The Value of FinTech for Retail Consumers*

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Abstract

We study the value of FinTech for retail consumers from individual overseas remittances on a FinTech platform. The value of FinTech mostly comes through overcoming various frictions such as high cost or time/spatial constraints of transaction. Using detailed transaction-level overseas remittance data from a leading FinTech firm in Korea, we find that the FinTech platform lowers remittance cost by 10.6% on average compared to traditional commercial banks. However, we find mixed results regarding the time/spatial flexibility provided by the FinTech platform that it may not always lead to the optimal timing of remittance transactions. While the FinTech platform can enhance consumer welfare by allowing constraint-free transactions with some advanced features in the platform, the flexibilities can also harm consumers by amplifying their behavioral bias.

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1. Introduction

Financial technology or "FinTech" has grown remarkably over the past few years. What was once considered a complex way of managing finance is now used by millions of people globally, due to the rise of online banking and mobile-first platforms. However, overall value of FinTech is not easy to measure in the midst of the FinTech revolution since not all firms or households are voluntarily accepting the new way of managing finance and not all of them are benefiting from the new technology (Choi and Loh (2019)).

There are some recent articles discussing the value of FinTech. Chen et al. (2019) study the value of FinTech innovation in the view of innovators/financial institutions. While they find substantial value creation to innovators, they find mixed results for other financial industry participants by their willingness to adopt new technology. When it comes to the value of FinTech for retail consumers, a large literature focuses on the topics that are related to consumer credit, i.e. constructing credit score using digital footprints (Berg et al. (2020), Agarwal et al. (2020)) or consumer benefits using digital lending platforms (Jagtiani and Lemieux (2017)). Since FinTech can improve information efficiency in credit allocation, the results are mostly on the positive role of FinTech on improving credit allocation problems.

In this paper, we study the value of FinTech for retail consumers by examining individual overseas remittances on a FinTech platform. Traditionally, overseas remittance for retail consumers has been difficult and expensive. According to a report from the World Bank on international remittances (World Bank (2019)), the global average cost of sending $200 gradually reduces from 9% in 2011 to 7% in 2019 but it is still high as 7%. As the overseas remittance has grown dramatically over the last decade, particularly to low- and middle-income countries, we naturally observe a fast growth of several FinTech firms in the overseas remittance market such as TransferWise or PayPal. We aim to understand the source of the benefits of FinTech to retail consumers and whether the cunsumers can maximize the benefits of FinTech when the technology is given to them.

We use detailed transaction-level overseas remittance data from one of the leading FinTech

firms in Korea, the Sentbe[1], for our analysis. There are several advantages using the data for our research question. First, detailed information on the timing and amounts of overseas remittances combined with rich demographic information about the consumers enables us to examine the determinants of individual remittance decisions. Second, most of our sample consumers are foreign workers[2] working in Korea who are typically low-skilled workers and need to transfer significant part of their earnings to support their families. Despite they are financially unsophisticated, the overseas remittance would take a large part of their income and they would exert their best efforts for the remittance decisions.

We first estimate the value of FinTech in terms of the cost reduction in overseas remittance transactions. Comparing the cost structures of overseas remittance between traditional banks and the FinTech firm, we find that the FinTech solution charges on average 10.6% cheaper cost than the cost of traditional banks. The sizable effect is largely due to the fact that the FinTech has a relative advantage in the remittance transactions with small amounts and our sample consumers are sending relatively small amounts around 721,906 Korean Won (KRW) on average (about 600 US dollars) due to their low income. We also find a significant variation in the cost reduction by the country of destination. The reduction is largest among users from Indonesia with 13.1% and smallest among users from India with 4.1%.

FinTech platform not only provide a cheaper solution for overseas remittance but also provide additional flexibility in remittance transactions. Compared to traditional banks, FinTech platform expands the users' opportunity sets by enabling them to overcome time and physical constraints. In case of traditional remittance transactions, individuals should visit a bank branch during the bank's working hours. 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 who need to travel significant distance to visit a bank branch, i.e. workers working in sparsely populated areas. FinTech allows users to execute remittance transactions regardless of time and physical

[1]Sentbe is a young FinTech platform provides easier and cheaper solution for money transfer abroad. More details about the service can be found at https://www.sentbe.com/en/.

