,720.

Digital banking can be more desirable compared to physical banking because of greater convenience or lower costs. However, greater digitalization could be associated with a loss of privacy or greater information capture by the bank. In addition, Agarwal et al. (2022a) report that overconsumption could be a side effect of digitalization. It would be difficult for us to quantify the costs of privacy loss or information capture. But we are able to estimate the monthly spending of each customer to proxy for consumption. We sum up all the spending-related categories of transactions, namely, point-of-sales spending, total cash withdrawals, bill payments to organizations (which includes payments to credit card companies), and fees paid to the bank. This is a useful variable for us to examine for any evidence of overspending as a side effect of digitalization. We report that the mean monthly spending in our data is S$3,535. A change in spending can also allow us to infer a change in savings, if we can assume that income stays constant.

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 usage locations, the distance should be similar during weekday non-working hours and during weekends and public holidays, both of which are times when the customer is more likely to be home. In contrast, the distances 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 the 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 the typically used banking location.

Although the average distance is about 5 km, this obviously does not mean that a customer prefers ATMs 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 about 40% of a customer's ATM transactions are done at ATMs within the first kilometer from their postal address. The second kilometer is much less important, where the usage fraction declines to about 10%. This fraction further declines the farther away the ATMs are.[15] To make sure this skewness is not driven by the distribution of ATMs, we plot (in lighter 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 about a 40% likelihood. This shows the importance of nearness to an ATM.

We have assumed so far that the postal address is the home. 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 are likely to be their workplaces, we plot the histogram of their ATM usage in increasing distance from this address in the second chart of Figure 3. We see that the distribution is less skewed compared to the first chart. Although such customers are still more likely to use ATMs close to their workplace, the strong reliance on the closest ATMs is not as stark. We conclude that the home

[15]To match this histogram with the 5 km mean we report in Table 1, one can take the weighted average of the km value in each bin using the fraction of usage as the weight, 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 category in this histogram is the 30+ km category which represents customers with an address at one end of the island using ATMs at the other end (e.g., a customer with an address in Tuas at the extreme west of the island making an ATM transaction at the airport which is at the extreme east.)

[16]To determine the address category, we add a "(S)" prefix to a postal code search at streetdirectory.com.

compared to the workplace 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 Closures and their Suitability as an Instrument

In this paper, we would like to examine if small frictions to physical banking access can induce customers to switch to digital banking. The ideal experiment would be to introduce small shocks to physical banking access to a random set of customers and measure their future digital banking behavior. Alas, it would be difficult to conduct such an experiment. The natural "experiment" that we use is an ATM closure, which affects only a small subset of the bank's customers and can provide a small friction to a customer's physical banking access.

We acknowledge that such a shock is only quasi-exogenous because the closure of an ATM is not random but is a result of a bank's re-optimization decision. But because of the high density of ATMs in our sample, when an ATM closes there are still many other ATMs in the vicinity and the affected customer experiences only a slight friction. It can be argued that a customer whose favorite ATM closes is akin to being randomly selected compared to other customers whose favorite ATMs did not close.[18]

Additionally, some of the closures we examine are not permanent but are temporary. These temporary closures are likely motivated by renovations at the ATM's location, such as a facility remodelling. Such cases are more likely to satisfy the exclusion restriction because the closure is more exogenous to the bank—that is, the closure is not related to the bank customer's future digital banking activity except through the increased friction caused by the closure. A temporary closure can be closer to a random assignment of physical frictions on the cross-section of customers. For example, Compass One is a mall located in the sub-urban town of Sengkang and the mall closed for renovation in late October 2015 and re-opened on

[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] The bank does 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.

September 1, 2016. Due to this renovation, the ATM in the mall closed from September 22, 2015 to September 24, 2016. While our baseline tests combines both types of closures, we will examine temporary and permanent closures separately in robustness tests. Because our results hold for both permanent closures and temporary closures, we believe that our instrument is not far from being a random assignment of physical frictions on the cross-section of customers.

As to the potential concern of whether there is an unobserved variable that drives both ATM closures and customers' digital banking adoption, we find that during our sample period, the bank was not aggressively closing ATMs to push people to digital banking. The number of ATM locations in our sample is 700 in January 2015 and 756 in December 2017. We also later report a propensity score-matched test which addresses the potential concern of selection.

We define an ATM closure as an ATM postal code where no more ATM transactions occur at the postal code for at least 30 consecutive 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.[19] These closures are spread out across the city as shown by the stars in Figure 1.

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 for whom the closed ATM is the one that is closest to their postal address, *regardless* of whether they used the ATM prior to its closure. While this second definition of a treatment group might overlap

[19]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.

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,n] 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. Panel C of Table 1 reports that 3% of our sample is defined as treated using this approach. Denoting the second treatment group, *Post Closure (Nearest ATM)* equals one for [0,n] 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 (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. Our goal is to examine whether this minor increase in friction can increase digital banking activity.

In the first stage tests, we examine the effect of ATM closures on physical frictions using panel regressions reported in Table 2. The dependent variable in columns (1) to (3) is *Distance to ATM*. 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.[20] Standard errors are clustered using the postal code of the customer's favorite ATM (if not available we use the most recent postal code of the customer's address) 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 remain statistically significant. 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*). The typical increase in friction reported here are not large, around 100m, and is due to the high ATM density (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 because of a closure, regardless of the distance, it must be that the customer now has more difficulty accessing an ATM.

The dependent variable is the log of one plus 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

[20]These two controls of beginning balance and monthly salary are useful for the second stage digital banking regressions later because time variation in the customer's account balance and monthly salary can influence monthly digital banking activity. These two controls appear less important for the regression of distance on ATM closures but need to be included here for consistency with the second stage. If we remove these two controls from all the regressions, we get very similar results (shown in the online appendix).

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.[21] 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, we use distance as our main proxy for frictions.[22]

4.2. Second Stage: Impact of Distance on Digital Banking Activity

In the second stage, we use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as instruments to estimate an instrumental variable (IV) regression to examine the impact of closure-induced frictions on 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 log of one plus the total number of digital banking transactions.[23] The main independent variable is the *Distance to ATM* instrumented by both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. As in the first stage, 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.

[21] From the Table 1-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.

[22] We also estimate our main results using the two closure instruments separately. The favorite ATM closure appears to induce larger economic effects than the nearest ATM closure. However, the nearest ATM results have greater statistical reliability. Both types of closures appear important and can on their own induce a substitution effect to digital banking when examined separately (shown in the online appendix). Hence our main results include both types of closures as instruments.

[23] We take the natural log to deal with potential nonlinearity in the digital banking transaction variables so as to reduce the influence of outliers on our results. And because observations for these variables can take a value of zero, we add one before taking the log to avoid undefined values. Our results are robust when we use raw value of the variables instead of using their log-transformed versions. An alternative is to use a Poisson estimation with high-dimensional fixed effects in a reduced-form set-up where the ATM closures enter directly as shocks and we find supportive evidence that closures lead to more digital banking, and the economic magnitudes are also similar.

We first report that the Cragg-Donald Wald F-statistic for the IV regression is 129.803. A value of above 100 easily passes the usual thresholds and shows that the instruments we employ for our study are not weak (Stock and Yogo (2005) and Staiger and Stock (1997) suggest ten as a rule of thumb).

The coefficient estimates show that customers indeed do more digital banking after ATM closures increase 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 one unit (i.e., 1 km) increase in *Distance to ATM* increases the dependent variable by 0.232. Since the typical change in distance is about 100m for an ATM closure, we will use one-tenth of the coefficient (i.e., a 0.0232 change) for understanding the economic relevancy of our results. Based on the average total number of digital transactions of 26.87, this is an increase of 0.654 transactions [exp(log(1+26.87)+0.0232)–1=27.52; 27.52–26.87=0.654], which is 2.4% of the average.

