Learning Through Social Networks: How Foreign Workers Optimize FinTech Usage for Remittances*

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Abstract

In this paper, we use data from one of Korea's leading FinTech firms to study how personal experience and one's social network's proficiency predict the optimal use of a financial technology for remittance payments. We find that the users improve the timing of remittance transactions by 1.7% with individual experience of cancellation feature. Using referral information to identify social networks among users, we find that the improvement in timing increases by 2.3% if the feature is used more by other social network members. Overall, we find that users gain both from personal learning-by-doing as well as from the experience of their social networks.

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1. Introduction

The use of financial technology or "FinTech" has surged over the past decade. FinTech has been applied to the delivery of broad categories of consumer financial services, such as digital payments, consumer credit, and personal financial investment, to reduce the costs and increase the convenience of financial transactions. For example, mobile banking allows its users to make payments at home using a mobile phone, without traveling to a bank, and outside of traditional banking hours. FinTech has also fostered competition amongst financial service providers, which has led to reduced in service costs.

However, it is not straightforward whether users can optimize their usage of technology by maximizing benefits while minimizing (behavioral) costs. For example, while autonomous robo-advisors help to improve individual investors' portfolio efficiency (D'Acunto et al. (2019); Loos et al. (2020)), lower commissions, greater ease of access, and speedier trade executions can lead to excessive and speculative trading that results in poorer performance (Barber and Odean (2002); Choi et al. (2002); Kalda et al. (2021)). On the other hand, learning-by-doing can play an important role; for example, the individual learning-by-trading in Seru et al. (2010) potentially attenuates behavioral costs in the long run.

In this paper, we study the role of social networks in helping users optimize their use of new technology using transaction-level international remittance data. The recent development of social networks as an important information dissemination channel (Chen et al. (2014); Cookson and Niessner (2020)) and the integration of FinTech with social networks (Heimer (2016); Cookson and Niessner (2020); Ammann and Schaub (2020); D'Acunto et al. (2020)) led us to examine an important but less-studied question on how individuals learn about smart technology usage through their social networks.

Our transaction-level international remittance data is from Sentbe, a leading FinTech firm in Korea offering digital money transfer services.[1] Our data offer several advantages for

[1] More than 200 million USD in total remittances was sent via the Sentbe platform from Korea to developing Asia over the 2019 calendar year.

studing the effect of social networks on consumer welfare. First, we can identify granular social networks among users. As with many FinTechs, Sentbe offers cash incentives for users to recommend the service to their friends: bonus credits that can be used to pay for future remittance payments. We use this referral data to construct social networks among our sample of workers.

Second, we can clearly measure the improvements in consumer welfare in international remittances using daily changes in the foreign exchange rate around remittance decisions. To evaluate whether workers optimize the timing of their remittance payments, we construct a measure that compares the exchange rates of actual remittance transactions to the exchange rates in the window of $[-5, +5]$ days around the executed transaction (*Optimality Score*$_{i,t}$ $[-5, +5]$).

Third, the FinTech platform in our study has a novel feature that allows us to measure learning in the social networks. The feature allows workers to cancel their orders within 24 hours, without any fee (hereafter, we refer to this as the cancellation feature), which is used by approximately 20 percent of users. Since users of the FinTech product are allowed to set multiple orders before choosing an order to be executed, the cancellation feature works like a free look-back option, which helps users improve the timing of their transactions and optimize their exchange rates. However, the cancellation feature is not a service the firm designed or intended to offer– and the feature was never advertised or explained to users by the firm. Instead, users only learned about the feature by themselves or through their social networks. This unique situation allows us to investigate information diffusion in a FinTech platform through social networks and the subsequent effect of this information diffusion on consumer welfare.

Finally, our sample includes users of the platform from nine Southeast Asian countries, who are mostly low-skilled workers sending a significant portion of their earnings back home to support their families. These data provide an ideal setup to test the learning effect within social networks, since our sample users are financially unsophisticated but exert their best effort in making remittance decisions, which have a large impact on their utility and wealth.

We first document some stylized facts on individual international remittances. The likelihood of sending a remittance, and the amount sent, is as high on Saturday and Sunday–when many banks are closed and workers might not be working–as on weekdays, showing that users value the flexibility offered by the FinTech to send remittance transactions during evenings and weekends. However, we find that the likelihood of a remittance transaction increases during the days that wages are typically paid, since many workers are urgently sending their earnings back home to support their families.

Regarding the optimality of remittance transactions, we find that workers in our sample were able to pick the highest (most advantageous) exchange rate in the window of $[-5, +5]$ days around the actual transaction by 0.02% on average. Compared to the finding that the average return per trade by retail day traders in the foreign exchange rate market is -0.035% (Ben-David et al. (2018)), this is a surprising result considering that our sample users are mostly financially unsophisticated migrant workers. Moreover, when we narrow the sample to workers with high average optimality scores, the effect strengthens by 0.39% on average.

The average exchange rate optimality score is significantly lower on days when wages are typically paid, showing that our sample users do not have substantial flexibility to wait and time the transaction. We also find that the optimality score: decreases with the worker's age, which might be related to users' tech-savviness; increases with the amount sent, which can proxy for the user's wages and skill level and amount of attention on the remittance transaction; is higher among female users than male users; and significantly varies by nationality.

Next, we find that optimality scores are related to how workers use the cancellation feature. We find that the likelihood of sending a remittance payment increases when users use the cancellation feature. We find that the optimality score increases from 0.015% to 0.062% if the worker ever used the *Cancellation* feature on the platform. However, the increase in the optimality score is mainly driven by the intensive usage of cancellation–we find that some users cancel multiple orders sequentially in order to optimize the timing of their order (hereafter *Sequential Cancellation*). The use of *Sequential Cancellation* significantly increases the average score from 0.015% to 0.162% while other uses of the cancellation feature have no effect (the average score significantly falls from 0.02% to 0.01%).

Finally, we explore the influence of social networks on workers' remittance behavior. We find that the remittance transactions are more clustered among the members of social networks. We calculate the average Herfindahl-Hirschman index (HHI) of remittance transactions for members of social networks and for matched pairs of users and find that the average HHI of social networks is 13.4% higher than the average HHI of the matching groups, and the difference is statistically significant.

The herding behavior in remittance transactions in social networks leads us to ask whether users would have learned information that helps them to improve remittance transactions, such as *Sequential Cancellation*, if they had not been part of the social network. We first examine individual learning on the use of *Sequential Cancellation* and find that workers who used *Sequential Cancellation* are more likely to use it again, and the frequency of using *Sequential Cancellation* increases over time. A one-standard-deviation increase in the individual experience of *Sequential Cancellation*, measured by the fraction of the number of past remittance transactions with *Sequential Cancellation* over the number of all past remittance transactions, increases 11% of one standard deviation of the usage of *Sequential Cancellation*.

We also find evidence of social learning and show that workers are more likely to use *Sequential Cancellation* when other members of their social networks use *Sequential Cancellation*. A one-standard-deviation increase in the social experience of *Sequential Cancellation*, measured by the fraction of the number of past remittance transactions with *Sequential Cancellation* by other members of social network over the number of all past remittance transactions by the other members, increases the usage of *Sequential Cancellation* by 1.7% of one standard deviation. The size of the effect is about 15% of the size of the effect from individual learning.

We find that the increased usage of *Sequential Cancellation* through individual and social learning increases the optimality score. With the usage of *Sequential Cancellation*, a one-standard-deviation increase in the individual experience of *Sequential Cancellation* increases the optimality score by 1.7% of one standard deviation. More important, a one-standard-deviation increase in the social experience of *Sequential Cancellation* increases the optimality score by 2.3% of one standard deviation. When we put two different channels of learning together, we find that the effect of social learning dominates the effect of individual learning.

Our paper contributes to the literature studying learning from personal experience. Kaustia and Knüpfer (2008) and Chiang et al. (2011) find that the past experiences in IPO participation affect future IPO subscriptions. Anagol et al. (2020) further find that successful IPO experience leads to high turnover in individual stock investment. Choi et al. (2009) find that the past return from a 401(k) account positively affects future contributions to the 401(k) account. Malmendier and Nagel (2011) and Malmendier and Nagel (2016) find that personal experience from financial markets affects future market participation. Agarwal et al. (2008) , studying the use of consumer credit cards, additionally find that recent experience is more important than old experience. Seru et al. (2010) document evidence of learning-by-doing in stock trading that retail investors either improve their trading skills and performance such as reducing disposition effects, or eventually stop trading after learning their poor ability. Chang et al. (2002) provide a theory of learning-by-doing in macro contexts. Our paper adds to the literature by focusing on the effect of the past experience of using a technology on the frequency and the efficiency of the future usage of the technology.

Our research is also related to the studies on peer effects. The role of social interaction has been discussed in various topics such as housing tenure decisions (Bailey et al. (2018)), welfare participation (Bertrand et al. (2000)), retirement plans (Duflo and Saez (2003)), stock market participation (Hong et al. (2004)), employee stock purchase plans (Ouimet and Tate (2020)), personal leverage choice (Kalda (2020)), personal consumption (De Giorgi et al. (2020)), and immigration outcomes (Munshi (2003), McKenzie and Rapoport (2007)). We use the referral network in a FinTech platform to find that knowledge on the efficient usage of a technology can be shared through social networks.

Finally, our paper contributes to the emerging literature on the value of FinTech. Chen et al. (2019) study the value of FinTech from the perspective of innovators and financial institutions. While they find substantial value creation for innovators, they find mixed results in the willingness of other financial industry participants to adopt new technology. Regarding the value of FinTech for retail consumers, recent studies find a positive role for FinTech in improving information efficiency in credit allocation. Berg et al. (2020) and Agarwal et al. (2020) discover the benefit of FinTech from constructing credit scores out of digital footprints. Jagtiani and Lemieux (2018) and Liskovich and Shaton (2018) find that FinTech benefits information efficiency on online lending platforms. Instead, our paper focuses on the important role of learning in social networks to maximize the value of FinTech for its users.

2. Data and Summary Statistics

2.1. FinTech Data on International Remittances

Globalization has increased labor migration. The number of international migrants reached nearly 272 million in 2019, up from 153 million in 1990 (United Nations (2019)). Many migrants are motivated by higher wages and better opportunities in foreign countries, and the growth in migration has been accompanied by an increase in the value of international remittances sent back to migrants' home countries (Lucas and Stark (1985), Funkhouser (1995), and Clemens and Tiongson (2017)). According to the World Bank, remittance flows to low- and middle-income countries reached 548 billion USD in 2019, from about 250 million migrant workers (World Bank (2020)). For some individual recipient countries, remittances can be as high as one-third of their GDP (World Bank (2019)).

Sending international remittances can be expensive, unsafe, and difficult for workers. The global average cost of sending 200 US dollars internationally has only fallen from 9% in 2011 to 7% in 2019, which is still a financial burden for migrant workers (World Bank (2019)). Most money is sent through cash couriers, informal methods of transferring money (such as

Hawala), money wiring services (such as Western Union), or banks. For example, according to a 2019 survey of migrant workers living in Korea, 81% of Nepali respondents informally sent money home mainly through individual brokers, known as Hundi, despite the high risk of theft (International Organisation for Migration (2019)). However, the use of FinTech to make international remittances has grown in recent years with the use of mobile apps and mobile money services such as TransferWise and PayPal Xoom.

Until recently, the remittance market in Korea was entirely controlled by large financial institutions—leading to high foreign transfer fees and costly delays. However, regulatory changes in 2017 disrupted the sector, allowing non-bank FinTech corporations to offer consumer remittance services. For our analysis, we use data from Sentbe, a Korean digital money transfer operator born from deregulation, which sent more than 200 million USD in accumulated remittances from Korea over the 2019 calendar year.[2] Sentbe has drastically reduced the cost of remittances to 1.2% of the total remitted amount, while the total remittance costs of sending money through a bank remain at about 8%. Typically, money sent via Sentbe is available for family members to collect within an hour, in contrast to the 2-3 days of delay of conventional bank services.

Our detailed transaction-level international remittance payment data include transaction details for each payment, including date, time, value, exchange rate, and destination country, plus individual-level demographic information on users. Sentbe's target users are foreign workers in Korea and include individuals mostly from nine Southeast Asian countries: Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, the Philippines, Thailand, and Vietnam. A key feature of our data is that we include low-skilled workers who send a significant portion of their earnings back home to support their families. Although these workers are financially unsophisticated, they exert their best effort in making remittance decisions, which have a large impact on their utility and wealth.

Table 1 reports summary statistics of our individual-transaction-level data, by destination

[2]For more information see: https://www.sentbe.com/en/.

country. Our sample has 14,078 individuals with 250,314 transactions from February 2016 to July 2019.[3] The largest share of workers in our sample are from the Philippines with 4,997 users (35%) who account for 143,123 transactions (57%) with an average transaction amount of 487,093 Korean won (KRW), approximately 420 USD. The next largest country represented in our sample is Vietnam, with 3,522 users (25%), followed by workers from Indonesia with 2,793 users (20%).

Workers in our sample send international remittance payments, on average, about 2.5 times a month with 653,271 KRW, approximately 600 USD, per remittance. There are notable patterns between amounts sent and remittance frequency by country: Workers from the Philippines, Indonesia, and Malaysia tend to remit more frequent, smaller denomination payments, while workers from India tend to remit less frequent, larger denomination payments. The average age of our sample individuals is about 31, but it varies from 27 to 33 across countries.

Figure 1 reports the time-series distribution of all transactions. The blue solid bar in Panel A reports the number of remittance transactions by calendar day. The number of transactions on the FinTech platform gradually increases over time.[4] As indicated in this figure, the monthly peak days of transactions, which correspond to the typical salary days, are mostly between the 10th and 18th of the month. These patterns are supported in Panel B, which reports the average number of remittance transactions per day of a given month and shows a peak in transactions during these dates.

Panel C reports the number of remittance transactions by day of the week. Remittance transactions are lowest during the weekends and highest on Monday. Panel D reports the number of remittance transactions within a day. The peak time of day is usually around

[3] We limit our sample to individuals whose nationality is matched to the remitted currency. For example, we do not include Koreans sending money to the countries. The only exception is for Cambodians, since the Cambodian Riel is pegged to the US dollar and Cambodians send US dollars to Cambodia.

[4] Note that there was a 5-month period without any remittance transactions in the middle of our sample period from July 17 to December 7, 2017. The service interruption was for acquiring a license for overseas remittances as required by a government deregulation decision in July 2017. We use the entire sample period from 2016 to 2019 for our main analysis, but using the sample only after July 2017 does not change our main results.

lunch time, but the transactions are, on average, higher after typical working hours. This indicates that the FinTech enables workers to overcome their time and spatial constraints, i.e. traveling to branches during normal business hours.[5] Finally, for the foreign spot exchange rates (foreign currency units per KRW), we use the spot exchange rate that the FinTech firm quoted on its app to its users. Figure 2 plots the spot exchange rates for our sample countries during our sample period.

2.2. Constructing the Optimality Score

FinTech has two major potential benefits for international remittances: reduction in the remittance fee for users and increased flexibility for users, which allow them to optimally time remittance transactions. We find that typical users of the FinTech save 11.5% on remittance transaction costs compared to the customers of traditional banks.[6] However, to compare the optimality in remittance timing across remittance transactions, we need to define an *Optimality Score*.

For each remittance transaction, we use daily exchange rates to compute a set of counterfactual amounts, assuming the transaction occurs on the other days in the window of $[-5, +5]$ days around the actual transaction.[7] We normalize the amount of the original remittance, in the receiving currency, such that at $t = 0$, the amount is equal to 1. The counterfactual amounts indicate whether a remitted payment receives the optimal exchange rate within a 10-day horizon. If the highest value occurs on day 0, this indicates that the user was able to select the day with the best exchange rate to transact within a 10-day window. If the peak occurs prior to day 0, this implies that the user should have sent the transaction earlier, and

[5] The constraint is particularly binding for those who are tied to their jobs during the bank's working hours, i.e., low-skilled workers, or those who need to travel a significant distance to visit a bank branch, i.e., workers employed in sparsely populated areas. If so, they have to pay even higher costs for remittance transactions at special bank branches that exploit the limited number of access points. For the Southeast Asian workers in our sample, there are bank branches for weekend remittances that charge even higher fees than regular bank services.

[6] These results are presented in Appendix A.

[7] We test the robustness of the results to different windows such as $[-5, +2]$ and $[-5, 0]$ and obtain similar results.

a peak following day 0 suggests that the user should have made the transaction a few days later to optimize the exchange rate.[8]

Panel A of Figure 3 shows an example of a remittance transaction by a Vietnamese user on August 28, 2018. The black solid line represents relative exchange rates in the window of $[-5, +5]$ days around the actual transaction to the exchange rate of the actual transaction. The user was able to pick the best day to transact within a 10-day window. To quantify the optimality of the transaction, we measure the area between the reference point, the horizontal line at 1, and the relative exchange rates and define the value as the $\textit{Optimality Score}_{i,t}\ [-5, +5]$. In this example, the $\textit{Optimality Score}_{i,t}\ [-5, +5]$ is 0.0083, indicating that the exchange rate applied to the actual transaction was higher than the exchange rates in the window of $[-5, +5]$ days around the actual transaction by 0.8% on average.