[2]Foreign workers in our sample are from Bangladesh, China, Indonesia, India, Cambodia, Malaysia, Philippine, Pakistan, Thailand, and Vietnam.

location.

When a new technology arrives and relaxes pre-existing constraints on consumers, would it be always beneficial to consumers? In theory, rational agents should better off with additional flexibility in their choice set. But in the spirit of Barber and Odean (2000) who find that active trading may harm investors' wealth, individuals may be worse off with additional flexibility particularly when the sample individuals are financially unsophisticated.

We examine the determinants of individual remittance decision and the performance of the remittance decisions. We find that our sample individuals are much more likely to transact during weekdays than during weekends. In addition, we observe significant number of remittance transactions outside of working hours of banks. Considering that individuals can only transact during lunch time in weekdays or weekends if they have to use traditional banks for remittance transactions, the findings imply a severe constraint that could have imposed on individual consumers if the FinTech did not exist.

We find two other determinants of remittance decision that are available to individuals through the FinTech platform. First is the *Cancellation* feature provided in the platform. The FinTech platform allows users to hold multiple remittance orders up to 24 hours and users only need to decide which orders to execute before they expire. We find that the usage of the feature is more likely among young female users and for the remittance transactions with large amounts. We also find that sample individuals from the countries with better financial development use the feature more. By the nature of the *Cancellation* feature, it must be strongly associated with the probability of remittance transaction since the usage shows that the users are timing the market to transact. Indeed, we find that the probability of remittance transaction increases by 35% when the feature is used.

Next determinant is the lagged percentage change in spot exchange rate of remitting currency. By merging the lagged daily percentage changes in spot exchange rate of currencies to the individuals from the corresponding countries, we find that sample individuals are more likely to transact when the lagged spot exchange rates appreciate. In economic terms, for

every 1 standard deviation increase in spot exchange rate on the previous day, the likelihood of remittance transaction increases 4.2%. The result remains same with the dummy variable for the appreciation of spot exchange rate on the previous day. This shows that individuals are responding to the appreciation of spot exchange rate when it comes to overseas remittance decision.

What makes individuals transact more after the appreciation of spot exchange rate? One potential reason is the behavioral bias of our sample individuals. Individuals are known to suffer the "law of small numbers" (Tversky and Kahneman (1971)) and likely to expect balanced outcome to the presumed rate. If the appreciation of spot exchange rate on the previous day makes individuals to expect a depreciation in the following day, we would expect more remittance transactions by individuals followed by the appreciations of spot exchange rate. If this expectation is not supported by the realization of spot exchange rate, individuals would perform worse due to the behavior.

To understand the link between the determinants and the optimality in overseas remittance timing, we define an optimality measure for each remittance transaction by computing a set of counterfactual amounts in receiving currency if the transaction occurs in the other days in the window of [-5, +5] around the actual transaction. Normalizing the amounts by the original amounts of remittance in receiving currency at $t = 0$, the measure equals to 1 at $t = 0$. Having the peak at $t = 0$ means that the individual was able to get the best exchange rate in 2-weeks window. Having the peak before (after) $t = 0$ means that the individual could have done better if he/she transacted few days earlier (later).

We define the average difference in receiving amounts between $t = 0$ and the other days in the window of [-5,+5] as the *Optimality Score* $[-5, +5]$. We find high optimality score among younger users with significant variation by their nationalities. For the individuals with the optimality score in the top 1/3 among our sample individuals, the receiving amounts at $t = 0$ are on average 0.54% higher to the amounts in the window of [-5,-1] and 0.49% higher to the amounts in the window of [1,5].

We find that the sending amounts are positively associated with the optimality score but only during the pre-transaction period of [-5,-1]. This indicates that the individuals put extra effort in picking remittance timing for the larger remittances since the effort only can affect on the optimality in pre-transaction period. We also find that the optimality score falls during the *Salary Days*. Since many of our sample individuals should send money to support their families at home country, they may not have much room to choose an optimal remittance timing during *Salary Days*.