Column (2) uses the log of one plus 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 100m increase in *Distance to ATM* increases the number of financial digital transactions by 0.0121. Since the average of the number of financial digital transactions is 2.50, this is an increase of 0.0426 transactions [exp(log(1+2.50)+0.0121)–1=2.95; 2.95–2.50=0.0426], which is 1.7% of the average.

Column (3) uses the log of one plus the total dollar amount of digital transactions as the dependent variable. We find that a 100m increase in *Distance to ATM* increases the total dollar amount of digital transactions by 0.0381. This implies that the total dollar amount of digital transactions went up by about 3.9%.[24] The effect on the transacted amount seems larger than that on the number of transactions indicating that the dollar amount per transaction also went up.

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

[24]Since the mean dollar amount for financial digital transactions is S$2,036, this is an increase of S$ 79 [exp(log(1+2,036)+0.0381)–1=2,115; 2,115–2,036=79], which is 3.9% of the average.

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 for the degree of financial inclusion, this suggests there is no significant change in financial inclusion or account activeness. Hence, there is no evidence that ATM closures cause the customer to disengage with the bank. Or it might be that the reduction in ATM transactions and the increase in digital transactions offsets each other.

Overall, this section illustrates our key results. An ATM closure causes only a slight inconvenience to an affected customer as their ATM usage distance increases by about 100m. This magnitude is not large due to the high ATM density in the city. Interestingly, we find evidence of a substitution effect as there is a corresponding increase in digital banking activity in the post-closure period. This is evidence that an ATM closure serves as a small friction to induce the customer towards greater 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.

4.3. Reduced-Form Results

We can perform the above tests in a different way by regressing digital banking activity directly on the post-closure dummies in a reduced-form set up. The resulting coefficients can then be simply interpreted as the impact of ATM closures on digital banking without going through the distance measure. These results are shown in Table 4 where we continue to find that ATM closures are associated with an increase in digital banking activity for the treated customers. For example, in specification 1 of Table 4, the closure of a favorite ATM results in a coefficient of 0.035 in the total digital banking activity, which is equivalent to a 3.7% increase from the average. The closure of the nearest ATM produces a coefficient of 0.020, which is equivalent to an increase of 2.1% from the average.[25] These magnitudes are not very different from the 2.4% increase total digital banking activity that we obtained from the distance-based second stage results.

Figure 4 shows the reduced-form plots of the outcome variables around the ATM closures. We plot these using the favorite ATM closure event since the economic magnitudes appear larger for such closures. To ensure that these plots control for time effects, customer effects, and the effects from the nearest ATM closures, we first regress the outcome variable on year-month fixed effects, customer fixed effects, and the *Post Closure (Nearest ATM)* dummy variable. Then we plot the average of the resulting regression residuals in event months around the favorite ATM closure.

The first two charts of Figure 4 plot the first-stage variables–ATM usage distance and total ATM activity. We see that the usage distance to an ATM increases and the total number of ATM transactions drops around the closure, consistent with our Table 2 regression evidence that a closure-affected customer sees an increase in the physical friction to their ATM access. The next two charts plot the measures of total digital banking activity and total digital banking amounts transacted around the favorite ATM closure. The visual evidence is also consistent with our main result that digital banking increases around ATM closures. Also plotted are the average residuals of control customers, who are propensity score matched in the month before closure using distance and ATM and digital banking activity. We can see that the control individuals do not show any sharp response to the closure event.

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 a large set of other outcome variables, such as those that relate to financial/digital

[25] The magnitudes are computed as follows: exp(log(1+26.87)+0.035)-1=27.863, which is 3.7% of the average; and exp(log(1+26.87)+0.020)-1=27.433, which is 2.1% of the average.

inclusion and other measurable customer-level behavior. Third, we divide the sample according to age groups and other criteria. 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 the end-2017 closures reopened subsequently as our data from the bank end 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 facility (e.g., 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 in the event months leading 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 in the post-closure period. If these results also hold for temporary closures, this would mean that a returning ATM does not move the customer completely back to traditional banking.

Table 5 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 results for total number digital banking transactions, the total number of digital financial transactions, and the total dollar amounts of digital transactions all indicate that the impact of temporary and permanent closures on digital banking activity are statistically significant and look similar.[26]

Overall, we do not find evidence in this section that our results only show up in permanent ATM closures.[27] The results for temporary closures are similar to those on permanent

[26] In a test reported in the online appendix, we split the sample of temporary closures based on the median number of days closed (which is 65) and we find that longer-duration temporary closures have stronger results. This shows that very short-duration temporary closures might not introduce sufficient friction to induce a significant substitution to digital banking in the post-closure period. Closures need to be long enough to nudge customers into behavioral change.

[27] Agarwal et al. (2022b) who also use data from DBS suggest that some ATMs were closed in 2017 in

closures. This shows that customers who increase digital banking after temporary closures do not completely revert to traditional means when the closed ATM reopens. This evidence is consistent with results from 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 other outcome variables, most of which are related to an adoption of a specific digital banking technology. The richness of our banking transactions data allows us to identify various types of financial behavior. We examine the following financial-related activity as additional outcome variables: 1) POS transactions which have been shown (e.g., in Bachas et al. (2020)) to have many positive spillover benefits; 2) Transfers, which are regular funds transfers that 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 funds transfers require; 4) GIRO autodebit transactions, which make bill payments more efficient; 5) SAYE automatic savings transactions, a proxy for disciplined savings; 6) Total cash withdrawn in a month, separated also into whether those withdrawals occurred at ATMs or at convenience stores; 7) a spending measure to examine if there are any changes to a customer's consumption; and finally 8) a dummy variable indicating the future closure of any savings/checking account by the customer to serve as a proxy for the negative consequences of ATM closures.

Table 6 reports the second-stage results, i.e., using the fitted distance's effect on these

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 (shown in online appendix). Second, as mentioned earlier, 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.

new outcome variables. For brevity, the coefficients of the control variables are not reported. The first two models show that both the number and dollar amount of POS transactions go up. Inferring the rough economic magnitude from one-tenth of the coefficient of the dollar amount regression, the dollar amount of POS transactions increases by about 1.73% for a 100m increase in *Distance to ATM*.

The next set of models use the number and dollar amount of Transfer transactions as the dependent variables. We find that both the number and dollar amount of Transfer transactions significantly increase. The dollar amount of Transfer transactions increases by 2.76% for a 100m 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 100m increase in *Distance to ATM* increases the amounts of FAST transaction usage by 2.34%.

We then examine the number of GIRO transactions and the dollar amount of GIRO transactions as dependent variables. We find that the usage of GIRO transactions also increases. The dollar amount of GIRO transactions increases by 1.26% for a 100m increase in *Distance to ATM*.

The next two models use the number and total dollar 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 0.74% for a 100m increase in *Distance to ATM*.

Models (11) to (13) examine the potential substitution effect from physical ATMs to cash withdrawals at convenience stores. In model (11), we have the expected result that cash transacted at ATMs decline due to the ATM closures. Model (12) interestingly shows that cash withdrawals at convenience stores (labelled POS withdrawals) goes up. This means customers rely more on POS cash withdrawal locations instead of ATM locations—a substitution effect between two different means of physical banking. But on aggregate, as model (13) shows, the effect of closures on total withdrawals is still negative. This is because POS withdrawals are not widely used among customers, and when totalled with ATM withdrawals, the latter dominates.