We provide other examples in Panel B of Figure 3. The top-left figure is the same as that in Panel A. The top-right figure reports a remittance transaction by an Indian user on November 16, 2018, with an $\textit{Optimality Score}_{i,t}\ [-5, +5]$ of 0.0028. This means that the exchange rate applied to the actual transaction was higher than the exchange rates in the window of $[-5, +5]$ days around the actual transaction by 0.3% on average. Since the peak occurs prior to day 0, this implies that the user should have sent the transaction earlier to optimize the exchange rate. $\textit{Optimality Score}_{i,t}\ [-5, +5]$ can also be negative. The bottom-left figure reports a remittance transaction by an Indonesian user on June 26, 2018, with an $\textit{Optimality Score}_{i,t}\ [-5, +5]$ of -0.0018, and this indicates that the exchange rate for the actual transaction was lower than the exchange rates in the window of $[-5, +5]$ days around the actual transaction by 0.2% on average. The bottom-right figure reports a remittance transaction by a Vietnamese user on January 22, 2019, with an $\textit{Optimality Score}_{i,t}\ [-5, +5]$ of -0.0068, indicating that the exchange rate for the actual transaction was lower by 0.7% on average than the exchange rates in the window of $[-5, +5]$ days around the actual transaction. Indeed, we find that the transaction was done at the worst time in the 10-day window.

[8] We provide some robustness checks of the measure in Appendix B.

2.3. Usage of the *Cancellation* Feature on the Platform

The FinTech platform we study has a novel feature that allows users to cancel their orders within 24 hours, without any fee. We name this the cancellation feature. Since users are allowed to set multiple orders before choosing an order to be executed, it acts as a free look-back option given to users locked into an exchange rate for up to 24 hours, allowing users to improve the timing of their transactions.

Panel A of Table 2 shows examples of remittance orders and cancellations. For example, an Indonesian user placed a remittance order at 8:42 PM on June 20, 2019, at an exchange rate of 12,216 Indonesian rupiah (IDR) per 1,000 KRW. The user transferred 2,150,000 KRW to the platform at 7:35 PM on June 21, 2019, to receive an exchange rate that was 0.3% higher than the market exchange rate of 12,174 IDR per 1,000 KRW. The same user placed another remittance order at 9:17 PM on June 21, 2019, at an exchange rate of 12,178 IDR per 1,000 KRW but cancelled the order at 3:40 PM on June 22, 2019, as the market exchange rate was 0.2% higher than the exchange rate associated with the submitted order.

Some of our sample users exploit the cancellation feature more systematically to improve their remittance timings. Panel B of Table 2 shows an example of a *Sequential Cancellation*. A Philippine user initially submitted an order at 8:42 AM on January 17, 2017, at an exchange rate of 42.212 Philippine peso (PHP) per 1,000 KRW. As the KRW appreciated thereafter, the user cancelled 11 orders in a row before transferring 1,000,000 to the platform at 6:43 PM on January 18, 2017, at an exchange rate of 42.717 PHP per 1,000 KRW. The user was able to obtain a 1.2% higher exchange rate than the initial order by using *Sequential Cancellation*.

Figure 4 visualize the example. The red horizontal dotted line represents the orders that were later cancelled, and the blue horizontal solid line represents orders that were executed. We observe upward steps for the 11 cancelled orders but a downward step for the transacted order, indicating that the user only exercised the look-back option when the option was in the money. It is also notable that transaction orders and cancellations are mostly made outside of banks' working hours (the blue shaded area represents typical bank working hours in Korea, from 9:00 AM to 3:30 PM).

We report various time-series distributions of remittance transactions that used the cancellation feature in Figure 1. The red dashed bar represents the number of remittance transactions with the cancellation feature by calendar day in Panel A, by the day of the month in Panel B, by the day of the week in Panel C, and by hour in Panel D. The time-series distribution of the cancellation feature resembles the distribution of remittance transactions. Interestingly, cancellation was never intended as a service to be offered to users but was a byproduct of a technical solution: Since the firm is not a depository institution, it has to allow time (24 hours)[9] for users to transfer local currency for remittance transactions to the firm's account. For this reason, the feature was never advertised or explained to users by the FinTech firm. Users only learned about the feature by themselves or through their social networks. This unique feature allows us to investigate information diffusion in a FinTech platform and the subsequent effect of the information diffusion on consumer welfare.

2.4. Social Networks

Social networks have been a key factor in explaining various phenomena, including the effect of learning through social networks (Hirshleifer (2020)) and the effect on migration dynamics through social networks (Munshi (2003), McKenzie and Rapoport (2007)). A key feature of FinTech platforms is the social networks that are associated with the adoption and growth of the services (i.e., personal referrals). As with many FinTechs, Sentbe offers cash incentives for users to recommend the service to their friends: bonus credits that can be used to pay for future remittance payments. We use this referral data to construct social networks among our sample of migrant workers.

We report an example of a social network among Philippine users in our sample. Panel A of Table 3 reports 21 Philippine users with a referrer, registration date, area of residence, and type of occupation. We label users in alphabetical order by the time of registration

[9]It was 24 hours in our sample period but was shortened to 6 hours thereafter.

to the system. We find that they live in a similar residential area and have a similar type of occupation. Figure 5 reports the referral relationships between the 21 users. User A recommends the service to other 16 users (B, C, D, E, F, G, H, J, K, L, M, N, O, P, Q, and R). User C recommends it to user I, user G recommends it to user U, user Q recommends it to user T, and user R recommends it to user S. We define this group of 21 individuals as a social network.

We define referral networks with at least four members as a social network. We find 190 social networks in our sample, and the average number of users in a social network is 7.38 with a standard deviation of 10.33. Among the 14,078 sample users, about 10% are associated with a social network.

2.5. Measures of Learning

To examine the learning effects through social networks, we adopt the concept of reinforcement learning based on the principle of "the law of effect" (Thorndike (1898)), which implies that choices that have led to good outcomes in the past are likely to be repeated in the future. The game theory literature finds that the reinforcement learning model performs better than the forward-looking model or Bayesian updating model in explaining the evolution of individual behaviors (Roth and Erev (1995), Erev and Roth (1998), Charness and Levin (2005)).

Reinforcement learning is also widely used in the household finance literature when studying the role of past individual experience on future behaviors regarding IPO participation (Kaustia and Knüpfer (2008), Chiang et al. (2011), Anagol et al. (2020)); contributions to 401(k) savings plans (Choi et al. (2009)); stock or bond market participation (Malmendier and Nagel (2011), Malmendier and Nagel (2016)); and credit card usage patterns (Agarwal et al. (2008)).

Based on reinforcement learning, we expect that workers with more positive, beneficial experiences from the cancellation feature will use it more in the future. We construct a measure of individual experience with *Sequential Cancellation* at day t as the ratio of the accumulated number of remittance transactions that are associated with *Sequential Cancellation* by user i to the accumulated number of total remittance transactions by day $t-5$ by user i.[10] We define $Individual\ Experience(Cancellation)_{i,t}$ as follows:

$$Individual\ Experience(Cancellation)_{i,t} = \frac{\sum_{\tau<t-5} Remittance\ Transactions_{i,\tau}\ with\ Sequential\ Cancellation}{\sum_{\tau<t-5} Remittance\ Transactions_{i,\tau}}.$$

Similarly, we construct a measure of social experience at day t as the ratio of the accumulated number of remittance transactions that are associated with *Sequential Cancellation* by all other workers $j \neq i$ in worker's i social network to the accumulated number of total remittance transactions by day $t-5$ by all other workers $j \neq i$ in worker i's social network. We define $Social\ Experience(Cancellation)_{i,t}$ as follows:

$$Social\ Experience(Cancellation)_{i,t} = \frac{\sum_{j\neq i,\tau<t-5} Remittance\ Transactions_{i,\tau}\ with\ Sequential\ Cancellation}{\sum_{j\neq i,\tau<t-5} Remittance\ Transactions_{i,\tau}}.$$

2.6. Summary Statistics

Table 4 reports the summary statistics of 250,314 remittance transactions by 14,078 users. The average log sending amount is 12.676, about 653,271 KRW, with a standard deviation of 1.27. $Salary\ Days_t$ is a dummy variable that is equal to 1 for all remittance payments made between the 10th and 18th of each month and 0 otherwise. About 37% of remittance transactions occur during this window of salary days, which may be explained by the fact that workers quickly send a significant portion of their salaries back home to support their families.

[10] Since our main variable of interest is $Optimality\ Score_{i,t}$ $[-5,+5]$, we allow 5 days of lag when we compute the learning measure to minimize the confounding effects through overlapping windows.

Another control variable is $D\_\{\Delta SPOT_{c,t} > 0\}$, a dummy variable for spot rate change. Individuals suffer from the disposition effect (e.g., Odean (1998), Seru et al. (2010)). Therefore, we also expect that our sample individuals would execute more remittances when the KRW has appreciated relative to the foreign currency. To control for this behavioral bias, we define a dummy variable indicating the appreciation of KRW relative to the sending currency. The dummy variable ($D\_\{\Delta SPOT_{c,t} > 0\}$) equals 1 when the change in spot rate of currency c on day t, $\Delta SPOT_{c,t} > 0$, is positive and 0 otherwise. $D\_\{\Delta SPOT_{c,t} > 0\}$ has a mean of 0.42 with a standard deviation of 0.49, indicating that 42% of remittance transactions are followed by the depreciation of KRW relative to users' home currencies.

We report the average optimality score, defined in the previous section, of all remittance transactions. $\textit{Optimality Score}_{i,t}$ $[-5, +5]$ has a mean of 0.02% with a standard deviation of 0.33%. Using all transactions in our dataset, Figure 6 plots the average exchange rates in the window of $[-5, +5]$ days around the actual transactions made by workers. The exchange rates are normalized by the exchange rate applied to the actual transactions. Panel A uses all transactions to find the peak occurring at day 0 with $\textit{Optimality Score}_{i,t}$ $[-5, +5]$ of 0.02%. This means that the workers in our sample were able to pick the highest exchange rate in the window of $[-5, +5]$ days around the actual transaction by 0.02% on average. Compared to the finding that the average return per trade by retail day traders in the foreign exchange market is -0.035% (Ben-David et al. (2018)), this is a surprising result since our sample users are mostly unsophisticated migrant workers.

If we sort users by the average $\textit{Optimality Score}_{i,t}$ $[-5, +5]$, the magnitude increases. Panel B of Figure 6 reports the average optimality score of the top 1/3 users in terms of their average $\textit{Optimality Score}_{i,t}$ $[-5, +5]$. We find that the peak occurs on day 0 with an $\textit{Optimality Score}_{i,t}$ $[-5, +5]$ of 0.39%, which means that the workers were able to pick the highest exchange rate in the window of $[-5, +5]$ days around the actual transaction by 0.39% on average.

In Table 4, we also report summary statistics on the use of the cancellation feature. Among the 250,314 transactions in our sample, about 10% are associated with the usage of *Cancellation*. We find 7,992 transactions that are associated with *Sequential Cancellation*–multiple cancellations of the same executed order–which is about 3% of our sample. That is, Sequential Cancellation accounts for about 30% of *Cancellation*. *Other Cancellation* indicates transactions with *Cancellation* that are not examples of *Sequential Cancellation*.

Regarding measures of learning-by-doing, $Individual\ Experience(Cancellation)_{i,t}$ has a mean of 0.026 with a standard deviation of 0.078. This indicates that an average worker has employed *Sequential Cancellation* in about 3% of his or her past remittance transactions. The number jumps to 13% if we consider the average of users with at least one experience of *Sequential Cancellation*.

$Social\ Experience(Cancellation)_{i,t}$ has a mean of 0.003 with a standard deviation of 0.012, which indicates that the average worker has social experience of *Sequential Cancellation* in about 0.3% of the past remittance transactions by members of his or her social network. The number jumps to 0.9% for workers who are affiliated with any social network.

3. Empirical Results

3.1. Individual Remittance Behavior

We examine how workers decide when to send a remittance payment. First, we use a linear probability model to estimate the conditions that increase the likelihood of a remittance transaction. The dependent variable in Columns (1)-(4) of Table 5 is a dummy variable $D\_\{Remittance_{i,t}\}$, which indicates whether any remittance transaction occurred on day t by user i. We construct a balanced sample, equal to 1 on days that a worker sends a remittance payment, zero otherwise. This increases our sample size to 4,796,763.[11] $D\_\{Remittance_{i,t}\}$ equals 1 if user i conducts any remittance transaction on day t and 0 otherwise. The variable

[11] The sample construction for this regression is somewhat different from the sample for other regressions. While other regressions use transaction-level data, this regression uses individual-day-level data.

has a mean of 0.044, showing that users conduct remittance transactions on about 4.4% of days.

Usage of the cancellation feature implies that users are attentive to market conditions, and should be associated with an increase in the likelihood of remittance transactions. The main independent variables in Column (1) are *Sequential Cancellation* and *Other Cancellation*. We include $Salary\ Days_t$ as a control variable with individual fixed effects and area-country-year-month fixed effects. The fixed effects are used to control for potential differences in individual characteristics, local economic conditions of the users, and receiving currencies. We cluster all standard errors at the area-country and country-year-month level. We find that the likelihood of a remittance transaction increases by 3% when a user uses *Sequential Cancellation* or *Other Cancellation*. Note that the likelihood of a remittance transaction increases on $Salary\ Days_t$.

If individuals are subject to the disposition effect, we would expect more remittance transactions following appreciations of the spot exchange rate. Column (2) uses a dummy variable of $D\_\{\Delta SPOT_{c,t-1} > 0\}$ that equals 1 if $\Delta SPOT_{c,t-1}$ is positive and 0 otherwise. We find that the users in our sample are more likely to transact after the appreciation of the spot exchange rate on the previous day.

In Column (3), we use a $Weekend_t$ dummy as an independent variable. We find that individuals are 1.2% less likely to conduct remittance transactions during weekends. Since the unconditional probability of remittance transaction is about 4.4%, the effect is a roughly 27.3% reduction (-0.012/0.044=-0.273) in the likelihood of remittance transaction. The significant reduction in remittances during weekends demonstrates the severity of the constraints that would have been imposed on users without the FinTech. In Column (4), we include all the independent variables, $Sequential\ Cancellation_{i,t}$, $Other\ Cancellation_{i,t}$, $D\_\{\Delta SPOT_{c,t-1} > 0\}$, and $Weekend_t$, in the regression and find that the effects are similar.

We also examine the conditions that increase the volume of remittance transactions. While the effect on the likelihood of remittance transactions is the effect on the extensive margin, the effect on the amount of remittance transaction is the effect on the intensive margin. In Column (5), the main independent variables are $Sequential\ Cancellation_{i,t}$, and $Other\ Cancellation_{i,t}$. The amount of remittance transaction increases with $Sequential\ Cancellation_{i,t}$ and $Other\ Cancellation_{i,t}$, but the effect is larger with $Sequential\ Cancellation_{i,t}$. In Columns (6) and (7), we also find that the amount of remittance transaction increases with $Salary\ Days_t$, increases with a positive $\Delta SPOT_{c,t-1}$, and decreases with $Weekend_t$.

3.2. Optimal Remittance Transactions

What makes a remittance transaction optimal? In this section, we examine when users can achieve optimal timing for remittance transactions. Table 6 reports the summary statistics of $Optimality\ Score_{i,t}$ $[-5, +5]$ (%) by various user and transaction characteristics. The average optimality score in 250,314 remittance transactions is 0.02%, as we report in Panel A of Figure 6, but with a high standard deviation of 0.33%.

There are some notable patterns in optimality scores. We find that the optimality score decreases with age, which might be related to users' tech-savviness. The score increases with the amount sent, which should proxy for the user's level of attention to the remittance transaction. Female users show higher optimality scores than male users.

We next examine the optimality score by the variables associated with the individual remittance behavior in the previous section. First, the remittance transactions during *Salary Days* show significantly lower optimality scores than those on other days. This indicates that workers have little discretion in timing transactions during the *Salary Days* since most of the workers need to support their families back home.

Second, we find that the average optimality score increases from 0.015% to 0.062% when the users use any cancellation feature in their transactions–but the increase in the optimality score is mostly from transactions with *Sequential Cancellation*. The use of *Sequential Cancellation* significantly increases the average score from 0.015% to 0.162%, while the use of *Other Cancellation* significantly reduces the average score from 0.02 to 0.01. The effect of *Sequential*

Cancellation on optimality scores is visually depicted in Panel C of Figure 6.

Finally, we find that the average optimality score significantly increases from -0.084% to 0.166% when workers make remittance transactions following the appreciation of the KRW during the 24 hours before the remittance order is executed.

3.3. Social Networks and Individual Remittance Behavior

3.3.1. Clustered Remittance Transactions in Social Networks

We first examine whether social networks have a significant effect on a worker's remittance behavior. If so, we expect to observe clustered remittance transactions among workers in social networks. Panel B of Table 3 shows an example of the time stamps of the remittance transactions that occurred within a social network in Panel A on May 10 and 11, 2017. Followed by user C, who submitted a remittance order at 12:10 PM, different users in the social network sequentially submitted remittance orders on the same day and the following day.

Figure 7 compares the daily number of remittances in May 2017 of the users in the social network in Figure 5 to their matched users. For each social network, we construct a hypothetical matched group with the same number of individuals who are individually matched to the individuals in the social network by propensity score matching using matching variables, including nationality, gender, age, registration year, area of residence, occupation type, the number of remittances, the number of *Sequential Cancellations*, the number of *Other Cancellations*, and the average amounts of remittances in that month. The blue dashed bar shows the daily number of remittances in the social network and the orange solid bar shows the daily number of remittances in the matched group.

To quantify the degree of clustering, we compute the HHI of remittance transactions sent within the month. In the example of Figure 7, the HHI of workers in the social network is 0.143, while the HHI of the workers in the matched group is 0.07. When we calculate the average HHI for all social networks in all trading months, the average HHI of social networks is 0.159, while the average HHI of matched groups is 0.140, so the average HHI of social networks is 13.6% higher than the average HHI of the matching groups with a t-statistics of 4.83. In other words, remittance transactions seem to be more clustered among workers in social networks.

3.3.2. Learning in Social Networks

Knowing that workers exhibit herding behavior in making remittance transactions within social networks, we next examine whether they learn from their peers' information that helps them to improve the optimality of their remittance transactions–such as *Sequential Cancellation*–through social networks.

In Table 7, we report the results of learning about *Cancellation* in the social networks. The dependent variable is a dummy variable for *Sequential Cancellation*$_{i,t}$ that equals 1 if worker i uses *Sequential Cancellation* between day $t-5$ and day t and 0 otherwise. In Column (1), the main independent variable is $Individual\ Experience(Cancellation)_{i,t}$, which is the ratio of the accumulated number of remittance transactions that are associated with *Sequential Cancellation* by worker i, to the accumulated number of total remittance transactions sent by day $t-5$ by worker i. We include amounts sent, *Salary Days*$_t$, and $D\_\{\Delta SPOT_{c,t-1} > 0\}$ with area-country-year-month fixed effects.[12] We find that a one-standard-deviation increase in $Individual\ Experience(Cancellation)_{i,t}$ increases *Sequential Cancellation* by 11% of one standard deviation (0.243*0.078/0.176=0.11). That is, a user is more likely to use *Sequential Cancellation* as his or her experience of using *Sequential Cancellation* accumulates.

In Column (2), the main independent variable is $Social\ Experience(Cancellation)_{i,t}$, which is the ratio of the accumulated number of remittance transactions that are associated with *Sequential Cancellation* by all other workers $j \neq i$ in i's social network to the accumulated number of total remittance transactions by day $t-5$ by all other workers $j \neq i$ in i's social net-

[12]We do not include individual fixed effects in this regression since the autoregressive relationship between the dependent and independent variables combined with dynamic panel structure causes inconsistency of estimates (Nickell's bias (Nickell (1981)).

work. We find that a one-standard-deviation increase in $Social\ Experience(Cancellation)_{i,t}$ increases *Sequential Cancellation* by 1.7% of a standard deviation (0.252*0.012/0.176=0.017). When other members of a worker's social network increasingly use *Sequential Cancellation*, the worker also becomes more likely to use *Sequential Cancellation.* Column (3) includes both measures of learning to find a similar result that both individual learning and learning from social networks are at work.

Figure 8 illustrates the learning of *Sequential Cancellation* in the social network illustrated in Figure 5. In the figure, nodes represent workers, and the arrows show referral relationships between workers. When a worker uses *Sequential Cancellation*, the color of the node turns gray. As a worker's experience accumulates and $Individual\ Experience(Cancellation)_{i,t}$ increases, the size of the worker's node grows. Note that the usage of *Sequential Cancellation* gradually spreads across the network over time.

How different will the usage of *Sequential Cancellation* be in different foreign exchange market environments? As an option's value increases with the volatility of its underlying asset, the value of *Sequential Cancellation* would similarly increase with the volatility in foreign exchange rates, and workers would demand the feature more in high-volatility environments. In Appendix Table 3, we extend Table 7 by introducing tercile dummies for foreign exchange rate volatility, measured by the standard deviation of the 10-minute rate of change in the foreign exchange rate from the application time to the payment time. We find that the usage and learning of *Sequential Cancellation* are more likely to occur in a high-volatility environment.

3.3.3. Optimal Remittance Timing through Learning in Social Networks

How does learning impact the optimality of remittance timing? In Table 8, we first report panel regression results on optimality scores. As in Table 6, Column (1) shows that $log(SendAmount_{i,t})$ and $Cancellation_{i,t}$ increase the optimality score while $Salary\ Days_t$ reduces the score when we include individual fixed effects and area-country-year-month fixed effects.

In Column (2), we decompose $Cancellation_{i,t}$ into $Sequential\ Cancellation_{i,t}$ and $Other\ Cancellation_{i,t}$ and find a similar result to that in Table 6. The usage of $Sequential\ Cancellation_{i,t}$ significantly increases $Optimality\ Score_{i,t}$, while the usage of $Other\ Cancellation_{i,t}$ decreases the score. Column (3) additionally includes $D\_\{\Delta SPOT_{c,t} > 0\}$ and reports that $Other\ Cancellation_{i,t}$ loses statistical significance and $D\_\{\Delta SPOT_{c,t} > 0\}$ shows a significant positive effect on the score. This means that the use of cancellation on a day with a depreciating KRW is a counterproductive use of the feature and decreases the optimality score.

The main independent variable in Column (4) is $Individual\ Experience(Cancellation)_{i,t}$. We find that $Individual\ Experience(Cancellation)_{i,t}$ is positively associated with the optimality score despite the statistical insignificance. As a worker's experience with $Sequential\ Cancellation_{i,t}$ accumulates, the worker is more likely to make better remittance transactions. This is similar to the learning-by-trading in Seru et al. (2010).

In Column (5), the main independent variable is the interaction between *Sequential Cancellation* and *Individual Experience(Cancellation)*. We find that the positive effect of $Individual\ Experience(Cancellation)$ on the optimality score mostly comes from the usage of *Sequential Cancellation*. While the usage of *Sequential Cancellation* itself increases the optimality score, a one-standard-deviation increase in $Individual\ Experience(Cancellation)_{i,t}$ further increases $Optimality\ Score_{i,t}$ $[-5, +5]$ (%) by 1.7% of a standard deviation when *Sequential Cancellation* is used (0.073*0.078/0.332=0.017). Workers improve their use of *Sequential Cancellation* as they gain experience using it.

Column (6) uses $Social\ Experience(Cancellation)_{i,t}$ as the main independent variable. We find no significant increase in the optimality score with $Social\ Experience(Cancellation)_{i,t}$ itself. This means that workers do not improve their optimality score simply because their friends in social networks use more *Sequential Cancellation*. Instead, Column (7) shows that the positive effect of $Social\ Experience(Cancellation)_{i,t}$ materializes when workers actually use *Sequential Cancellation* themselves. While the use of *Sequential Cancellation* itself increases the optimality score, a one-standard-deviation increase in $Social\ Experience(Cancellation)_{i,t}$ further increases *Optimality Score*$_{i,t}$ $[-5, +5]$ (%) by 2.3% of a standard deviation when *Sequential Cancellation* is used (0.642*0.012/0.332=0.023). In other words, workers improve their usage of *Sequential Cancellation* as their friends in social networks accumulate more experience with it.

Column (8) uses $Individual\ Experience(Cancellation)_{i,t}$, $Social\ Experience(Cancellation)_{i,t}$, and their interaction terms with $Sequential\ Cancellation_{i,t}$ as the main independent variables. When we jointly include these two different learning channels, we find that the effect of social learning dominates the effect of individual learning.

As discussed above, we expect that the value of *Sequential Cancellation*, which is similar to a look-back option, should be higher in a high-volatility environment. In Appendix Table 4, we extend Table 8 by introducing tercile dummies for foreign exchange rate volatility, measured by the standard deviation of the 10-minute rate of change in the foreign exchange rate from the application time to the payment time. We indeed find that the increase in the optimal score through *Sequential Cancellation* is more significant in a high-volatility environment.

3.3.4. Realized Return from Using *Sequential Cancellation*

In the previous section, we find that the usage of *Sequential Cancellation* improves *Optimality Score*$_{i,t}$ $[-5, +5]$ (%) and that both individual and the social experience further increase the score. While the increase in the optimality score describes the improvement in remittance timing, here we examine the realized return from the usage of *Sequential Cancellation*.

In Table 9, we report summary statistics on the realized return from using *Sequential Cancellation*. We calculate the realized return as the exchange rate charged for the actual remittance divided by the rate for the initial order of the *Sequential Cancellation*. The average realized return from using *Sequential Cancellation* in 7,992 remittance transactions is 0.27%, indicating that using *Sequential Cancellation* enables users to obtain a 0.27% higher rate on average. However, the realized return is highly right-skewed. When we divide the realized return into deciles, the average realized return of the highest decile is around 1%.

Regarding heterogeneity, we also report the average realized return by amount sent, nationality, and foreign exchange rate volatility. We first report the average realized returns by three groups of amounts sent: below the 30th quantile (Below Q30), between the 30th and 70th quantiles (Q30-Q70), and above the 70th quantile (Above Q70). While the average realized return with larger amounts sent shows a higher realized return from the usage of *Sequential Cancellation*, the distribution is wider in the groups with larger amounts sent. For example, in the top decile, the realized return is 0.85% for the lowest group but 1.12% for the highest group.

We then report the average realized return using *Sequential Cancellation* by nationality. Users from Pakistan, Vietnam, India, and Bangladesh seem to show good performance. Notably, Pakistani users exhibit the highest returns, and this is consistent with the fact in Table 6 that they show the highest optimality score. In the highest decile, we find that Pakistani users could earn an average realized return of 3.58%. We also report the average realized return from using *Sequential Cancellation* by foreign exchange rate volatility. Since *Sequential Cancellation* plays a similar role as a look-back option, its value of it should increase with volatility. We indeed find a higher average realized return during periods of higher foreign exchange rate volatility.

These results indicate that the realized return from the usage of *Sequential Cancellation* is highly right-skewed and sizable but varies by individual characteristics and surrounding economic environments.

4. Conclusion

In this paper, we study the role of social networks in helping users optimize their use of a new technology. We use data from one of the leading FinTech firms in Korea, including transaction-level data on international remittances and referral data among workers, which we use to identify social networks among the workers. We also measure how experience using a desirable FinTech feature–an order cancellation option–helps workers optimize their exchange rate. We find that workers' personal experience using the FinTech product, and the experience of the worker's social network increase the frequency and efficiency of workers' use of the feature.

References

Agarwal, S., S. Alok, P. Ghosh, and S. Gupta. 2020. Financial inclusion and alternate credit scoring for the millennials: Role of big data and machine learning in FinTech. Working paper, National University of Singapore.

Agarwal, S., J. C. Driscoll, X. Gabaix, and D. Laibson. 2008. Learning in the credit card market. Working paper, National Bureau of Economic Research.

Ammann, M., and N. Schaub. 2020. Do Individual Investors Trade on Investment-related Internet Postings? *Management Science* .

Anagol, S., V. Balasubramaniam, and T. Ramadorai. 2020. Learning from noise: Evidence from India's IPO lotteries. *Journal of Financial Economics, Forthcoming* .

Bailey, M., R. Cao, T. Kuchler, and J. Stroebel. 2018. The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy* 126:2224–2276.

Barber, B. M., and T. Odean. 2002. Online investors: Do the slow die first? *Review of Financial Studies* 15:455–488.

Ben-David, I., J. Birru, and V. Prokopenya. 2018. Uninformative feedback and risk taking: Evidence from retail forex trading. *Review of Finance* 22:2009–2036.

Berg, T., V. Burg, A. Gombović, and M. Puri. 2020. On the rise of FinTechs: Credit scoring using digital footprints. *Review of Financial Studies* 33:2845–2897.

Bertrand, M., E. F. Luttmer, and S. Mullainathan. 2000. Network effects and welfare cultures. *Quarterly Journal of Economics* 115:1019–1055.

Chang, Y., J. F. Gomes, and F. Schorfheide. 2002. Learning-by-doing as a propagation mechanism. *American Economic Review* 92:1498–1520.

Charness, G., and D. Levin. 2005. When optimal choices feel wrong: A laboratory study of Bayesian updating, complexity, and affect. *American Economic Review* 95:1300–1309.

Chen, H., P. De, Y. J. Hu, and B.-H. Hwang. 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27:1367–1403.

Chen, M. A., Q. Wu, and B. Yang. 2019. How valuable is FinTech innovation? *Review of Financial Studies* 32:2062–2106.

Chiang, Y.-M., D. Hirshleifer, Y. Qian, and A. E. Sherman. 2011. Do investors learn from experience? Evidence from frequent IPO investors. *Review of Financial Studies* 24:1560–1589.

Choi, J. J., D. Laibson, B. C. Madrian, and A. Metrick. 2009. Reinforcement learning and savings behavior. *Journal of Finance* 64:2515–2534.

Choi, J. J., D. Laibson, and A. Metrick. 2002. How does the internet affect trading? Evidence from investor behavior in 401 (k) plans. *Journal of Financial Economics* 64:397–421.

Clemens, M. A., and E. R. Tiongson. 2017. Split decisions: Household finance when a policy discontinuity allocates overseas work. *Review of Economics and Statistics* 99:531 – 543.

Cookson, J. A., and M. Niessner. 2020. Why don't we agree? Evidence from a social network of investors. *Journal of Finance* 75:173–228.

D'Acunto, F., A. G. Rossi, and M. Weber. 2020. Crowdsourcing peer information to change spending behavior. *Chicago Booth Research Paper* .

De Giorgi, G., A. Frederiksen, and L. Pistaferri. 2020. Consumption network effects. *Review of Economic Studies* 87:130–163.

Duflo, E., and E. Saez. 2003. The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *Quarterly Journal of Economics* 118:815–842.

D'Acunto, F., N. Prabhala, and A. G. Rossi. 2019. The promises and pitfalls of robo-advising. *Review of Financial Studies* 32:1983–2020.

Erev, I., and A. E. Roth. 1998. Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria. *American Economic Review* 88:848–881.

Funkhouser, E. 1995. Remittances from international migration: A comparison of El Salvador and Nicaragua. *Review of Economics and Statistics* 77:137–146.

Heimer, R. Z. 2016. Peer pressure: Social interaction and the disposition effect. *Review of Financial Studies* 29:3177–3209.

Hirshleifer, D. 2020. Presidential address: Social transmission bias in economics and finance. *Journal of Finance* .

Hong, H., J. D. Kubik, and J. C. Stein. 2004. Social interaction and stock-market participation. *Journal of Finance* 59:137–163.

International Organisation for Migration. 2019. Migration in Nepal: A country profile 2019. International Organisation for Migration (IOM) Geneva, Switzerland.

Jagtiani, J., and C. Lemieux. 2018. Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business* 100:43–54.

Kalda, A. 2020. Peer financial distress and individual leverage. *Review of Financial Studies* 33:3348–3390.

Kalda, A., B. Loos, A. Previtero, and A. Hackethal. 2021. Smart(phone) investing? A within investor-time analysis of new technologies and trading behavior. Working paper, National Bureau of Economic Research.

Kaustia, M., and S. Knüpfer. 2008. Do investors overweight personal experience? Evidence from IPO subscriptions. *Journal of Finance* 63:2679–2702.

Liskovich, I., and M. Shaton. 2018. Selection into informative consumer credit markets. Working paper.

Loos, B., A. Previtero, S. Scheurle, and A. Hackethal. 2020. Robo-advisers and investor behavior. *University of Technology of Sydney Working Paper* .

Lucas, R. E. B., and O. Stark. 1985. Motivations to remit: Evidence from Botswana. *Journal of Political Economy* 93:901–918.

Malmendier, U., and S. Nagel. 2011. Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126:373–416.

Malmendier, U., and S. Nagel. 2016. Learning from inflation experiences. *Quarterly Journal of Economics* 131:53–87.

McKenzie, D., and H. Rapoport. 2007. Network effects and the dynamics of migration and inequality: Theory and evidence from Mexico. *Journal of Development Economics* 84:1–24.

Munshi, K. 2003. Networks in the modern economy: Mexican migrants in the US labor market. *Quarterly Journal of Economics* 118:549–599.

Nickell, S. 1981. Biases in dynamic models with fixed effects. *Econometrica* 49:1417–1426.

Odean, T. 1998. Are investors reluctant to realize their losses? *Journal of Finance* 53:1775–1798.

Ouimet, P., and G. Tate. 2020. Learning from coworkers: Peer effects on individual investment decisions. *Journal of Finance* 75:133–172.