Model (14) shows the coefficient associated with the Spending outcome variable. This is a noisy measure of consumption based on classifying the relevant debit transactions in the customer's accounts. We find that spending declines due to the ATM closures and this is statistically significant. If we assume that the customer's income is unchanged, this can be consistent with the customer saving more, supporting our earlier SAYE results. Also, since the coefficient is not positive, we can say that in our sample there is no obvious evidence of overconsumption due to the increased digitalization. We of course do not observe whether the customer spends using another bank's accounts but our salary credit and auto-debit screens make it more likely that these customers use DBS as the primary bank.

A customer could also close their account with DBS. In model (15), the dependent variable is an account closure dummy which equals one from month $t-3$ onwards if a customer closes a savings or checking account in month t. There are unclosed accounts with no further transactions after a certain month and we also consider these as "closed" on the month where transactions cease. Once set to one, the value of this dummy remains as one until month t, or until the end of the sample period if this customer continues to have other unclosed savings or checking accounts. This variable allows us to identify if an ATM closure leads to a higher likelihood of future account closure for the customer. If they do, this could be one of the downsides of an ATM closure on the bank's profits.

We see that there is no statistically significant relation between the increased friction from ATM closures and subsequent account closures. Hence, on the extensive margin, the bank does not face more account closures from customers affected by the ATM closures. We believe this is evidence that the closures in our sample are not big negative shocks that annoy the affected customers into closing their accounts, but are merely minor frictions to the physical landscape which induces them to reoptimize their ATM access and in the process they are nudged towards more digital banking. Note however that this does not mean we claim that banks can close ATMs freely to cut expenses and boost profitability. While we find that customers are not leaving the bank after the minor friction shocks we examine, this cannot be extrapolated to apply also to major friction shocks which we do not examine.[28]

Overall, we find in this section that the ATM closure-induced distance friction brings about a significant behavior change in the affected customers. The small push from an ATM closure not only increases digital banking activity in general, but this spills over to other fintech-related outcome variables like POS transactions, funds transfer services, autodebit bill payment transactions, automatic saving plan contributions, and a reduction in cash usage. And there is no obvious evidence of negative side effects such as the closure of accounts or overconsumption.

5.3. Subsample Analyses

5.3.1. By Age

In Table 7, we estimate the results for different age groups. We split our sample into age terciles so that we have a similar 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 tercile (2/3) has customers from ages 34 to 47 with an average age of 40. The third tercile (3/3) consists of customers above 48 and their average age is 58.

In models (1)–(9), we find that the increase in the number and the dollar 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

[28] In a test reported in the online appendix, we examine a proxy for banking fees paid by customers using Knittel and Stango (2009)'s price measure of total account fees divided by the account balance. At the customer level, this measure is noisy due to small denominators and we use various levels of winsorization, from 0% to 5%. There is evidence that this measure is lower after ATM closures, consistent with Knittel and Stango (2009)'s finding that ATM network density is positively related to fees, although the coefficient is not statistically significant when outliers are accounted for with greater winsorization. As the bank is unlikely to be closing ATMs for the purpose of reducing the affected customer's fees, we interpret the slight negative effect on fees to be consistent with the avoidance of physical banking fees facilitated by more digital banking.

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 older age groups.

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 banking 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 this substitution.

5.3.2. By Time, Location-type, or Salary

In results reported in the online appendix, we look at subsamples along a few other dimensions. We first separate the sample into two groups based on the fraction of a customer's past ATM transactions that occur during working hours. Nonworking-hour times might be less costly for customers. We find that our results that ATM closures induce more digital banking are significant in both groups but indeed look stronger for the customers in the higher working-hours fraction group. This shows that closure-affected customers who usually access ATMs during working hours face a greater friction which induces them more towards digital banking.

Second, we separately look at ATM closures according to the type of location. 11 of the 109 closures are classified as shopping mall locations and the majority of the remainder are ATMs closures at business building locations. We see that the relation between ATM closures and digital banking behavior is strong and significant for closures at both types of locations. Shopping mall closures, although there are only a small number of them, seem to induce a slightly greater impact compared to the business location closures.

We also examine wealth effects, using the median salary to separate the sample into two groups. Presumably, those with above-median salaries will have a higher opportunity cost of time, so it might benefit them more to increase their use of the digital platform to harness the time saved by digital banking. However, if learning requires an upfront time investment, those with a higher opportunity cost of time might be less willing to invest the time. We show that our results are not driven by any one group as the coefficients are significant and do not look very different in both groups.

Overall, the analyses here allow us to characterize the settings where our results appear stronger—younger customers, working-hour ATM users, and shopping mall locations.

5.4. ATM Usage Decline as Alternative Proxy for Friction

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 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 because of a closure, regardless of the distance, it must be that the customer now has more difficulty accessing an ATM.

We report the IV regression estimates in Table 8. The key independent variable is the log of one plus the total number of 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 one plus 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, that is, a 1% reduction in the total number of ATM transaction leads to a 0.71% increase in the total number of digital transactions.

Column (2) uses the log of one plus the total number of digital financial transactions and column (3) uses the log of one plus 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 0.37% increase in the number of digital financial transactions and a 1.03% increase in the dollar amount of digital transactions.

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 nudge for the substitution of physical banking services by an increase in digital banking activity.

5.5. 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 a set of available 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 ATM 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. In Panel A of Table 9, we report similar results when the regressions are estimated using only this control sample alongside the treated observations in the resulting smaller panel.

In Panel B of Table 9, we add a new dimension to the matching in Panel A by now selecting instead only customers who live in the same postal district as the treated customer.[29] This accounts for the potential selection concern that the bank chose to close ATMs in districts where customers were most ready to go digital. But we find in Panel B very similar results to those in Panel A that do not have this same-district match. Since matching based on district does not yield different inferences from matching without using district, we believe a selection bias is unlikely to be a major concern for our analysis.

5.6. Stacked Difference-in-Difference Sample

As an alternative to our panel regression approach, we construct a stacked difference-in-difference sample following the methodology of Gormley and Matsa (2011). For each of the 36 months in our three-year sample, we construct a cohort of treated and untreated customers using customer-month observations (when available) for the six months before and the 12 months after the closure event. Treated customers are those who have experienced either a favorite ATM or a nearest ATM closure that month. Untreated customers for the cohort are those who did not experience any closures in the sample. Post Closure is defined as a dummy that equals one from event-month 0 to 12 for a customer in the cohort who experienced an ATM closure, and zero otherwise. We then stack the cohorts from the different closure months and estimate the impact of closures on our digital banking outcome variables on the resulting

[29] Postal districts are defined by the Urban Redevelopment Authority at https://www.ura.gov.sg/Corporate/-/media/Corporate/Property/PMI-Online/List_Of_Postal_Districts.pdf.

stacked panel. We include year-month fixed effects and customer fixed effects by cohorts. We then estimate the impact of the *Post Closure* dummy on the digital banking activity outcome variables. Results reported in the online appendix show that our conclusions are robust to this alternative specification. The friction from ATM closures continues to be positively associated with the post-closure digital banking activity.

5.7. 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 that 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 two additional 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 about 2 km (reported in Table 1) instead of a mean of about 5 km for the original *Distance to ATM* measure.

In results reported in the online appendix, when we regress this new clustered distance measure on both ATM closure shocks, we get a coefficient of 0.085 for the *Post Closure (Favorite ATM)* dummy, and a coefficient of 0.061 for the *Post Closure (Nearest ATM)* dummy. It is not surprising that the increase in the distance, 61–85 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 (shown in the online appendix) are still robust—digital banking activity goes up because of the distance friction induced by the closure of the ATM. Hence, we believe our results are likely not sensitive to the lack of a workplace address in our baseline sample.