Roth, A. E., and I. Erev. 1995. Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. *Games and Economic Behavior* 8:164–212.

Seru, A., T. Shumway, and N. Stoffman. 2010. Learning by trading. *Review of Financial Studies* 23:705–739.

Thorndike, E. L. 1898. Animal intelligence. *Nature* 58:390–390.

United Nations. 2019. International migrant stock 2019. United Nations Department of Economic and Social Affairs, Population Division New York.

World Bank. 2019. Migration and remittances: Recent developments and outlook. Migration and development brief 31, World Bank, Washington, DC.

World Bank. 2020. COVID-19 crisis through a migration lens. Migration and development brief 32, World Bank, Washington, DC.

Table 1: Individual Remittance Transactions by Nationality

We report the summary statistics of individual remittance transactions by users' nationality. Our sample includes individual transactions from February 2016 to July 2019 for the remittances to nine Southeast Asian Countries including Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, the Philippines, Thailand, and Vietnam. We report the number of sample users, their number of remittance transactions, average amount sent per transaction in Korean won (KRW), and the average number of remittance transactions per month. We also report average age by user nationality.

		Number of Total		Amount Sent (KRW)		# of Remittances	
Country	Data Starts	Customers	Remittances	Mean	Median	per Month	Age
Bangladesh	Jul-18	237	1,299	947,817	500,000	1.83	31
Cambodia	Jul-18	349	3,833	674,937	426,560	2.87	28
India	Aug-18	857	6,114	1,425,213	1,115,310	1.79	33
Indonesia	Oct-16	2,793	44,797	666,386	275,000	2.47	30
Malaysia	Jul-18	88	1,152	797,056	502,500	2.86	27
Pakistan	Jul-18	601	4,811	948,653	652,360	2.07	32
Philippines	Feb-16	4,997	143,123	487,093	248,860	2.78	32
Thailand	Apr-18	634	7,922	1,157,152	850,000	2.48	32
Vietnam	Jun-16	3,522	37,263	986,912	520,000	1.93	28
Total	Feb-16	14,078	250,314	653,271	317,410	2.50	31

Table 2: Examples of Remittance, Cancellation and Sequential Cancellation

We report examples of remittance, cancellation, and sequential cancellation. Action Type is either Remittance or Cancellation. Application Time (t_1) is the time of application of each transaction order. Action Time (t_2) is the time of action. If an order is paid, then it is denoted as Remittance, and if it is cancelled, then it is denoted as Cancellation. $SPOT_{t_1}$ ($SPOT_{t_2}$) is the spot rate to 1,000 KRW at time t_1 (t_2). Sent Amount (KRW) is the amount of Korean won at the Application Time (t_1). Panel A reports examples of remittances and cancellations of an Indonesian user. Panel B reports an example of sequential cancellations of a Philippine user.

Panel A: Examples of Remittances and Cancellations by an Indonesian User

Action Type	Application Time (t_1)	Action Time (t_2)	$SPOT_{t_1}$		$SPOT_{t_2}$	Amount (KRW)
Remittance	2019-06-20 8:42:53 PM	2019-06-21 7:35:47 PM	12,216	$>$	12,174	2,150,000
Cancellation	2019-06-21 9:17:15 PM	2019-06-22 3:40:59 PM	12,178	$<$	12,199	2,005,000

Panel B: An Example of Sequential Cancellation by a Philippine User

Action Type	Application Time (t_1)	Action Time (t_2)	$SPOT_{t_1}$		$SPOT_{t_2}$	Amount (KRW)
Cancellations	2017-01-17 8:42:35 AM	2017-01-17 2:36:21 PM	42.212	$<$	42.391	1,000,000
	2017-01-17 2:37:02 PM	2017-01-17 3:14:47 PM	42.391	$<$	42.445	1,000,000
	2017-01-17 3:15:09 PM	2017-01-17 3:46:56 PM	42.445	$<$	42.481	1,000,000
	2017-01-17 3:47:26 PM	2017-01-17 4:52:57 PM	42.481	$<$	42.499	1,000,000
	2017-01-17 4:53:24 PM	2017-01-17 5:14:28 PM	42.499	$<$	42.535	1,000,000
	2017-01-17 5:14:53 PM	2017-01-17 5:23:49 PM	42.535	$<$	42.553	1,000,000
	2017-01-17 5:23:32 PM	2017-01-17 8:04:32 PM	42.553	$<$	42.589	1,000,000
	2017-01-17 8:04:10 PM	2017-01-17 9:41:35 PM	42.589	$<$	42.626	1,000,000
	2017-01-17 9:41:27 PM	2017-01-18 5:12:45 PM	42.626	$<$	42.662	1,000,000
	2017-01-18 5:12:32 PM	2017-01-18 5:31:54 PM	42.662	$<$	42.699	1,000,000
	2017-01-18 5:31:24 PM	2017-01-18 6:44:07 PM	42.699	$<$	42.717	1,000,000
Remittance	2017-01-18 6:43:57 PM	2017-01-19 6:43:57 PM	42.717	$>$	42.499	1,000,000

Table 3: An Example of a Social Network

We report a real example of a social network among Philippine users with the list of users and the clustering behavior in users' remittances within the network. Panel A reports the list of users in the network. We label the users by the order of their registration date. We report the referrer, registration date, area of residence, and occupation type of each user. Panel B reports an example of the clustered remittance transactions by the users in the network on May 10 and 11, 2017.

Panel A: List of Users in a Social Network

User	Referrer	Registration Date	Area of Residence	Occupation Type
A		2016-03-21	Daegu	Factory Worker
B	A	2016-04-07	Gumi-si, Gyeongsangbuk-do	Factory Worker
C	A	2016-04-19	Daegu	Factory Worker
D	A	2016-04-20	Busan	Factory Worker
E	A	2016-04-21	Hwaseong-si, Gyeonggi-do	Factory Worker
F	A	2016-04-25	Busan	Wage Worker
G	A	2016-04-26	Daejeon	Housewife
H	A	2016-05-09	Ulsan	
I	C	2016-07-08	Gimpo-si, Gyeonggi-do	Factory Worker
J	A	2016-07-13	Gimhae-si, Gyeongsangnam-do	Factory Worker
K	A	2016-07-13	Asan-si, Chungcheongnam-do	Factory Worker
L	A	2016-08-01	Busan	Factory Worker
M	A	2016-08-02	Yangju-si, Gyeonggi-do	Factory Worker
N	A	2016-08-03	Paju-si, Gyeonggi-do	Factory Worker
O	A	2016-08-07	Nonsan-si, Chungcheongnam-do	Factory Worker
P	A	2016-08-10	Gimpo-si, Gyeonggi-do	Factory Worker
Q	A	2016-08-11	Gimpo-si, Gyeonggi-do	Factory Worker
R	A	2016-09-10	Siheung-si, Gyeonggi-do	Factory Worker
S	R	2017-06-30	Siheung-si, Gyeonggi-do	Factory Worker
T	Q	2017-12-04	Daegu	Factory Worker
U	G	2018-03-02	Bucheon-si, Gyeonggi-do	Wage Worker

Panel B: Clustered Remittance Transactions, Example of May 10th and 11th in 2017

User	Referrer	Remittance Time	Area of Residence	Occupation Type
C	A	2017-05-10 12:10:28 PM	Daegu	Factory Worker
L	A	2017-05-10 3:04:50 PM	Busan	Factory Worker
A		2017-05-10 4:13:10 PM	Daegu	Factory Worker
L	A	2017-05-10 6:14:23 PM	Busan	Factory Worker
D	A	2017-05-10 6:45:18 PM	Busan	Factory Worker
M	A	2017-05-11 8:05:00 AM	Yangju-si, Gyeonggi-do	Factory Worker
E	A	2017-05-11 10:30:22 AM	Hwaseong-si, Gyeonggi-do	Factory Worker
A		2017-05-11 12:19:35 PM	Daegu	Factory Worker

Table 4: Summary Statistics of Individual Remittance Transactions

We report the summary statistics of individual remittance transactions. $\log(SendAmount_{i,t})$ is the log of the amount sent (KRW) of an individual i on day t. $D\_\{\Delta SPOT_{c,t} > 0\}$ is a dummy variable that equals 1 if $\Delta SPOT_{c,t} > 0$ and 0 otherwise, where $\Delta SPOT_{c,t}$ is the lagged daily change in the spot rate of currency c from $t-1$ to t. $Cancellation_{i,t}$ is a dummy variable that equals 1 if an individual i has at least one usage of *Cancellation* of a remittance from $t-5$ to t and 0 otherwise. $Sequential\ Cancellation_{i,t}$ is a dummy variable that equals 1 if an individual i uses a *Sequential Cancellation* for a remittance from $t-5$ to t and 0 otherwise. $Other\ Cancellation_{i,t}$ is any *Cancellation* that is not a *Sequential Cancellation*. $Salary\ Days_t$ is a dummy variable that equals 1 for days between the 10th and 18th of each month and 0 otherwise. $Optimality\ Score_{i,t}$ $[-5,+5]$ (%) is the average percentage difference between the actual spot rate charged on a remittance on day t and the spot rates in the 10-day window of $[-5,+5]$. $Individual\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* among remittances until $t-5$. $Social\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* by social network members among their remittances until $t-5$. All the continuous variables are winsorized at the 1% and 99% levels.

Variable	Observations	Mean	Std.Dev.	5th Perc.	95th Perc.
$\log(SendAmount_{i,t})$	250,314	12.676	1.272	10.650	14.732
$Salary\ Days_t$	250,314	0.377	0.485	0	1
$D\_\{\Delta SPOT_{c,t} > 0\}$	250,314	0.415	0.493	0	1
Optimality Score					
$Optimality\ Score_{i,t}$ $[-5,+5]$ (%)	250,314	0.020	0.332	-0.508	0.596
Cancellation					
$Cancellation_{i,t}$	250,314	0.094	0.291	0	1
$Sequential\ Cancellation_{i,t}$	250,314	0.032	0.176	0	0
$Other\ Cancellation_{i,t}$	250,314	0.062	0.241	0	1
Measure of Experience					
$Individual\ Experience(Cancellation)_{i,t}$	250,314	0.026	0.078	0	0.167
$Social\ Experience(Cancellation)_{i,t}$	250,314	0.003	0.012	0	0.018

Table 5: The Behavior of Remittance Transactions

We report the panel regression results of the determinants of individual remittance decisions. In Columns (1)-(4), dependent variable is the dummy variable $D\_\{Remittance_{i,t}\}$ that equals 1 if individual i remits currency c on day t and 0 otherwise. Column (1) reports the resultsm when using $Sequential\ Cancellation_{i,t}$ and *Other Cancellation* as the main independent variable. $Sequential\ Cancellation_{i,t}$ is a dummy variable that equals 1 if individual i uses *Sequential Cancellation* within 5 days of a remittance transaction on day t. $Other\ Cancellation_{i,t}$ is any *Cancellation* that is not a *Sequential Cancellation*. We include $Salary\ Days_t$ as a control variable with individual fixed effects and area-country-year-month fixed effects. Column (2) reports the results when using a dummy variable $D\_\{\Delta SPOT_{c,t-1} > 0\}$ that equals 1 if $\Delta SPOT_{c,t-1}$ is positive and 0 otherwise, where $\Delta SPOT_{c,t-1}$ is the lagged change in the spot exchange rate of currency c from $t-2$ to $t-1$. Column (3) reports the result using a dummy variable $Weekend_t$ that equals 1 if day t is weekend date and 0 otherwise. Column (4) reports the results when including $Sequential\ Cancellation_{i,t}$, $Other\ Cancellation_{i,t}$, $Weekend_t$, and $Salary\ Days_t$ as the main independent variables. In Columns (5)-(8), we use $\log(SendAmount_{i,t})$ as the dependent variable. The table reports point estimates with t-statistics in parentheses. All standard errors are clustered at the area-country and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$D\_\{Remittance_{i,t}\}$				$\log(SendAmount_{i,t})$			
$Sequential\ Cancellation_{i,t}$	0.031***			0.032***	0.241***			0.220***
	(7.60)			(7.75)	(14.55)			(13.71)
$Other\ Cancellation_{i,t}$	0.030***			0.030***	0.127***			0.134***
	(9.05)			(9.01)	(12.73)			(13.35)
$D\_\{\Delta SPOT_{c,t-1} > 0\}$		0.003***		0.002***		0.070***		0.042***
		(3.74)		(3.24)		(8.30)		(5.23)
$Weekend_t$			-0.012***	-0.012***			-0.141***	-0.128***
			(-8.79)	(-8.79)			(-16.41)	(-15.19)
$Salary\ Days_t$	0.015***	0.015***	0.015***	0.015***	0.173***	0.174***	0.171***	0.171***
	(9.22)	(9.26)	(9.34)	(9.41)	(12.57)	(12.78)	(12.86)	(13.08)
Observations	4,796,763	4,796,763	4,796,763	4,796,763	250,314	250,314	250,314	250,314
Adjusted R^2	0.030	0.030	0.031	0.031	0.314	0.314	0.315	0.316
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area-Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Summary Statistics of Optimality Scores

We report the descriptive statistics of the optimality score, *Optimality Score*$_{i,t}$ $[-5,+5]$ (%), by different characteristics of individual users. We first report the average optimality score by age, amount sent, and gender. We divide the sample by age into three groups: Below 30, 30s, and Above 30s. We divide the sample by amount sent into three groups of below the 30th quantile (Below Q30), between the 30th and 70th quantile (Q30-Q70), and above the 70th quantile (Above Q70). We also report the average optimality score by the determinants of remittance decisions such as *SalaryDays*, the usage of *Cancellation*, the usage of *Sequential Cancellation*, the usage of *Others Cancellation*, and the sign of $\Delta SPOT_{c,t}$.

	Number of		Average Optimality Score (%)				Difference in Mean
Group	Users	Remittances	Mean	Std. Dev.	5th Perc.	95th Perc.	(t-statistics)
Total	14,078	250,314	0.020	0.332	-0.508	0.596	
Age							
Below 30s	7,075	111,473	0.020	0.332	-0.508	0.598	-
30s	6,790	117,362	0.020	0.334	-0.508	0.599	(-0.24)
Above 30s	1,169	21,479	0.017	0.325	-0.495	0.572	(-0.83)
Amount Sent							
Below Q30	9,721	75,093	0.006	0.325	-0.509	0.561	-
Q30-Q70	11,861	99,723	0.010	0.330	-0.512	0.579	(1.38)
Above Q70	11,756	75,498	0.047	0.342	-0.497	0.646	(7.50)
Gender							
Female	3,507	75,068	0.026	0.330	-0.494	0.599	-
Male	10,571	175,246	0.017	0.334	-0.512	0.595	(-2.09)
Salary Days							
No	13,698	156,022	0.047	0.329	-0.478	0.619	-
Yes	12,093	94,292	-0.025	0.334	-0.549	0.557	(-3.31)
Usage of *Cancellation*							
No	13,991	226,856	0.015	0.330	-0.509	0.584	-
Yes	6,314	23,458	0.062	0.350	-0.486	0.690	(8.75)
Usage of *Sequential Cancellation*							
No	14,055	242,322	0.015	0.331	-0.510	0.584	-
Yes	2,828	7,992	0.162	0.354	-0.395	0.824	(13.11)
Usage of *Other Cancellation*							
No	14,039	234,848	0.020	0.332	-0.507	0.596	-
Yes	5,180	15,466	0.010	0.337	-0.524	0.598	(-2.34)
$\Delta SPOT_{c,t}$							
≤ 0	13,617	146,449	-0.084	0.303	-0.575	0.423	-
> 0	13,119	103,865	0.166	0.317	-0.327	0.752	(19.88)

Table 7: Learning About *Sequential Cancellation*

We report the panel regression results of the usage experience of transactions with *Sequential Cancellation* on individuals' usage of *Sequential Cancellation*. All regression results include area-country-year-month fixed effects. The dependent variable is a dummy variable $Sequential\ Cancellation_{i,t}$ that equals 1 if an individual uses *Sequential Cancellation* for a remittance at t. Column (1) reports the results when using $Individual\ Experience(Cancellation)_{i,t}$ as the main independent variable. $Individual\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* among remittances until $t-5$. Column (2) reports the results when using $Social\ Experience(Cancellation)_{i,t}$ as the main independent variable. $Social\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* by social network members among their remittances until $t-5$. Individual controls are age and an indicator for gender. The table reports point estimates with t-statistics in parentheses. All standard errors in the panel regressions are clustered at the area-country and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)
Variables	$Sequential\ Cancellation_{i,t}$		
$Individual\ Experience(Cancellation)_{i,t}$	0.243***		0.242***
	(9.83)		(9.95)
$Social\ Experience(Cancellation)_{i,t}$		0.252**	0.200*
		(2.01)	(1.94)
$\log(SendAmount_{i,t})$	0.006***	0.006***	0.006***
	(11.32)	(10.74)	(11.28)
$Salary\ Days_t$	-0.001	-0.001	-0.001
	(-0.81)	(-0.84)	(-0.81)
$D\_\{\Delta SPOT_{c,t} > 0\}$	0.029***	0.029***	0.029***
	(19.45)	(19.24)	(19.49)
Observations	250,314	250,314	250,314
Adjusted R^2	0.082	0.072	0.083
Individual FE	No	No	No
Individual Controls	Yes	Yes	Yes
Area-Country-Year-Month FE	Yes	Yes	Yes

Table 8: Learning of ***Sequential Cancellation*** and Optimal Remittance Timing

We report the panel regression results on learning of *Sequential Cancellation* and the optimal remittance timing. The main dependent variable is $Optimality\ Score_{i,t}$ $[-5,+5]$ (%). Individual fixed effects and area-country-year-month fixed effects are included in all the results. Column (1) reports the results when using $\log(SendAmount_{i,t})$, $Salary\ Days_t$, and $Cancellation_{i,t}$ as the main independent variables. Column (2) reports the results with $Seqeuntial\ Cancellation_{i,t}$ and $Other\ Cancellation_{i,t}$ replacing $Cancellation_{i,t}$. Column (3) reports the results when additionally including $D\_\{\Delta SPOT_{c,t} > 0\}$. Column (4) and (5) reports the results when using $Individual\ Experience(Cancellation)_{i,t}$ and its interaction with $Seqeuntial\ Cancellation_{i,t}$. $Individual\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* among remittances until $t-5$ at the individual level. Columns (6) and (7) report the results when using $Social\ Experience(Cancellation)_{i,t}$ and its interaction with $Seqeuntial\ Cancellation_{i,t}$. $Social\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* among remittances until $t-5$ at the social-network level. Column (8) reports the results when including both $Individual\ Experience(Cancellation)_{i,t}$ and $Social\ Experience(Cancellation)_{i,t}$ and their interactions with $Seqeuntial\ Cancellation_{i,t}$. The table reports point estimates with t-statistics in parentheses. All standard errors in the panel regressions are clustered at the area-country and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	$Optimality\ Score_{i,t}$ $[-5,+5]$ (%)							
$\log(SendAmount_{i,t})$	0.009***	0.009***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(7.45)	(7.28)	(4.97)	(4.97)	(4.97)	(4.97)	(4.97)	(4.97)
$Salary\ Days_t$	-0.067***	-0.067***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***	-0.066***
	(-3.14)	(-3.15)	(-3.13)	(-3.13)	(-3.13)	(-3.13)	(-3.13)	(-3.13)
$Cancellation_{i,t}$	0.031***							
	(6.83)							
$Sequential\ Cancellation_{i,t}$		0.122***	0.066***	0.068***	0.062***	0.066***	0.064***	0.061***
		(12.86)	(8.37)	(8.61)	(7.45)	(8.36)	(8.12)	(7.35)
$Other\ Cancellation_{i,t}$		-0.011***	0.002	0.002	0.002	0.002	0.002	0.002
		(-2.64)	(0.47)	(0.47)	(0.52)	(0.47)	(0.47)	(0.52)
$D\_\{\Delta SPOT_{c,t} > 0\}$			0.249***	0.249***	0.249***	0.249***	0.249***	0.249***
			(20.64)	(20.64)	(20.64)	(20.64)	(20.64)	(20.64)
$Individual\ Experience(Cancellation)_{i,t}$				0.026	0.015			0.015
				(1.63)	(0.88)			(0.87)
$\times\ Sequential\ Cancellation_{i,t}$					0.073*			0.068
					(1.69)			(1.56)
$Social\ Experience(Cancellation)_{i,t}$						0.076	0.042	0.042
						(0.45)	(0.24)	(0.24)
$\times\ Sequential\ Cancellation_{i,t}$							0.642**	0.578*
							(2.01)	(1.87)
Observations	250,314	250,314	250,314	250,314	250,314	250,314	250,314	250,314
Adjusted R^2	0.067	0.070	0.198	0.198	0.198	0.198	0.198	0.198
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area-Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Summary Statistics of the Realized Return from Using *Sequential Cancellation*

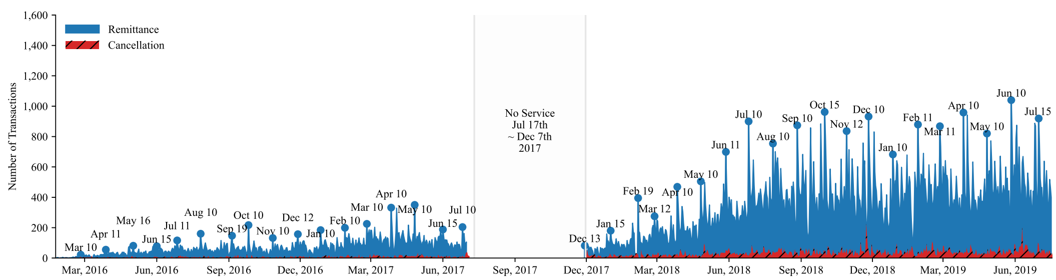
We report the descriptive statistics of the realized return from using *Sequential Cancellation* by different characteristics of individual users. The realized return from using *Sequential Cancellation* is the exchange rate charged for the actual remittance divided by the rate for the initial order of the *Sequential Cancellation*. The average realized return from using *Sequential Cancellation* is reported in percentage (%). We first report the average realized return from using *Sequential Cancellation* by amount sent and nationality. We divide the sample by amount sent into three bins: below the 30th quantile (Below Q30), between the 30th and 70th quantiles (Q30-Q70), and above the 70th quantile (Above Q70). We also report the average realized return from using *Sequential Cancellation* by the foreign exchange rate volatility that is the standard deviation of the 10-minute rate of change in foreign exchange rates during the periods between the application and payment of the actual remittance. We divide the sample by volatility into three groups of below the 30th quantile (Below Q30), between the 30th and 70th quantiles (Q30-Q70), and above the 70th quantile (Above Q70).

	Number of		Summary Statistics		Decile Average of the Realized Return (%)									
Group	Users	Remittances	Mean (%)	Std. Dev. (%)	1	2	3	4	5	6	7	8	9	10
Total	2,828	7,992	0.268	0.326	0.015	0.042	0.072	0.115	0.165	0.206	0.261	0.360	0.485	0.966
Amount Sent														
Below Q30	1,168	2,398	0.234	0.290	0.013	0.037	0.052	0.088	0.131	0.186	0.233	0.312	0.442	0.853
Q30-Q70	1,590	3,196	0.264	0.298	0.014	0.040	0.068	0.110	0.160	0.204	0.262	0.365	0.492	0.926
Above Q70	1,338	2,398	0.309	0.387	0.019	0.058	0.108	0.153	0.198	0.222	0.298	0.391	0.524	1.123
Nationality														
Bangladesh	19	28	0.261	0.305	0.014	0.035	0.053	0.119	0.144	0.234	0.327	0.389	0.394	0.930
Cambodia	32	69	0.227	0.180	0.030	0.043	0.081	0.138	0.201	0.228	0.283	0.372	0.682	
India	184	432	0.268	0.300	0.013	0.039	0.062	0.097	0.152	0.226	0.292	0.366	0.477	0.947
Indonesia	428	904	0.197	0.206	0.010	0.026	0.047	0.081	0.122	0.143	0.198	0.265	0.390	0.688
Malaysia	26	84	0.165	0.163	0.007	0.015	0.024	0.067	0.119	0.152	0.215	0.263	0.327	0.486
Pakistan	105	255	0.837	1.050	0.052	0.121	0.196	0.269	0.365	0.449	0.683	1.071	1.619	3.576
Philippines	1,388	4,691	0.240	0.254	0.013	0.040	0.058	0.094	0.138	0.188	0.251	0.334	0.454	0.834
Thailand	154	559	0.186	0.180	0.016	0.039	0.066	0.094	0.128	0.157	0.183	0.247	0.331	0.611
Vietnam	492	970	0.384	0.244	0.196	0.206	0.207	0.208	0.210	0.361	0.417	0.504	0.627	0.952
Foreign Exchange Rate Volatility														
Low	1,141	2,114	0.238	0.283	0.012	0.037	0.059	0.102	0.145	0.197	0.237	0.317	0.437	0.841
Middle	1,429	2,697	0.238	0.278	0.011	0.034	0.055	0.096	0.144	0.195	0.236	0.328	0.443	0.840
High	1,656	3,181	0.315	0.381	0.024	0.055	0.097	0.143	0.194	0.227	0.308	0.405	0.557	1.145

Figure 1: Time-series of Individual Remittance Transactions and Cancellations

We plot various time-series distributions of individual remittances and cancellations. Panel A plots the daily number of remittances and cancellations in our sample period. The circle markers indicate the days with the monthly peak of remittance transactions. The FinTech service was not available from July 17 to December 7, 2017. Panel B plots the number of remittances and cancellations on each day of a month. Panel C plots the number of remittances and cancellations on each day of a week. Panel D plots the number of remittances and cancellations in each 10 minutes of a day. The shaded interval indicates the banks' operating hours and the marker indicates 12:20 PM when the maximum number of remittances in a day occurs.

Panel A: Number of Daily Remittances and Daily Cancellations in Our Sample Period



Panel B: Distribution of the Number of Remittances and Cancellations within a Month

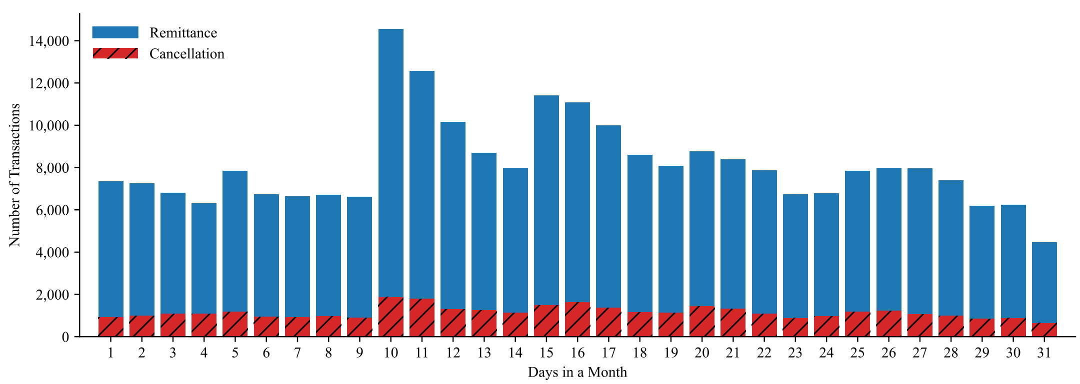
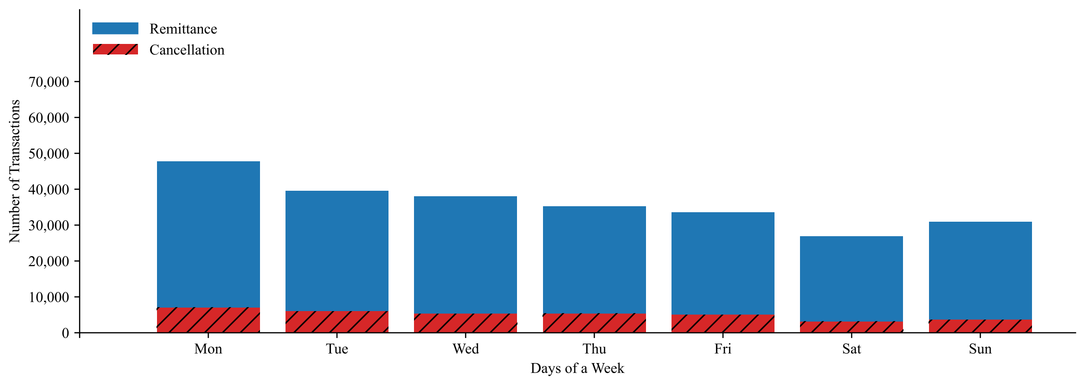


Figure 1 Continues

Panel C: Distribution of the Number of Remittances and Cancellations within a Week



Panel D: Distribution of the Number of Remittances and Cancellations within a Day

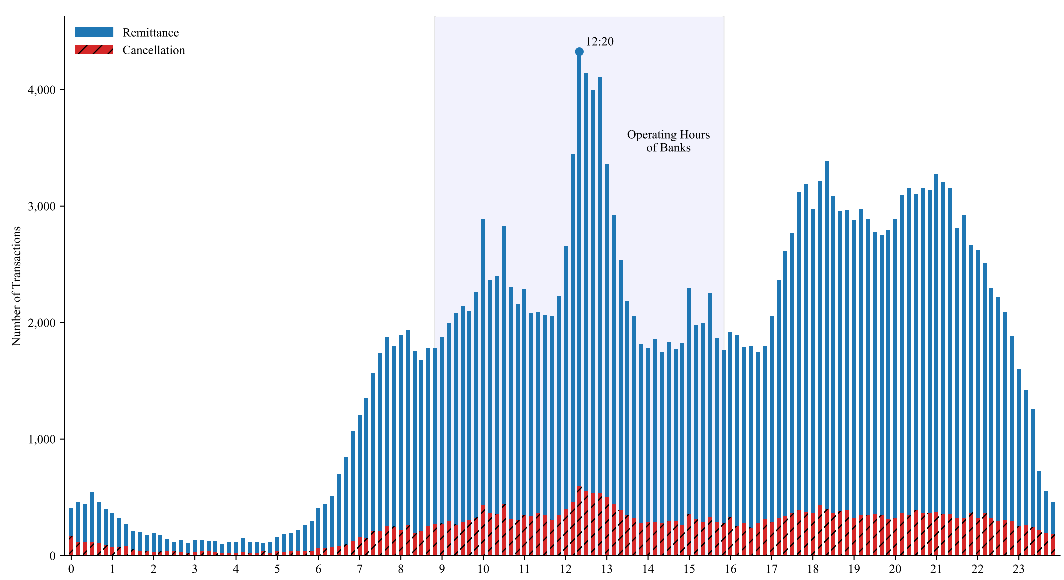


Figure 2: Spot Exchange Rates

We plot the spot exchange rates of the currencies for nine Southeast Asian countries in our sample. The sample period is from February 2016 to July 2019. Countries may have different starting dates due to the different starts of the FinTech service for each country.

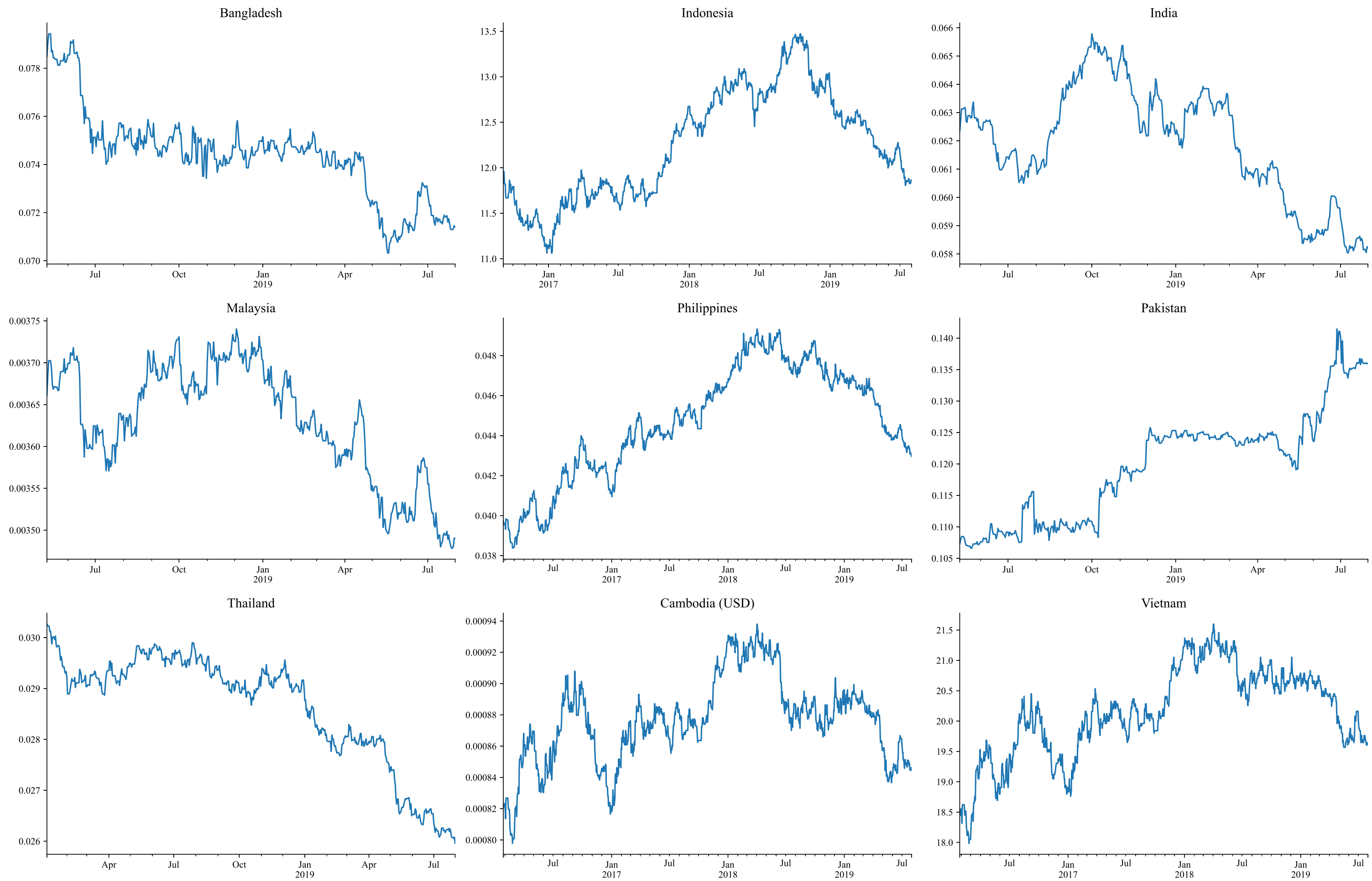


Figure 3: Examples of Calculating Optimality Score

We report some examples of calculating optimality scores using real examples in the data. In Panel A, we plot the spot exchange rate in the window of $[-5, +5]$ days relative to the spot exchange rate on day 0 using an example of a Vietnamese user on August 28, 2018. The difference in the average relative rate from 1, which is 0.0083 in this case, is defined as the optimality measure. Panel B reports other examples of optimality scores. The top-left figure reports the same example as in Panel A.