5.8. Alternative Approaches for Count-Based Outcome Variables

Some of our outcome variables are count-based, such as the total number of digital banking transactions. In our baseline tests, we use the log of one plus these variables to mitigate the impact of outliers. Cohn, Liu, and Wardlaw (2022) report that there can be problems with such log transformations and suggest alternative approaches to deal with count data. In Panel A of Table 10, we reproduce our baseline IV regression results using the raw values of digital banking activity instead of their log-transformed versions. Panel A shows that our results are similar. In Panel B of the table, we estimate for the count-based digital banking activity a reduced-form Poisson model with fixed effects. We can see that these estimations also produce the result that ATM closures lead to an increase in digital banking activity.

6. Conclusion

We use novel consumer banking data to examine whether small physical frictions can help move customers toward digital banking. Our data come 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 although it could also be associated with problems such as overconsumption. We show that the substitution from physical to digital banking facilitates several spillover outcomes. 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, but there is no evidence of increased consumption. In terms of cross-sectional differences, these effects are generally stronger for younger age groups. While we are not able to conclusively speak about welfare enhancement since we do not observe whether savings or consumption were optimal prior to the ATM closures, these results provide evidence that consumer financial behavior is significantly impacted by the small friction provided by an ATM closure.

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 banking, which could provide other spillover effects.

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Table 1: Summary Statistics

Our sample includes customer-month observations from January 2015 to December 2017. Panel A reports their demographics, namely age; monthly salary in thousands of Singapore dollars; monthly account beginning balance in thousands; *Distance to ATM* a transaction-weighted distance to their used ATMs from the provided customer address; and *Distance to ATM (Clustered)*, an alternative measure of the distance to ATM using top three geographical centers of the clusters of a customer's ATM transactions. 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 total S$ amount of monthly transactions. We also report the total number of account-level transactions recorded in the customer's savings and checking accounts. For other banking transactions, we report the number and S$ amount of POS transactions; Transfer (regular funds transfers) transactions; FAST transactions (instant funds transfers); GIRO transactions (automatic bill payments); SAYE automatic savings transactions; the total S$ amount of cash withdrawals at ATM locations, at POS locations, and in total; and the total S$ amount of spending. In Panel C, *Post Closure (Favorite)* equals one 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 months. *Post Closure (Nearest)* equals one from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. Std. dev., Standard deviation.

Variables		Obs	Mean	Std. Dev.	10th	50th	90th
Panel A: Customer Demographics							
Age		5,994,130	42.18	14.49	24.00	41.00	63.00
Monthly Salary (S$'000)		5,994,130	2.27	5.89	0.00	0.75	5.67
Begining Balance (S$'000)		5,994,130	19.09	71.85	0.05	2.50	44.10
Distance to ATM		5,994,130	5.08	4.59	0.44	3.87	11.54
Distance to ATM (Clustered)		5,994,130	1.96	2.15	0.17	1.27	4.66
Panel B: Customers' Banking Activity							
ATM Transactions	Total #	5,994,130	8.26	8.47	1.00	6.00	17.00
	Non-Financial #	5,994,130	1.26	3.50	0.00	0.00	4.00
	Average S$ Per Transaction	5,994,130	372	1,236	50	200	800
Digital Transactions	Total #	5,994,130	26.87	48.40	0.00	6.00	78.00
	Financial #	5,994,130	2.50	6.53	0.00	0.00	8.00
	Monthly Total S$	5,994,130	2,036	14,067	0.00	0.00	4,539
Total # of Account-level Transactions		5,994,130	27.54	22.03	8.00	23.00	52.00
Other Transactions (Monthly Total)							
	# of POS Transactions	5,994,130	8.76	11.21	0.00	5.00	22.00
	S$ of POS Transactions	5,994,130	817	2,185	0.00	337	2,080
	# of Transfer Transactions	5,994,130	2.54	7.26	0.00	1.00	7.00
	S$ of Transfer Transactions	5,994,130	1,826	14,613	0.00	3	3,570
	# of FAST Transactions	5,994,130	0.75	2.48	0.00	0.00	2.00
	S$ of FAST Transactions	5,994,130	878	5,978	0.00	0.00	1,600
	# of GIRO Transactions	5,994,130	0.70	0.46	0.00	1.00	1.00
	S$ of GIRO Transactions	5,994,130	933	6,328	0.00	168	1,836
	# of SAYE Transactions	5,994,130	0.17	0.59	0.00	0.00	0.00
	S$ of SAYE Transactions	5,994,130	73.54	428.51	0.00	0.00	0.00
	S$ of Cash Withdrawal (Cash WDL)	5,994,130	1,717	4,045	160	1,000	3,480
	S$ of POS Withdrawal (POS WDL)	5,994,130	2.50	22.87	0.00	0.00	0.00
	S$ of Total Cash Withdrawal (Total WDL)	5,994,130	1,720	4,045	170	1,000	3,480
	S$ of Total Spending	5,994,130	3,535	8,708	350	2,058	7,065
Panel C: ATM Closure Shock							
Post Closure (Favorite ATM)		5,994,130	0.03	0.16	0.00	0.00	0.00
Post Closure (Nearest ATM)		5,994,130	0.05	0.22	0.00	0.00	0.00

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 models (1)–(3) is the *Distance to ATM*, a transaction-weighted distance to their used ATMs from the provided customer address. In model (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 months. In model (2), we use the *Post Closure (Nearest ATM)* as the main independent variable. *Post Closure (Nearest ATM)* equals one from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. In model (3), we use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the main independent variables. The dependent variable for models (4)–(6) is the log of one plus the total number of ATM transactions (Txns). Controls include the 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 by the customer's favorite ATM. with * and *** respectively denote statistical significance at the 10% and 1% 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***
	(2.65)		(1.82)	(-14.44)		(-13.98)
Post Closure (Nearest ATM)		0.128***	0.117***		-0.010***	-0.001
		(7.35)	(7.02)		(-4.29)	(-0.61)
Beginning Balance	0.0002***	0.0002***	0.0002***	0.0001***	0.0001***	0.0001***
	(3.98)	(3.97)	(3.97)	(10.38)	(10.35)	(10.38)
Monthly Salary	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(7.59)	(7.59)	(7.58)	(9.91)	(9.91)	(9.91)
Observations	5,994,130	5,994,130	5,994,130	5,994,130	5,994,130	5,994,130
R-squared	0.573	0.573	0.573	0.654	0.654	0.654
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Customer fixed effects	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 IV regression estimates of the effect of ATM usage distance on customers' digital banking activity using ATM closure shocks as IVs. 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 IVs. *Post Closure (Favorite ATM)* equals one 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 months. *Post Closure (Nearest ATM)* equals one 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 model (1) is the log of one plus the total number of digital transactions (Txns), that for model (2) is the log of one plus the total number of digital financial transactions, that for model (3) is the log of one plus the total S$ amount of digital transactions, and that for model (4) is the log of one plus the total number of account-level transactions. 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 by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 129.803. *** denotes statistical significance at the 1% level.

	(1)	(2)	(3)	(4)
	log(1+# of Digital Txns)		log(1+S$ of	log(1+# of
Variables	Total	Financial	Digital Txns)	Account Txns)
$\widehat{\text{Distance to}}$ ATM	0.232***	0.121***	0.381***	-0.011
	(5.54)	(5.44)	(4.90)	(-0.79)
Beginning Balance	0.0002***	0.0002***	0.001***	0.0004***
	(5.83)	(8.84)	(10.83)	(12.36)
Monthly Salary	0.004***	0.003***	0.013***	0.005***
	(10.14)	(10.47)	(11.34)	(10.76)
Observations	5,994,130	5,994,130	5,994,130	5,994,130
R-squared	0.709	0.646	0.690	0.734
Year-month fixed effects	Yes	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes	Yes

Table 4: Reduced-Form Regression

We report panel regression estimates of the effect of ATM closure shocks on customers' digital banking activity. The main independent variables are *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. *Post Closure (Favorite ATM)* equals one 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 months. *Post Closure (Nearest ATM)* equals one 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 model (1) is the log of one plus the total number of digital transactions(Txns), that for model (2) is the log of one plus the total number of digital financial transactions, and that for model (3) is the log of one plus the total S$ amount of digital transactions. 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 by the customer's favorite ATM. *** denotes statistical significance at the 1% level.