Panel A: Example for the Definition of Optimal Remittance Timing

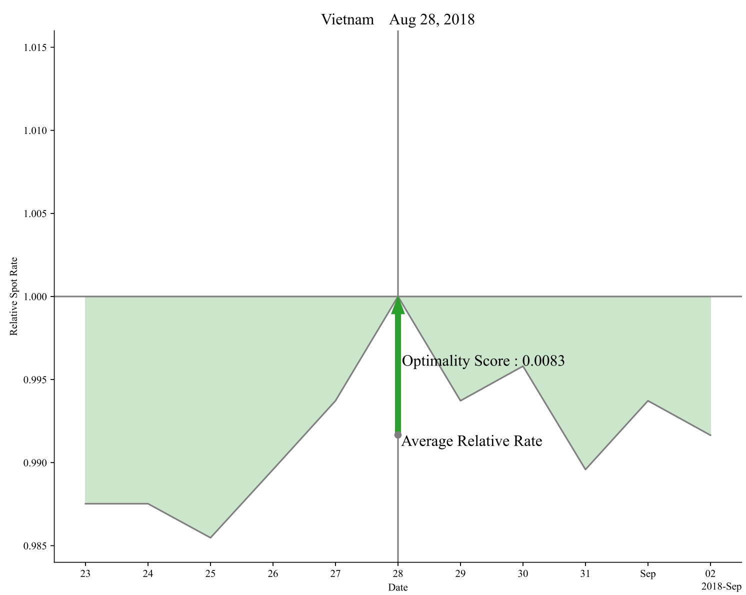


Figure 3 Continues

Panel B: Other Examples

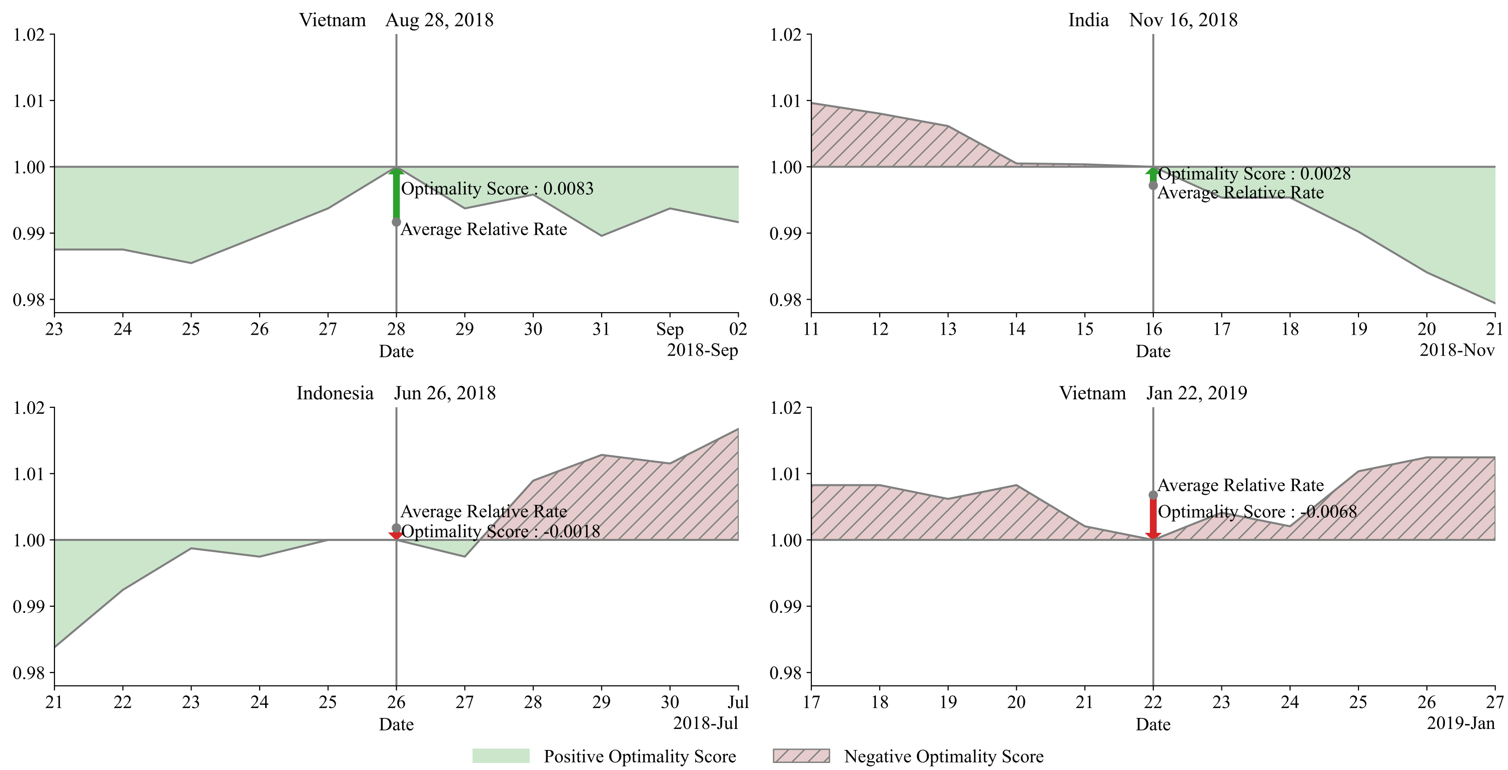


Figure 4: An Example of Sequential Cancellation

We plot an example of sequential cancellation by a Philippine user. The x-axis is time, and the y-axis is the spot rate of Philippine peso (PHP) per 1,000 Korean won (KRW). The vertical bars in the figure are the start (midnight) of each day. The horizontal solid (dotted) blue (red) line represents remittances (cancellations). The left end of each horizontal line is the application time, and the right end is the paid (blue) or cancelled (red) time. The end of the upward or downward line starting from the right end of each horizontal line is the spot rate for each paid or cancelled time. The blue-shaded areas represent the operating hours of ordinary commercial bank branches that are from 9:00 AM to 3:30 PM.

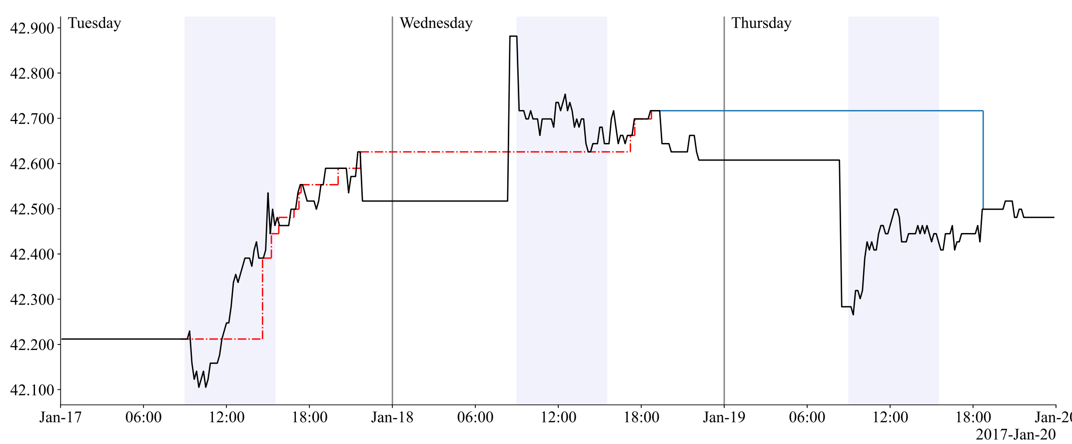


Figure 5: An Example of Social Network

We report an example of a social network among Philippine users. We label the users by the order of their registration dates with the FinTech platform. In this example, user A recommends the platform to B, C, D, E, F, G, H, J, K, L, M, N, O, P, Q, and R. User C recommends the platform to I. User G recommends the platform to U. User R recommends the platform to S. User Q recommends the platform to T.

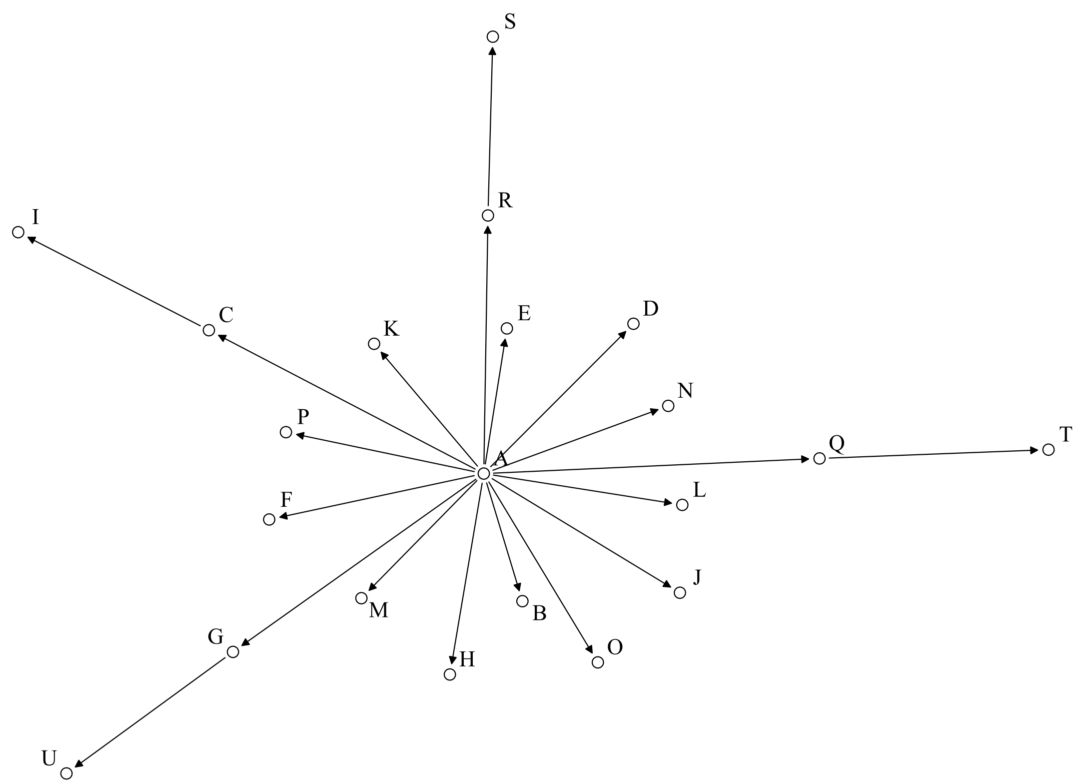


Figure 6: Optimality of Remittance Transactions

We plot the average optimality of remittance transactions in the sample. For each remittance transaction, we compute hypothetical remittance amounts in the receiving currency associated with different exchange rates before or after the actual remittance. We normalize these amounts from -5 to $+5$ days with the original amounts of remittance in the receiving currency on day 0. Panel A reports the average relative spot exchange rate using the full sample. We report the 95% confidence interval around the line. Instead of using the full sample, Panel B only uses the sample of individuals in the top 1/3 of all sample individuals in terms of optimality. The box plots report the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution. Panel C plots the average optimality of remittance transactions with the usage of *Cancellation* and *Sequential Cancellation*. The left panel is for the usage of *Cancellation*, and the right is for the usage of *Sequential Cancellation*. The solid line reports the relative spot exchange rate of users with *Cancellation* (*Sequential Cancellation*), and the dashed line reports the relative spot exchange rate of users without *Cancellation* (*Sequential Cancellation*). We report 95% confidence intervals associated with the two lines. All the standard errors are clustered at the area-country and country-year-month level.

Panel A: Average Optimality in the Full Sample

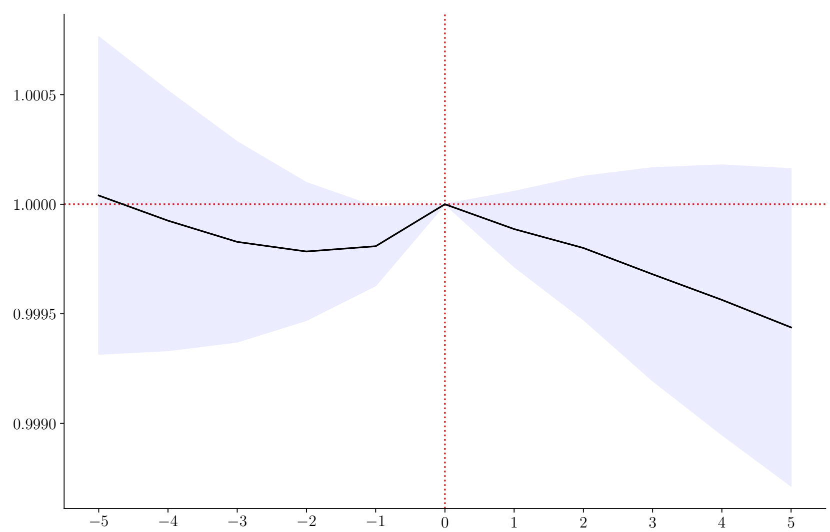
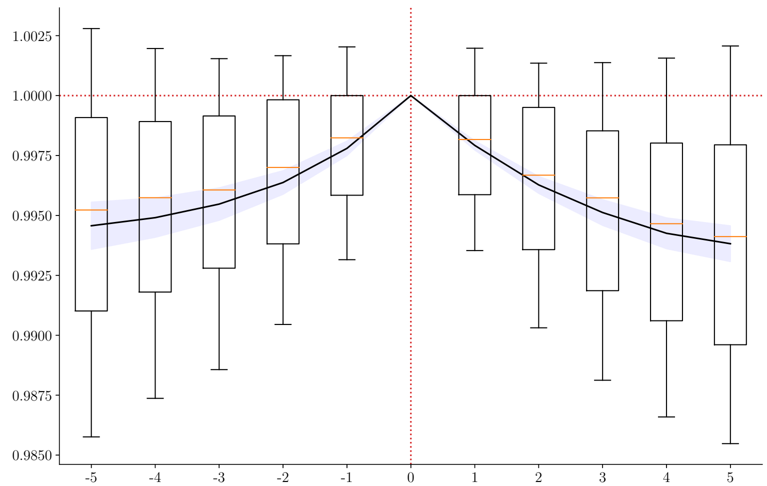


Figure 6 Continues

Panel B: Average Optimality of the Users in the Top 1/3



Panel C: Average Optimality by the Usage of *Cancellation* or *Sequential Cancellation*.