	(1)	(2)	(3)
	log(1+# of Digital Txns)		log(1+S$ of
Variables	Total	Financial	Digital Txns)
Post Closure (Favorite ATM)	0.035***	0.018***	0.049***
	(5.06)	(4.74)	(3.46)
Post Closure (Nearest ATM)	0.020***	0.010***	0.036***
	(3.96)	(4.07)	(3.72)
Beginning Balance	0.0002***	0.0002***	0.001***
	(8.99)	(10.69)	(11.51)
Monthly Salary	0.005***	0.003***	0.014***
	(10.87)	(10.91)	(11.54)
Observations	5,994,130	5,994,130	5,994,130
R-squared	0.843	0.795	0.781
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes

Table 5: Temporary and Permanent ATM Closures (IV Regression using ATM Closure Shocks)

We report Instrumental Variable (IV) regression estimates of the effect of ATM usage distance on customers' digital banking activity using temporary and permanent ATM closure shocks as IVs. 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 ATMs. Panel B reports the regression results for permanent closures excluding customers who experienced any temporary closures of their favorite or nearest ATMs. We use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IVs. *Post Closure (Favorite ATM)* equals one 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 months; *Post Closure (Nearest ATM)* equals one 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 model (1) is the log of one plus the total number of digital transactions, that for model (2) is the log of one plus the total number of financial digital transactions, and that for model (3) is the log of one plus the total S$ amount of digital transactions. 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 by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 32.918 in Panel A and 108.702 in Panel B. ** and *** respectively denote statistical significance at the 5% and 1% 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**
	(2.40)	(2.15)	(2.12)
Beginning Balance	0.0002***	0.0002***	0.001***
	(4.71)	(7.68)	(9.84)
Monthly Salary	0.004***	0.003***	0.012***
	(8.23)	(8.81)	(9.86)
Observations	5,367,297	5,367,297	5,367,297
R-squared	0.713	0.661	0.679
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes
Panel B: Permanent ATM Closures			
$\widehat{\text{Distance to}}$ ATM	0.201***	0.115***	0.366***
	(4.91)	(5.16)	(4.44)
Beginning Balance	0.0002***	0.0002***	0.001***
	(5.86)	(8.57)	(10.50)
Monthly Salary	0.004***	0.003***	0.013***
	(9.88)	(10.07)	(10.88)
Observations	5,609,306	5,609,306	5,609,306
R-squared	0.742	0.659	0.696
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes

Table 6: Using Other Banking Activity as Outcome Variables (IV Regression using ATM Closure Shocks)

We report Instrumental Variable (IV) regression estimates of the effect of ATM usage distance on customers' other digital banking technology-related activity using ATM closure shocks as IVs. The dependent variables associated with each model are as follows. Models (1) and (2) use the monthly number and total S$ amount of POS transactions, respectively. Models (3) and (4) use the number and S$ amount of regular transfer transactions respectively. Models (5) and (6) use the number and S$ amount of FAST transactions (instantaneous transfers), respectively. Models (7) and (8) use the number and S$ amount of GIRO transactions (autodebit bill payments), respectively. Models (9) and (10) use the number and S$ amount of SAYE transactions (automatic savings transactions), respectively. Model (11) uses the total S$ cash amount transacted through ATMs (*Cash WDL*). Model (12) uses the S$ cash amount withdrawn through POS locations (*POS WDL*). Model (13) uses the S$ sum of cash withdrawals through both ATMs and POS locations (*Total WDL*). Model (14) uses the S$ amount of overall spending as the dependent variable. Model (15) uses a dummy variable indicating the customers who will close (or stop using) at least one of their accounts. 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 shocks. We use both *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)* as the IVs. *Post Closure (Favorite ATM)* equals one 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 months. *Post Closure (Nearest ATM)* equals one from the ATM closure event when the closed ATM is the one that is closest to the customer's postal address. 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 by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 129.803. Txns, Transactions. ** and *** respectively denote statistical significance at the 5% and 1% 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)	(5) log(1+# of FAST Txns)
$\widehat{\text{Distance to}}$ ATM	0.096***	0.173***	0.099***	0.276***	0.058***
	(3.90)	(3.09)	(4.47)	(3.44)	(3.22)

Variables	(6) log(1+S$ of FAST Txns)	(7) log(1+# of GIRO Txns)	(8) log(1+S$ of GIRO Txns)	(9) log(1+# of SAYE Txns)	(10) log(1+S$ of SAYE Txns)
$\widehat{\text{Distance to}}$ ATM	0.234***	0.016**	0.126**	0.013***	0.074***
	(2.96)	(2.22)	(2.04)	(3.21)	(3.15)

Variables	(11) log(1+S$ of Cash WDL)	(12) log(1+S$ of POS WDL)	(13) log(1+S$ of Total WDL)	(14) log(1+S$ of Spending)	(15) Account Closure
$\widehat{\text{Distance to}}$ ATM	-0.080***	0.141***	-0.073***	-0.070***	-0.003
	(-3.22)	(4.63)	(-2.98)	(-2.65)	(-0.37)

Table 7: Results According to Age Groups (IV Regression using ATM Closure Shocks)

We report IV regression estimates of the effect of distance to digital banking activity and other banking activity using ATM closure shocks as IVs in age group tercile subsamples. In models (1)–(3), the dependent variable is the log of one plus the number of total digital transactions. Model (1) reports the result of the youngest tercile (1/3), model (2) reports the result of the middle tercile (2/3), and model (3) reports the result of the oldest tercile (3/3). The main independent variable is the *Distance to ATM*, instrumented by *Post Closure (Favorite ATM)* and *Post Closure (Nearest ATM)*. 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 one plus the number of financial digital transactions (models (4)–(6)), the log of one plus the S$ amount of digital transactions (models (7)–(9)), the log of one plus the number of POS transactions (models (10)–(12)), the log of one plus the number of Transfer transactions (models (13)–(15)), the log of one plus the number of FAST transactions (models (16)–(18)), the log of one plus the number of GIRO transactions (models (19)-(21)), the log of one plus the number of SAYE transactions (models (22)–(24)), and the log of one plus the S$ amount of total monthly cash transacted through both ATM and POS (*Total WDL*; models (25)–(27)). Reported coefficient estimates have t-statistics in parentheses based on standard errors clustered by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 39.712 for the youngest tercile, 34.543 for the middle tercile, and 75.920 for the oldest tercile. ** and *** respectively denote statistical significance at the 5% and 1% 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**
	(4.22)	(3.33)	(2.76)	(4.18)	(3.10)	(2.12)	(4.05)	(2.96)	(2.05)

	(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**
	(3.27)	(2.43)	(2.85)	(3.82)	(2.87)	(2.08)	(1.09)	(2.69)	(2.56)

	(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 Total WDL)		
$\widehat{\text{Distance to}}$ ATM	0.041***	0.028**	0.009	0.026***	0.014	0.004	-0.015	-0.121**	-0.042
	(2.83)	(2.01)	(1.05)	(2.80)	(1.43)	(1.01)	(-0.40)	(-2.24)	(-1.22)

Table 8: 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 the favorite ATM closure shock as an IV. The main independent variable is the log of one plus the number of total ATM transactions, instrumented by *Post Closure (Favorite ATM)*. *Post Closure (Favorite ATM)* equals one 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 months. The dependent variable for model (1) is the log of one plus the Total Number of Digital Transactions, for model (2) is the log of one plus the Total Number of Financial Digital Transactions, and for model (3) is the log of one plus the total S$ amount of digital transactions. 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 by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 569.810. Txns, Transactions. *** denotes statistical significance at the 1% level.