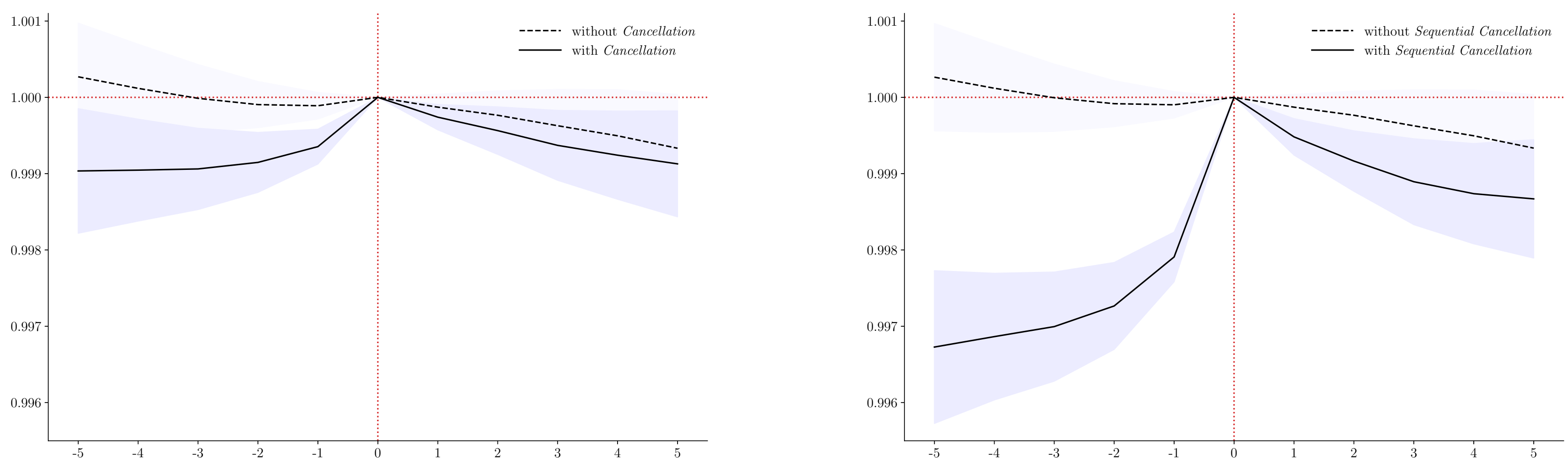


Figure 7: An Example of Clustered Remittance Transactions in a Social Network

We plot an example of clustered remittance transactions in a the social network in Figure 5 in May 2017. We plot the daily aggregate number of remittance transactions by the users in the social network (blue dashed bar) and their matching group without a social network (orange solid bar). The matching group is matched by propensity score matching using matching variables of remittance patterns such as the number of remittances, the number of *Sequential Cancellation*, the number of *Other Cancellation*, the average amounts of remittances in a month, and demographic information such as nationality, age, area of residence, and occupation type. We also plot the spot exchange rate of Philippine peso (PHP) in units of 1,000 Korean won (KRW).

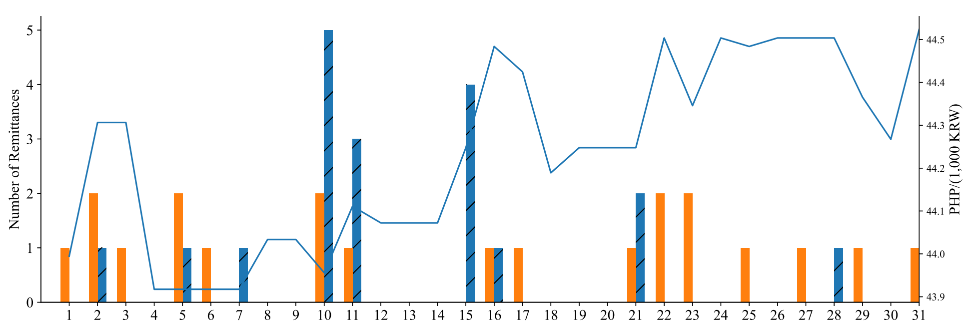
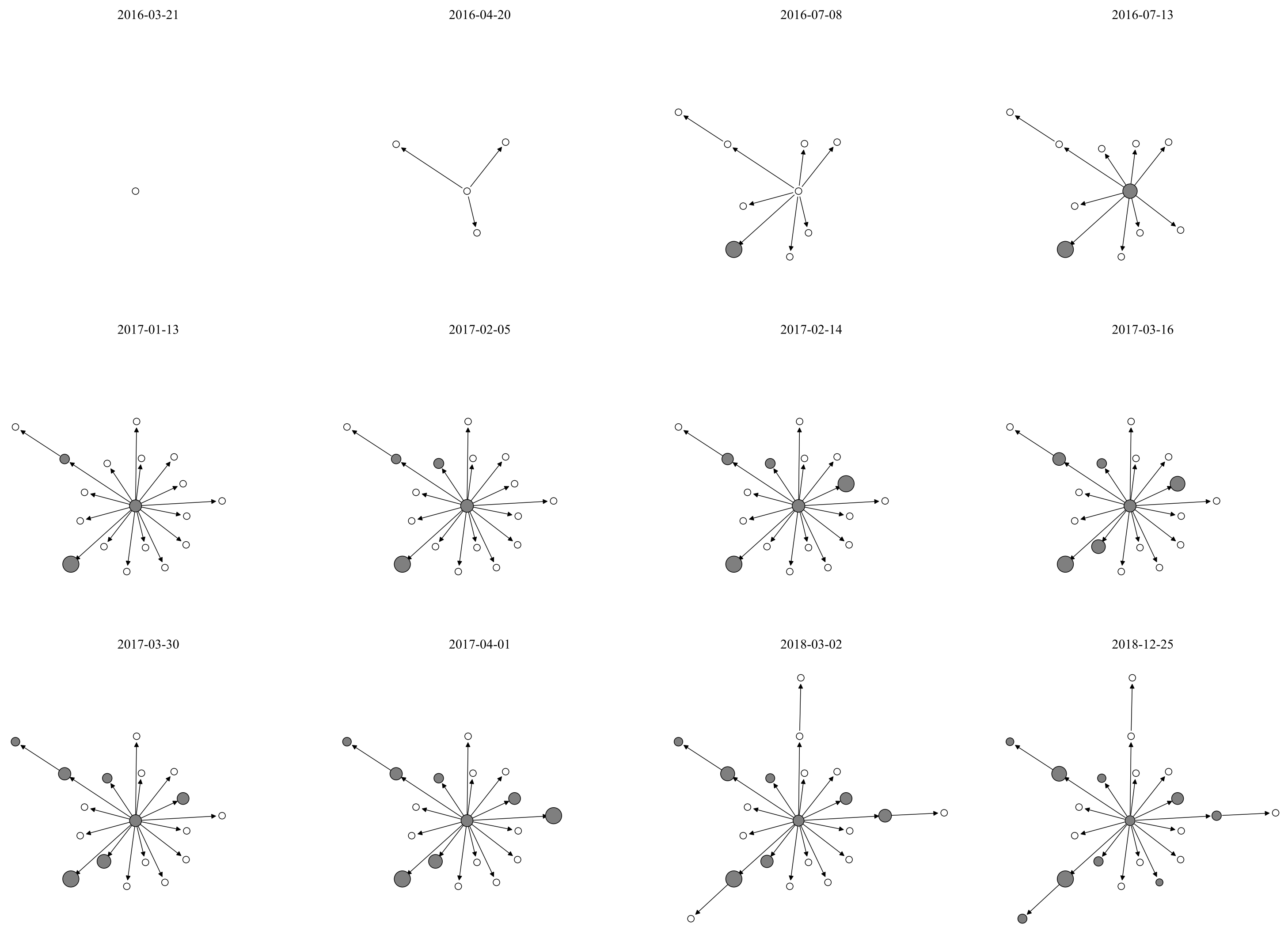


Figure 8: An Example of Learning on *Sequential Cancellation* within a Social Network

We plot an example of the evolution of learning about *Cancellation* within the social network in Figure 5. Nodes are individuals. Directed arrows point from recommenders to recommendees. The gray nodes represent the individuals who have used *Sequential Cancellation*. The size of node is proportional to $Individual\ Experience(Cancellation)_{i,t}$. Each figure is a snapshot of a particular date marked on the top of each figure. Each date selected represents either new individuals entering the network or users using *Sequential Cancellation*.



Appendix A: Estimating Cost Reduction by FinTech

The traditional method of overseas remittance entails five different layers of fees for outbound remittances. The first three are charged by local banks. The first is the fixed fee per remittance (Telegraphic Charge), second is a variable fee by remittance amount, and third is the margin on the foreign spot exchange rate. The last two are the fee charged by intermediary bank for using SWIFT (Brokerage Fee) and the fee charged by the foreign receiving bank. Here, we compare the first four fees between traditional banks and the FinTech firm.

We use the cost structure of two major banks in Korea, IBK Bank and Woori Bank, as a benchmark for the cost structure of traditional banks since many of our sample individuals use these banks as their main bank. Appendix Table 1 reports the cost structure.[13] Panel A compares the fee structures of IBK bank and Woori Bank to the fee charged by the FinTech firm. All three institutions charge 5,000 Korean won (KRW) (approximately 4 US dollars) as Telegraphic Charges. Traditional banks charge additional fees that vary by amount sent and charge 10,000 KRW as Brokerage Fees, while the FinTech firm does not charge them. Margins are about 1% but vary by bank and country of destination. Panel B reports the margin by country of destination. The FinTech firm charges a 1% margin for all countries, while the two banks differentiate their margins by country of destination.

Based on the fee structures in Appendix 1, Panel A of Appendix Figure 1 compares the remittance cost of the FinTech firm to the remittance cost of traditional banks by amount sent. The solid line reports the cost of remittance of the FinTech platform by amount sent, and the dashed line reports the cost of remittance of the traditional banks by amount sent. The difference between the two lines shows the relative cost reduction for each amount sent. For example, for 317,410 KRW in overseas remittance, which is the median sent amount in our dataset, the FinTech platform charges 5,000 KRW in Telegraphic Charge and 3,174 KRW as the margins. This sums to 8,174 KRW, which is about 2.5% of the amount sent.

[13] Here, we use the cost of remittance when individuals visit bank branches to conduct overseas remittance. Online platforms of the traditional banks offer cheaper solutions than branch visits. However, these were not available in our early sample period and are more expensive than the cost of the FinTech platform.

However, the traditional banks (e.g., IBK) charge 7.2% for the same amount of remittance (20000/317410+0.0094=7.2%).

Note that the difference is largest for transactions with smaller amounts. A large mass of our sample individuals sends relatively small amounts partly due to their low income. The green bar reports the distribution of amounts sent in remittance transactions. We can compute the average cost reduction for FinTech users using the empirical distribution of amounts sent as the weight. We find that a typical user using the FinTech saves 11.5% on remittance costs compared to the users using traditional banks. Panel B reports similar results by the country of destination.[14] The reduction is largest among users from Indonesia at 14.2% and smallest among users from India at 4.4%.

Appendix B: Robustness of *Optimality Score*$_{i,t}$ $[-5,+5]$ in Measuring the Optimal Transaction Timing

To check the robustness of the *Optimality Score*$_{i,t}$ $[-5,+5]$ in measuring optimality in remittance timing, Appendix Table 2 reports the results comparing the *Optimality Score*$_{i,t}$ $[-5,+5]$ and the relative ranking of spot exchange rates within an 11-day window. For each currency, we sort 11 spot exchange rates from -5 to 5 days of the remittance transaction to assign a ranking for the spot exchange rate on day 0, i.e., the ranking equals 11 if the spot exchange rate on day 0 is the highest within the window period and equals 1 if the spot exchange rate on day 0 is the lowest. If correctly measured, *Optimality Score*$_{i,t}$ $[-5,+5]$ should be positively correlated with the probability of having a higher ranking.

Panel A reports the logistic regression results using the dummy variables for the relative ranking as dependent variables. The dependent variable in Column (1) is $D\_\{Rank_{c,t} = 11\}$ (Highest), which equals 1 if the ranking of the spot exchange rate on day 0 is the highest and 0 otherwise. We include country-year-month fixed effects. We find that *Optimality Score*$_{i,t}$ $[-5,+5]$ is positively associated with the probability of the spot exchange rate on day

[14] We only conduct the analysis for 7 countries, excluding Bangladesh and Pakistan, since neither of the banks offers remittance services to those countries.

0 being the best rate in the window period. Column (2) uses $D\_\{Rank_{c,t} \geq 9\}$, which equals to 1 if the ranking of the spot exchange rate on day 0 is within the top 3 and 0 otherwise, and find similar results.

Alternatively, Column (3) uses $D\_\{Rank_{c,t} \leq 3\}$, which equals 1 if the ranking of the spot exchange rate on day 0 is within the bottom 3 and 0 otherwise, and find that the *Optimality Score*$_{i,t}$ $[-5, +5]$ is negatively correlated with the probability of the spot exchange rate on day 0 being the best rate in the window period. Column (4) uses $D\_\{Rank_{c,t} = 1\}$ (Lowest), which equals 1 if the ranking of the spot exchange rate on day 0 is the lowest and 0 otherwise, and find that the probability of the spot exchange rate on day 0 being the lowest is lower with *Optimality Score*$_{i,t}$ $[-5, +5]$. In Panel B, we find similar results using the Pearson correlation between *Optimality Score*$_{i,t}$ $[-5, +5]$ and the dependent variables in Panel A.

Appendix C: Volatility in Foreign Exchange Rates

As an option's value increases with the volatility of its underlying asset, the value of *Sequential Cancellation* would similarly increase with the volatility of foreign exchange rates. That is, higher volatility of foreign exchange rates will increase the usage of *Sequential Cancellation* and the return from *Sequential Cancellation*.

Appendix Table 3 reports the panel regression result of the effect of volatility on *Sequential Cancellation*. Volatility is the standard deviation of the 10-minute rate of change in the foreign exchange rate from the application time to the payment time. The main independent variables are dummy variables indicating terciles of volatility. $Volatility_t$ 2/3 ($Volatility_t$ 3/3) is 1 when volatility is in the second (highest) tercile.

In Column (1), when volatility is in the intermediate range, the probability of using *Sequential Cancellation* is 0.4% higher than in the lowest volatility periods. Regarding economic significance, it accounts for 2.3% of one standard deviation of *Sequential Cancellation* (0.004/0.176=0.023). Moreover, in the highest volatility periods, the probability is 0.8% higher than in the lowest volatility periods. It accounts for 4.5% of one standard deviation of *Sequential Cancellation* (0.008/0.176=0.045). This result indicates that users cancel their previous orders more frequently in volatile periods.

Appendix Figure 2 reports graphical evidence for the relationship between volatility and the usage of *Sequential Cancellation*. By using data aggregated at the country-week level, we present a scatter plot where the x-axis depicts residualized volatility from country and year-month fixed effects and the y-axis depicts the residualized ratio of using *Sequential Cancellation*. There is a positive and statistically significant relationship between volatility and the usage of *Sequential Cancellation*. A one-standard-deviation increase in volatility increases the ratio of using *Sequential Cancellation* by 19% of one standard deviation (0.368*0.020/0.039=0.189).

How does volatility affect learning? Column (2) reports that users with more past experience of using *Sequential Cancellation* have a higher probability of using *Sequential Cancellation* during volatile periods. In terms of economic significance, in the second tercile of volatility, a one-standard-deviation increase in *Individual Experience(Cancellation)*$_{i,t}$ increases *Sequential Cancellation* by 2.4% of a standard deviation (0.055*0.078/0.176=0.024). Furthermore, in the highest volatility tercile, a one standard deviation increase in *Individual Experience(Cancellation)*$_{i,t}$ increases 3.5% of a standard deviation of *Sequential Cancellation* (0.080*0.078/0.176=0.035).

In the case of social learning, in the highest volatility periods, users with more social experience with *Sequential Cancellation* have a higher probability of using *Sequential Cancellation*. Column (3) reports that in the highest volatility periods, a one-standard-deviation increase in *Social Experience(Cancellation)*$_{i,t}$ increases *Cancellation* by 1.3% of a standard deviation more than in the lowest volatility periods (0.190*0.012/0.176=0.013). However, the relationship is not statistically significant. In Column (4), when we include both individual and social learning measures, the result is similar.

In Appendix Table 4, we examine how volatility affects the optimality of remittance timing. Column (1) shows that in period with intermediate volatility, users achieve a 0.028%

higher *Optimality Score*, and the magnitude is statistically significant. In terms of economic significance, it equals 8.4% of one standard deviation of *Optimality Score* (0.028/0.332=0.084). In the highest volatility periods, *Optimality Score* is still higher than in the lowest volatility periods, but this finding is statistically insignificant. In Column (2), when we include the *Sequential Cancellation* in the regression, the coefficients on the dummy variables of volatility remain nearly unchanged. Column (3) indicates that the usage of *Sequential Cancellation* becomes more valuable in volatile periods. Although *Optimality Score* is the highest in the intermediate level of volatility periods, the benefit of using *Sequential Cancellation* to improve the *Optimality Score* is the highest in the highest volatility periods. In the highest volatility periods, the usage of *Sequential Cancellation* yields a 0.031% higher optimality score. In terms of economic significance, it equates to 9.3% of one standard deviation of *Optimality Score* (0.031/0.332=0.093). This is reasonable since the option value increases with the higher volatility.

Appendix Table 1: Cost Structure of Commercial Banks and FinTech

We report the cost structures for overseas remittances of two major commercial banks in South Korea and the FinTech firm. Panel A reports fees by type. Telegraphic Charges represents the fixed fee charged per remittance request. Sending Amount Fees denotes the variable fee by remittance amount. The commercial banks charge different fees for three different bins of amounts sent: *up to $500*, *from $500 to $2000*, and *over $2000*. Margin (%) is the average margin charged on the spot exchange rate of each currency. Brokerage Fees represents the fixed fee charged by the intermediary bank for using SWIFT. Panel B reports the margin on the spot exchange rate (%) by destination country. IBK Bank processes remittances to Indonesia, Malaysia, Thailand, and Cambodia. Woori Bank processes remittances to Indonesia, India, the Philippines, Thailand, Cambodia and Vietnam. Sentbe processes remittance transactions to Bangladesh, Indonesia, India, Malaysia, the Philippines, Pakistan, Thailand, Cambodia, and Vietnam. The data come from banks' websites, and the fees are reported in Korean won (KRW) except for the margin.