Variables	(1) log(1+# of Digital Txns) Total	(2) log(1+# of Digital Txns) Financial	(3) log(1+S$ of Digital Txns)
log(1+# of $\widehat{\text{ATM}}$ Total Txns)	-0.707***	-0.368***	-1.029***
	(-6.41)	(-6.09)	(-4.64)
Beginning Balance	0.0003***	0.0002***	0.001***
	(9.27)	(10.44)	(11.45)
Monthly Salary	0.006***	0.004***	0.017***
	(9.71)	(9.92)	(10.58)
Observations	5,994,130	5,994,130	5,994,130
R-squared	0.814	0.762	0.766
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes

Table 9: Propensity Score-Matched Sample

We report IV regression estimates of the effect of ATM usage distance on customers' digital banking activity using ATM closure shocks as IVs. The estimation method and variables used are as described in the legend of Table 3, except that instead of the full panel, a propensity score-matched sample is used for this analysis. In the month before closure for a treated customer (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, namely, distance to ATM, number of ATM transactions, number of digital banking transactions, number of account-level transactions, and monthly salary. Panel B adds to these five characteristics and an additional requirement that the search for a control customer has to be within the same postal district as the treated customer. Postal districts are as defined by the Urban Redevelopment Authority at https://www.ura.gov.sg/Corporate/-/media/Corporate/Property/PMI-Online/List_Of_Postal_Districts.pdf. 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 by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression is 181.166 in Panel A and 186.337 in Panel B. Txns, Transactions. *** denotes statistical significance at the 1% level.

Panel A: Matched Sample			
	(1)	(2)	(3)
	log(1+# of Digital Txns)		log(1+S$ of
Variables	Total	Financial	Digital Txns)
$\widehat{\text{Distance to}}$ ATM	0.124***	0.082***	0.262***
	(4.33)	(5.13)	(4.44)
Beginning Balance	0.0001***	0.0001***	0.001***
	(2.83)	(4.29)	(5.50)
Monthly Salary	0.005***	0.00356***	0.016***
	(9.59)	(9.80)	(9.92)
Observations	1,790,140	1,790,140	1,790,140
R-squared	0.805	0.731	0.741
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes

Panel B: Matched Sample within the Same Postal District			
$\widehat{\text{Distance to}}$ ATM	0.129***	0.069***	0.227***
	(4.55)	(4.64)	(4.11)
Beginning Balance	0.0003***	0.0003***	0.002***
	(6.13)	(8.37)	(10.94)
Monthly Salary	0.006***	0.004***	0.020***
	(10.36)	(10.26)	(10.69)
Observations	1,699,782	1,699,782	1,699,782
R-squared	0.803	0.751	0.753
Year-month fixed effects	Yes	Yes	Yes
Customer fixed effects	Yes	Yes	Yes

Table 10: Alternative Methods for Count-Based Outcomes

Panel A reports second-stage regression estimates from using digital banking outcome variables in their non-log forms. The main independent variable is *Distance to ATM* (a transaction-weighted usage distance to ATM from the provided customer address, instrumented by the two ATM closure shocks). In Panel A, the dependent variable for column (1) is the total number of digital transactions (Txns); that for column (2) is the total number of digital financial transactions; and that for column (3) is the total S$ amount of digital transactions. Panel B reports estimates from a Poisson model where the two ATM closure shocks directly enter as independent variables in a reduced-form estimation. The dependent variable for column (1) is the total number of digital transactions (Txns) and that for column (2) is the total number of digital financial transactions. Controls in both panels include monthly beginning account balance in thousands (*Beginning Balance*), monthly salary in thousands, year-month fixed effects (FEs), and customer FEs. For the Poisson estimations with customer FEs, observations with no variation in the dependent variable for the customer are dropped. Removing customer FEs for Panel B and restoring these dropped observations yields similar results. Coefficient estimates are reported with t-statistics in parentheses based on standard errors clustered by the customer's favorite ATM. The Cragg-Donald Wald F-statistic for the IV regression in Panel A is 129.803. ** and *** respectively denote statistical significance at the 5% and 1% levels.

Panel A: Non-log Dependent Variables

	(1)	(2)	(3)
	# of Digital Txns		S$ of
Variables	Total	Financial	Digital Txns
$\widehat{\text{Distance}}$ to ATM	8.550***	0.690***	1,018***
	(5.54)	(4.35)	(3.23)
Beginning Balance	0.0033***	0.001***	29.54***
	(3.58)	(7.30)	(5.82)
Monthly Salary	0.148***	0.016***	116.1***
	(10.23)	(10.17)	(5.24)
Observations	5,994,130	5,994,130	5,994,130
R-squared	0.405	0.652	0.190
Year-month FEs	Yes	Yes	Yes
Customer FEs	Yes	Yes	Yes

Panel B: Reduced-Form Poisson Regression

	(1)	(2)
	# of Digital Txns	
Variables	Total	Financial
Post Closure (Favorite ATM)	0.045***	0.038***
	(6.35)	(2.69)
Post Closure (Nearest ATM)	0.013**	0.006
	(2.55)	(0.82)
Beginning Balance	0.0002***	0.0002***
	(5.17)	(3.53)
Monthly Salary	0.002***	0.002***
	(8.99)	(9.06)
Observations	4,089,784	3,685,331
Year-month FEs	Yes	Yes
Customer FEs	Yes	Yes

Figure 1: ATM Network in Singapore

We mark DBS bank's ATM network in Singapore for the 2015–2017 sample period. Triangles represent building locations (postal codes) that have at least one ATM. Stars represent the 109 locations associated with ATM location closures in the sample period. Heat map colors denote the population density category which are based on the resident population per square kilometer reported in the population statistics provided at https://beta.data.gov.sg/ (Singapore residents by planning area, June 2016).