Panel A: Fee Structures

	IBK	Woori	Sentbe
Fee Type		Fee (KRW)	
Telegraphic Charges	5,000	5,000	5,000
Brokerage Fees	10,000	10,000	
Margin on Spot (%)	0.94	0.97	1.00
Send Amount Fees			
up to 500$	5,000	5,000	
500 to 2,000$	10,000	10,000	
from 2,000$	15,000	15,000	

Panel B: Margins

	IBK	Woori	Sentbe
Margin		(%)	
Bangladesh			1.00
Indonesia	0.90	0.93	1.00
India		0.98	1.00
Malaysia	0.96		1.00
Philippines		0.99	1.00
Pakistan			1.00
Thailand	0.94	1.00	1.00
Cambodia(USD)	0.95	0.97	1.00
Vietnam		0.83	1.00
All	0.94	0.97	1.00

Appendix Table 2: Validity of Optimality Score

We report the results of logistic regression and Pearson correlation between the optimality score and the rank of the spot exchange rate in a 2-week window. Panel A reports the logistic regression results using the dummy variables for the relative ranking as dependent variables. The dependent variable in Column (1) is $D\_\{Rank_{c,t} = 11\}$ (Highest) that equals 1 if the spot exchange rate on day 0 is the highest in the window and 0 otherwise. The main independent variable is $Optimality\ Score_{c,t}\ [-5, +5]$ which is the optimality score on day t for currency c measured in the window of $[-5, +5]$. We include country-year-month fixed effects. Column (2) uses $D\_\{Rank_{c,t} \geq 9\}$ that equals 1 if the ranking of the spot exchange rate on day 0 is within the top 3 in the window and 0 otherwise. Column (3) uses$D_\{Rank_{c,t} \leq 3\}$ that equals to 1 if the ranking of the spot exchange rate in day 0 is within the bottom 3 in the window and 0 otherwise. Column (4) uses $D\_\{Rank_{c,t} = 1\}$ (Lowest) that equals 1 if the ranking of the spot exchange rate on day 0 is the lowest in the window and 0 otherwise. Panel B reports the Pearson correlation of the dummies of ranking ($D\_\{Rank_{c,t} = k\}$) and $Optimality\ Score_{i,t}\ [-5, +5]$. The table reports point estimates with t-statistics in parentheses and the p-value of the Pearson correlation in square brackets. All standard errors in the logistic regressions are clustered at country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: Logistics Regression

	(1) $D\_\{Rank_{c,t} = 11\}$ (Highest)	(2) $D\_\{Rank_{c,t} \geq 9\}$	(3) $D\_\{Rank_{c,t} \leq 3\}$	(4) $D\_\{Rank_{c,t} = 1\}$ (Lowest)
$Optimality\ Score_{i,t}\ [-5, +5]$	8.336***	9.717***	-10.155***	-10.059***
	(13.56)	(20.69)	(-16.21)	(-15.30)
Observations	5,968	6,596	6,644	6,320
Adjusted R^2	0.501	0.562	0.589	0.544
County-Year-Month FE	Yes	Yes	Yes	Yes

Panel B: Pearson Correlation

	(1) $D\_\{Rank_{c,t} = 11\}$ (Highest)	(2) $D\_\{Rank_{c,t} \geq 9\}$	(3) $D\_\{Rank_{c,t} \leq 3\}$	(4) $D\_\{Rank_{c,t} = 1\}$ (Lowest)
$Optimality\ Score_{i,t}\ [-5, +5]$	0.392***	0.564***	-0.590***	-0.404***
	$\langle 0.00 \rangle$	$\langle 0.00 \rangle$	$\langle 0.00 \rangle$	$\langle 0.00 \rangle$
Observations	6,657	6,657	6,657	6,657

Appendix Table 3: Learning About *Sequential Cancellation* and Volatility

We report the panel regression results for volatility on the usage of *Sequential Cancellation* and learning of *Sequential Cancellation*. The dependent variable is a dummy variable $Sequential\ Cancellation_{i,t}$ that equals 1 if an individual uses *Sequential Cancellation* for remittance at t. Column (1) reports the result using $Volatility_t$ 2/3 and $Volatility_t$ 3/3 as the main independent variable. Volatility is the standard deviation of the 10-minute rate of change in the foreign exchange rate between the application time and payment time. The dummy variable $Volatility_t$ 2/3 ($Volatility_t$ 3/3) equals 1 when volatility is in the second (highest) tercile. Column (2) reports the results when using $Individual\ Experience(Cancellation)_{i,t}$ and its interactions with the dummy variables for volatility as the main independent variables. $Individual\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* among remittances until $t-5$. Column (3) reports the results when using $Social\ Experience(Cancellation)_{i,t}$ and its interactions with the dummy variables for volatility as the main independent variables. $Social\ Experience(Cancellation)_{i,t}$ is the ratio of using *Sequential Cancellation* by social network members among their remittances until $t-5$. Column (4) includes both $Individual\ Experience(Cancellation)_{i,t}$ and $Social\ Experience(Cancellation)_{i,t}$ and their interactions with dummy variables for volatility. We include individual control variables such as dummies for gender and age. The table reports point estimates with t-statistics in parentheses. All regression results include area-country-year-month fixed effects. All standard errors in panel regressions are clustered at the area-country and country-year-month levels. ***, **, and * denote 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)
Variables	$Sequential\ Cancellation_{i,t}$			
$Volatility_t 2/3$	0.004***	0.002*	0.004***	0.002*
	(3.36)	(1.81)	(3.16)	(1.82)
$Volatility_t 3/3$	0.008***	0.006***	0.008***	0.006***
	(5.24)	(3.90)	(4.99)	(3.61)
$Individual\ Experience(Cancellation)_{i,t}$		0.196***		0.195***
		(7.38)		(7.38)
$\times Volatility_t 2/3$		0.055**		0.056**
		(2.56)		(2.55)
$\times Volatility_t 3/3$		0.080**		0.078**
		(2.57)		(2.59)
$Social\ Experience(Cancellation)_{i,t}$			0.202***	0.170**
			(2.65)	(2.40)
$\times Volatility_t 2/3$			-0.031	-0.054
			(-0.31)	(-0.58)
$\times Volatility_t 3/3$			0.190	0.146
			(1.03)	(0.97)
$\log(SendAmount_{i,t})$	0.006***	0.005***	0.006***	0.005***
	(10.45)	(10.99)	(10.44)	(10.98)
$Salary\ Days_t$	-0.002	-0.002	-0.002	-0.002
	(-1.02)	(-1.00)	(-1.03)	(-1.00)
$D\_\{\Delta SPOT_{c,t-1} > 0\}$	0.029***	0.028***	0.029***	0.028***
	(18.94)	(19.25)	(18.99)	(19.28)
Observations	250,314	250,314	250,314	250,314
Adjusted R^2	0.073	0.083	0.073	0.083
Individual FE	No	No	No	No
Individual Controls	Yes	Yes	Yes	Yes
Area-Country-Year-Month FE	Yes	Yes	Yes	Yes

Appendix Table 4: Benefit of Using *Sequential Cancellation* in Volatile Periods

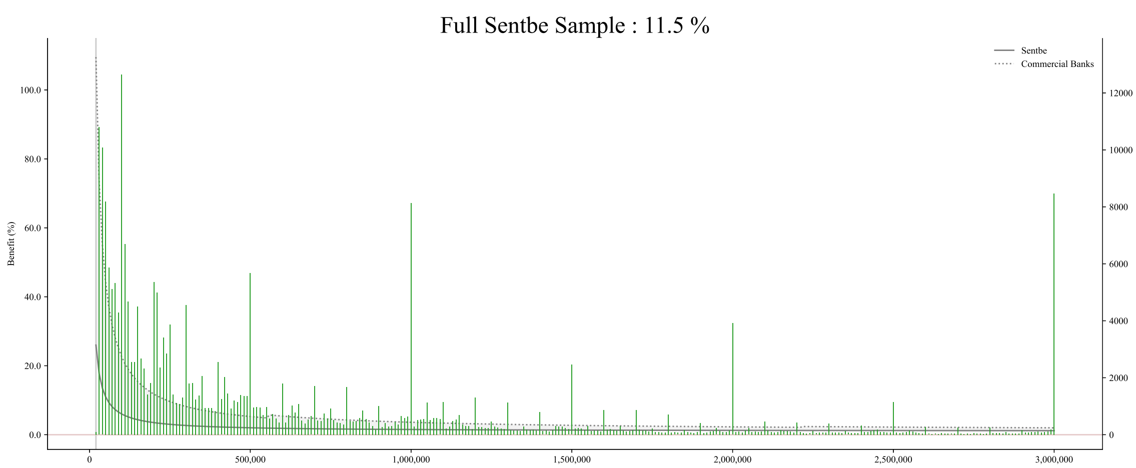
We report the panel regression results of the volatility on the usage of *Sequential Cancellation* and the optimal remittance timing. The main dependent variable is $Optimality\ Score_{i,t}$ $[-5,+5]$ (%). Column (1) reports result using $Volatility_t$ 2/3 and $Volatility_t$ 3/3 as the main independent variables. Volatility is the standard deviation of the 10-minute rate of change in the foreign exchange rate between the application time and payment time. The dummy variable $Volatility_t$ 2/3 ($Volatility_t$ 3/3) equals 1 when volatility is in the second (highest) tercile. Column (2) reports the results when using $Volatility_t$ 2/3, $Volatility_t$ 3/3, and $Seqeuntial\ Cancellation_{i,t}$ as the main independent variable. Column (3) reports the results when using the interactions of each of $Volatility_t$ 2/3 and $Volatility_t$ 3/3 with $Seqeuntial\ Cancellation_{i,t}$ as the main independent variable. All Columns include $\log(SendAmount_{i,t})$, $Salary\ Days_t$, $D\_\{\Delta SPOT_{c,t-1} > 0\}$, and $Other\ Cancellation_{i,t}$ as control variables. Individual fixed effects and area-country-year-month fixed effects are included in all the results. The table reports point estimates with t-statistics in parentheses. All standard errors in the panel regressions are clustered at the area-country and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)
Variables	$Optimality\ Score_{i,t}$ $[-5,+5]$ (%)		
$Volatility_t$ 2/3	0.028***	0.028***	0.028***
	(2.86)	(2.85)	(2.89)
$Volatility_t$ 3/3	0.022	0.022	0.021
	(1.51)	(1.49)	(1.42)
$Sequential\ Cancellation_{i,t}$		0.066***	0.053***
		(8.25)	(3.63)
$\times$ $Volatility_t$ 2/3			0.002
			(0.12)
$\times$ $Volatility_t$ 3/3			0.031**
			(2.10)
$\log(SendAmount_{i,t})$	0.006***	0.005***	0.005***
	(4.85)	(4.56)	(4.56)
$Salary\ Days_t$	-0.067***	-0.067***	-0.067***
	(-3.15)	(-3.16)	(-3.16)
$D\_\{\Delta SPOT_{c,t-1} > 0\}$	0.249***	0.247***	0.247***
	(21.83)	(21.73)	(21.73)
$Other\ Cancellation_{i,t}$	-0.002	0.002	0.002
	(-0.53)	(0.61)	(0.59)
Observations	250,314	250,314	250,314
Adjusted R^2	0.198	0.199	0.199
Individual FE	Yes	Yes	Yes
Area-Country-Year-Month FE	Yes	Yes	Yes

Appendix Figure 1: Comparison of Remittance Cost between FinTech and Commercial Banks

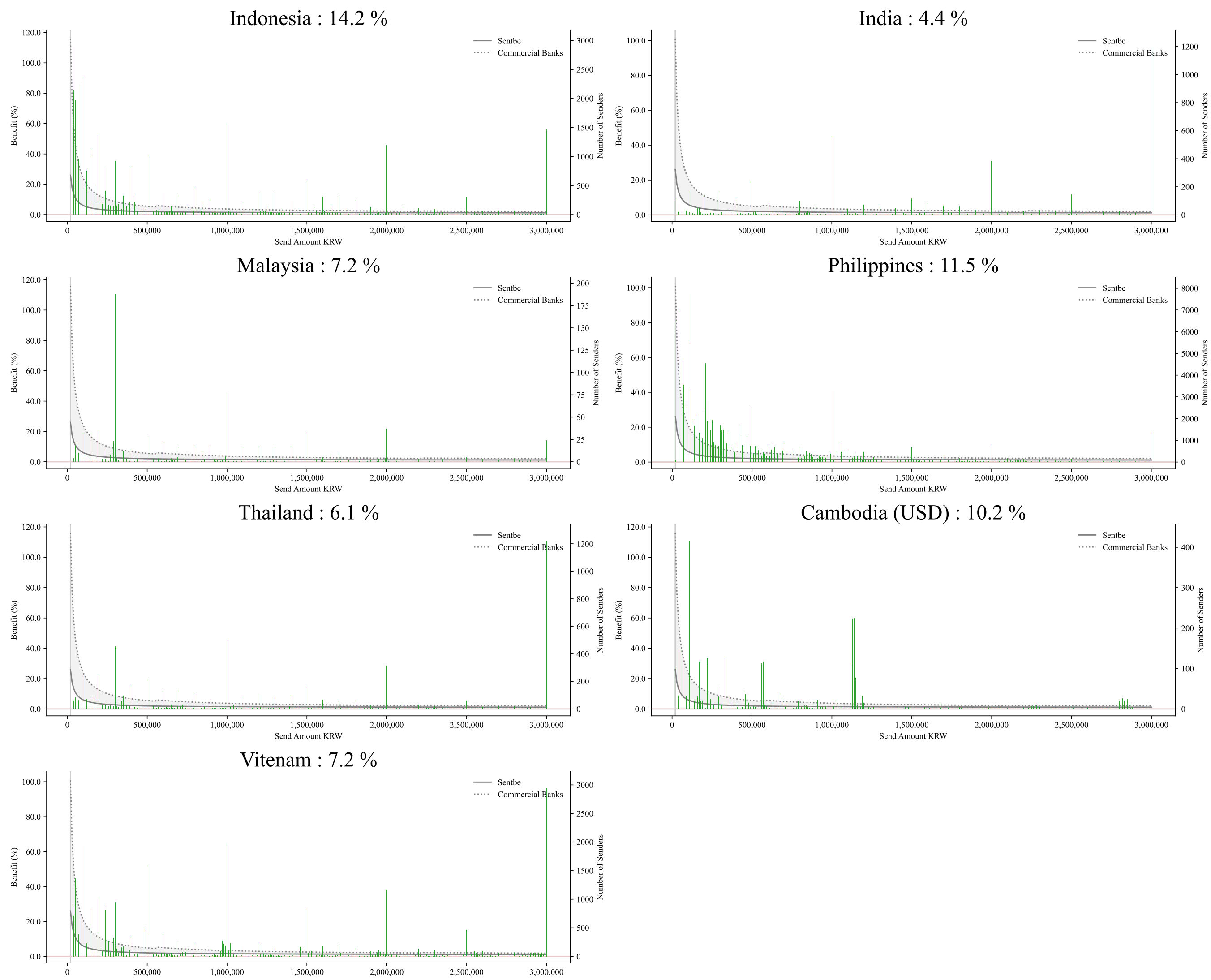
We compare the remittance cost between FinTech and commercial banks. Panel A uses all the remittance transactions for 9 countries in our sample. We report the amounts sent on the x-axis and the cost of remittance for these amounts on the y-axis. The solid line depicts the remittance cost associated with the amounts sent using FinTech platform, and the dashed line reports the remittance cost associated with the amounts sent using commercial banks. The difference between the two lines is the difference in remittance costs for the amounts. We also report the number of remittance transactions in our data by bins of 10,000 Korean won. We compute and report the transaction-weighted difference between the two lines to derive the average benefit from cost reduction using FinTech. Panel B plots similar results by country.

Panel A: Difference in Remittance Costs between FinTech and Commercial Banks



Appendix Figure 1 Continues

Panel B: Difference in Remittance Costs between FinTech and Commercial Banks by Country



Appendix Figure 2: Volatility and Usage of *Sequential Cancellation*

We present a scatter plot of volatility and the probability of using *Sequential Cancellation*. We construct country-week level data by aggregating the individual-transaction level data. The x-axis is a country-week level average of 24 hours of volatility in the foreign exchange rate, denoted in percentage. Volatility is residualized by a country fixed effect and year-month fixed effect. The y-axis is the country-week level residualized average ratio of using *Sequential Cancellation* in a remittance. The ratio using *Sequential Cancellation* is residualized by country and year-month fixed effects. We also plot a fitted line by regressing the residualized ratio of using *Sequential Cancellation* on the residualized volatility. Both volatility and the ratio of using *Sequential Cancellation* are winsorized at the 1% and 99% levels.