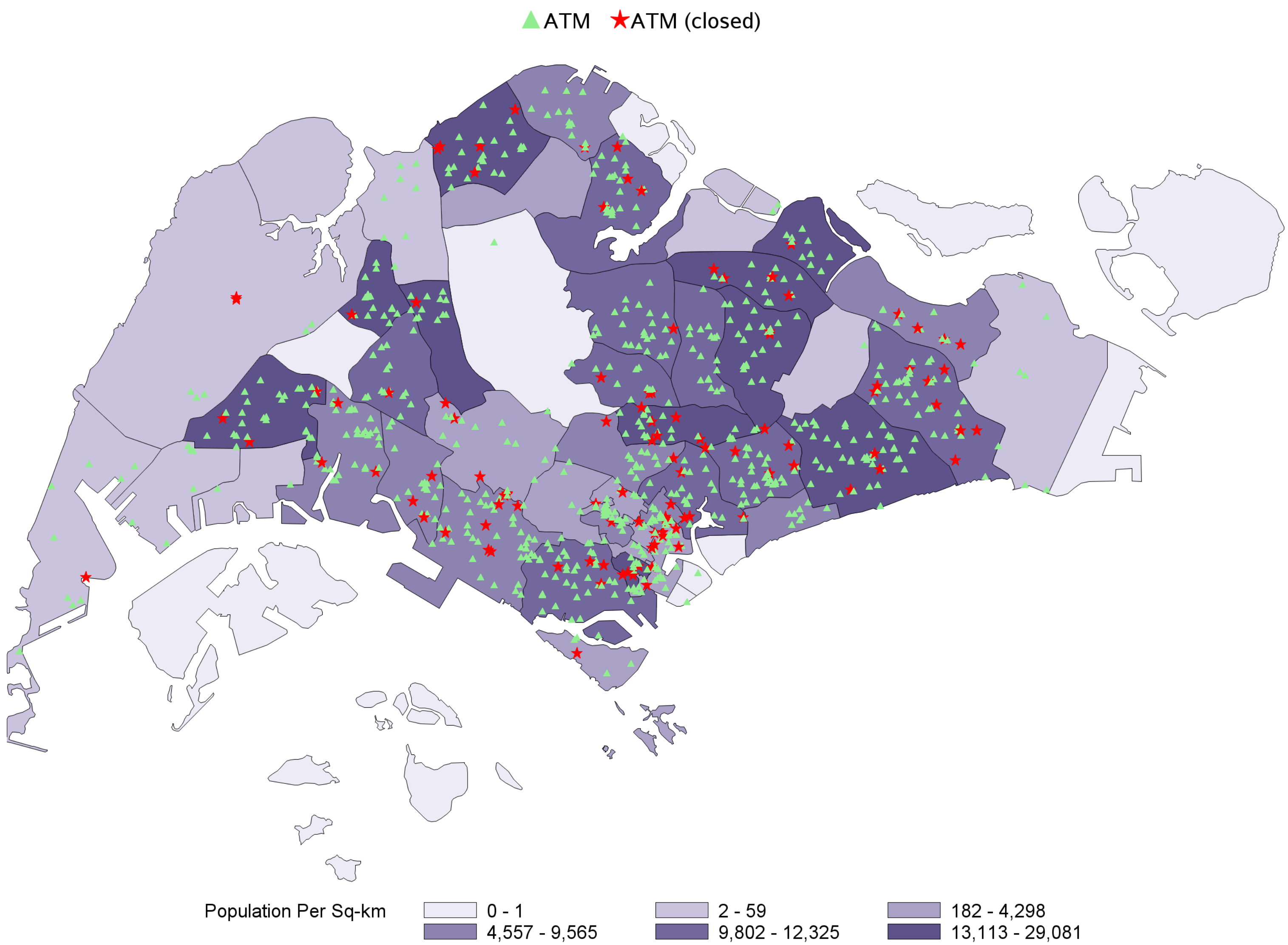


Figure 2: Distance to ATM by the Time of Usage

We report the time series of the average *Distance to ATM* by the time of usage. *Distance to ATM* 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 8:00 a.m. to 6:00 p.m. on non-public-holiday weekdays. The blue solid line represents the average *Distance to 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 autodebit transactions in the 2015–2017 sample.

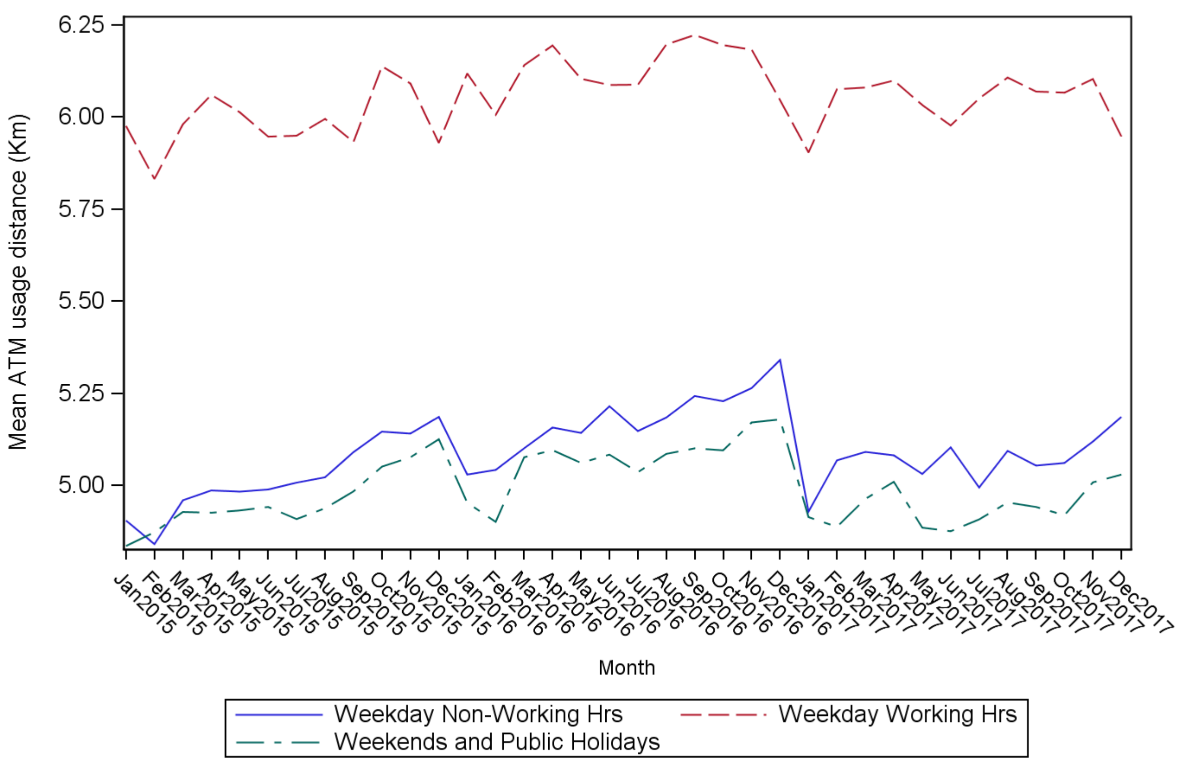
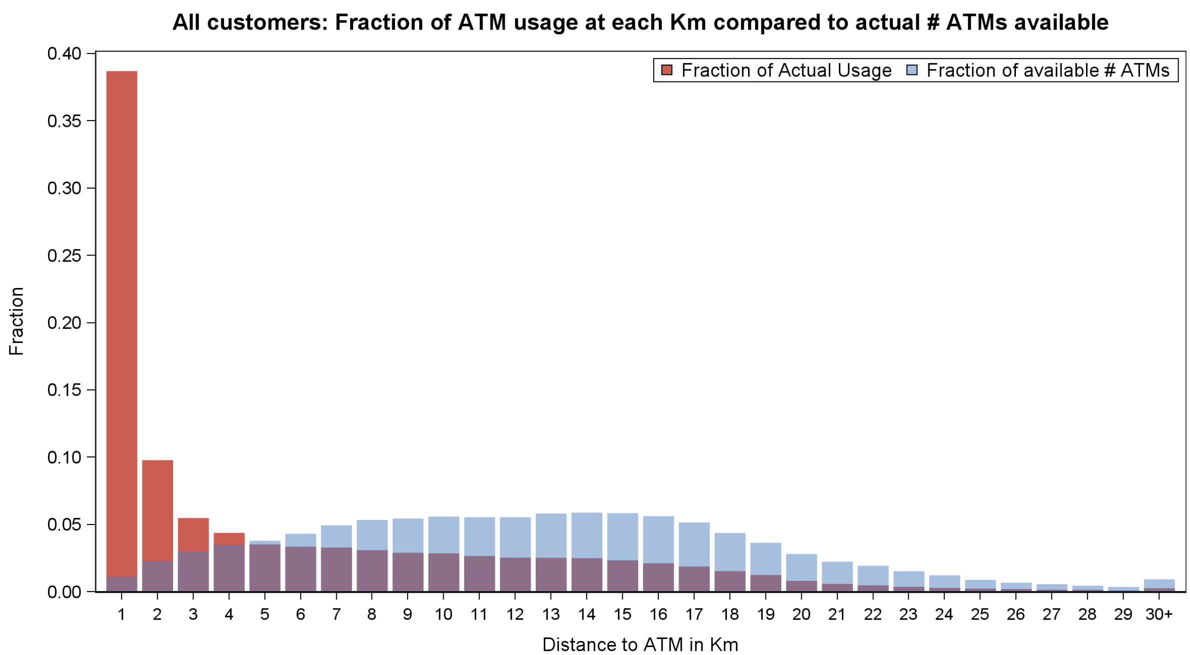


Figure 3: Distribution of ATM Usage by Distance

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 customer's 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 that distance from a typical customer's address. The bottom chart shows the average distribution of a customer's 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 adding a "(S)" prefix in a postal code search at streetdirectory.com and extracting the address category.



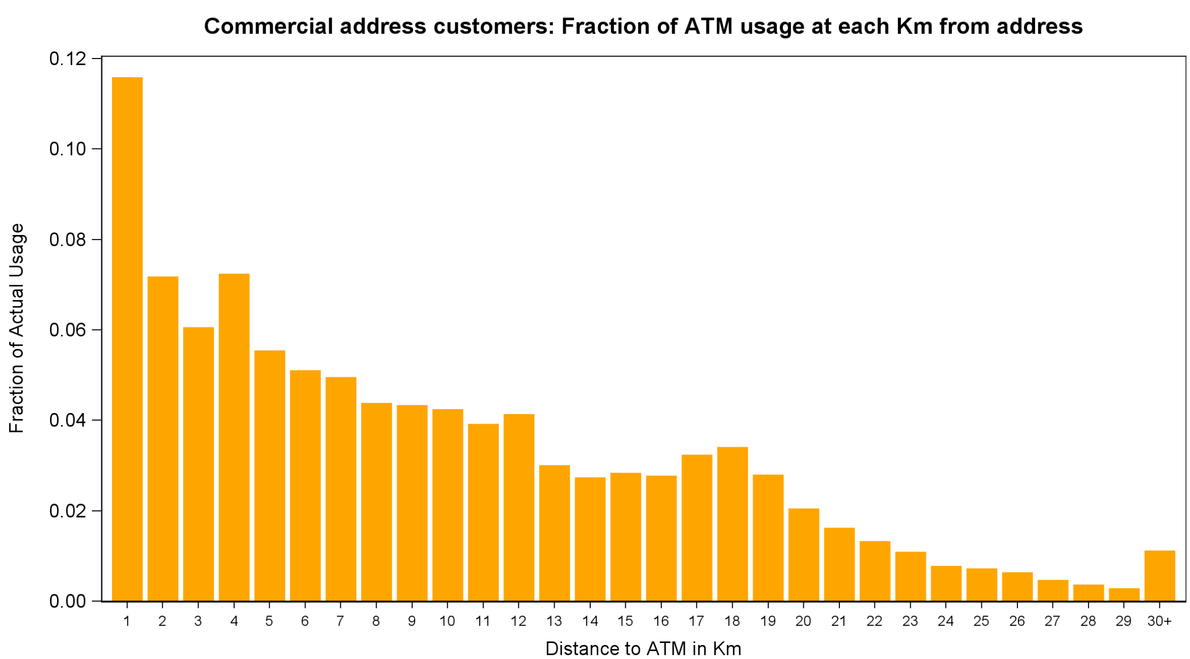


Figure 4: Distance to ATM, ATM Usage, and Digital Banking Around Favorite ATM Closures

We report the average residual *Distance to ATM* (Panel A), log(1+# *of ATM Total Txns*) (Panel B), log(1+# *of Digital Total Txns*) (Panel C), and log(1+# *of Total # of Digital Financial Txn*) (Panel D) around a favorite ATM closure. The residuals are estimated from a regression of the respective indicated variable on *Post Closure (Nearest ATM)*, *Beginning Balance*, and *Monthly Salary*, with year-month fixed effects and customer fixed effects. We then plot the average residual from the regression for the window of [–4, +6] months around the closure for the treated customers (solid lines), defined as those who experience the closure of their favorite ATM. A favorite ATM closure is when the closed ATM is the customer's favorite based on the number of times used in the prior three months. Also plotted are the average residuals of control customers (dashed lines), who are propensity score matched in the month before closure based on distance and ATM and digital banking activity. We keep only customers who appear in all the months of the window of [–4, +6] to ensure that the panel is balanced. Txns, Transactions.

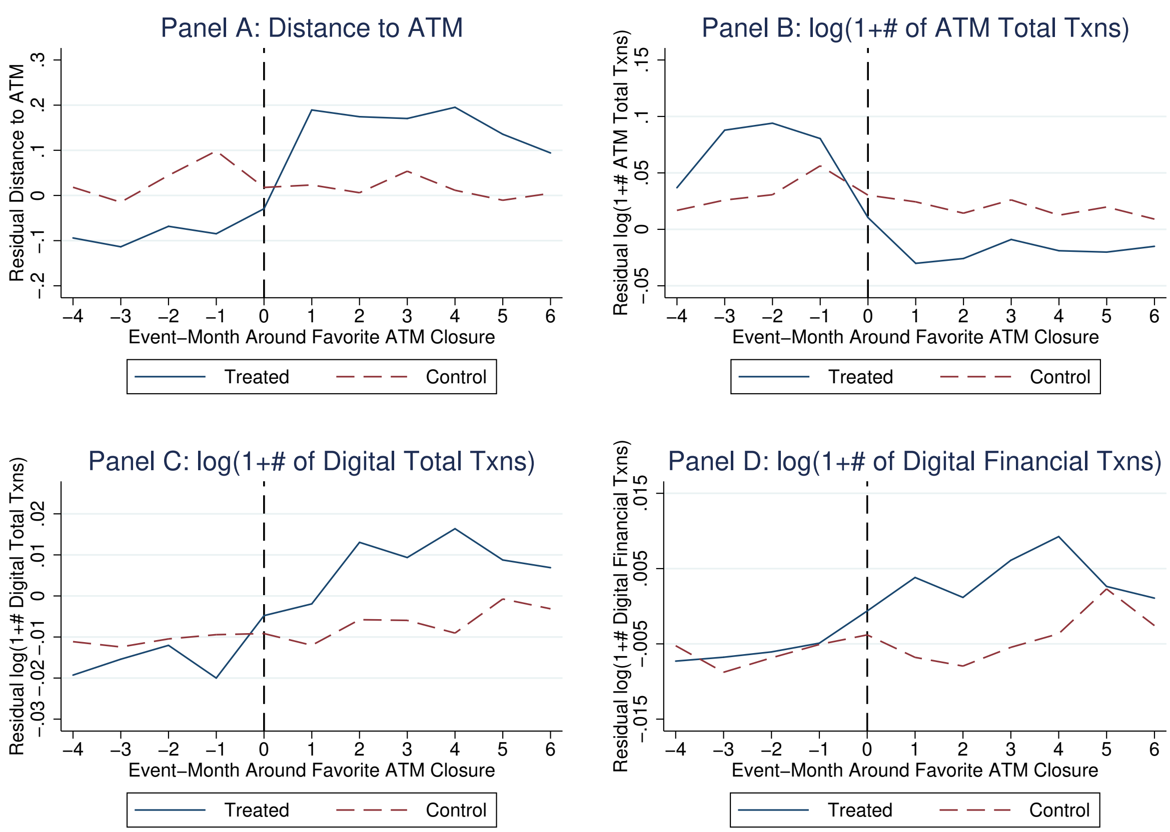


Figure 5: ATM Transactions Around Permanent and Temporary ATM Closures

We report the average number of ATM transactions at an ATM location around its closure 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 December 2017). A solid line plots the average number of ATM transactions around a permanent ATM closure. A dashed line plots the average number of ATM transactions around a temporary ATM closure.