The usage of *Cancellation* increases the optimality score. By using the option to hold multiple remittance orders up to 24 hours, individuals can enhance their optimal remittance timings. It is not surprising that the average spot exchange rate applied for actual remittance transactions is 1.84% higher than the average spot exchange rates of those cancelled orders associated with the actual remittances. We also find that the improvement in remittance timing only appears in pre-transaction period as expected by the nature of the feature.

When it comes to the lagged percentage change in spot exchange rate, the optimality score significantly increases when individuals follow the appreciation of spot exchange rate for their remittance transactions. This is surprising since we expected poor performance by individuals if their tendency of the remittances is due to the behavioral bias on the mean reversion of spot exchange rate. We find that the outperformance is mainly due to the mean-reverting behavior of the spot exchange rates in a short horizon of 2 weeks in our sample period for the sample currencies.

We then arrive at two alternative explanations for the results. First is the case when our sample individuals understand the short-term mean-reverting behavior of spot exchange rate and follow the signal for their remittance transactions. Second is the case when our sample individuals suffer the behavioral bias believing the mean reversion in spot exchange rates but the spot exchange rates turned out to be favorable to them. To distinguish the two alternative hypothesis, we use the social networks among sample individuals in the FinTech platform to examine the learning effects of these determinants in the social networks.

One of the key feature of FinTech is the social network that are associated with the platforms. Using the social networks identified in our data, we investigate whether there exists a learning through the social networks on the determinants for optimal remittance timing. As usual as other FinTech platforms, our sample individuals can recommend the FinTech to their friends in exchange of bonus credits that can be used for the future remittance transactions by the referrers. We construct social networks among our sample individuals using the referral data across them.

When other users in a social network have been using the *Cancellation* for their remittance transactions, we find that an individual in the social network is more likely to use the *Cancellation*. However, we do not find similar effect for the other determinant of optimal remittance timing, the appreciation of spot exchange rate. If our sample individuals rationally take the appreciation of spot exchange rate as a signal to improve the optimality of remittance timing, we should observe learning through the social network but we do not find it. Instead, we find that the individuals with more remittance experience with the appreciation of spot exchange rate show more aggressive behaviors in remittance transactions. This support the second hypothesis that the users were just lucky due to the realization of mean-reverting behavior of spot exchange rate in the sample period that are favorable to individuals' behavioral bias.

What does this imply to the value of FinTech to retail consumers? Additional flexibility in FinTech platform can allow users to improve their financial decisions though constraint-free transactions with some unique features in the technology such as *Cancellation* in our case. And the information can be spread out through the social networks to improve the decisions of other consumers in the networks. However, the additional flexibility can exacerbate the effect of the behavioral bias of retail consumers on their optimal decisions. Considering the general consensus of unpredictable short-term foreign exchange rate from a large body of empirical literature (i.e. Meese and Rogoff (1983)), the flexibility of remittance transactions may harm consumers' welfare when the short-term behaviors of spot exchange rate change

but the consumers remain overconfident on their ability of optimal decisions.

Our paper contributes to the literature on the value of FinTech. Chen et al. (2019) studies the value of FinTech in the view of innovators and financial institutions. Berg et al. (2020) and Agarwal et al. (2020) discover the benefit of FinTech from constructing credit score out of digital footprints. Jagtiani and Lemieux (2017) finds the benefit of FinTech from the information efficiency achieved by online lending platform. Instead, our paper focuses on consumers' benefit from FinTech discussing the value of cost reduction and the value of flexibility.

This paper also contributes to the literature on individual behaviors in investments. Barber and Odean (2000) finds that active trading may harm investors' wealth. Allowing more flexible choice of decision does not always improve individuals' decisions. While our paper finds the optimal remittance timings by sample individuals in a flexible FinTech platform, the optimal remittance timing is largely due the realization of favorable behavior of spot exchange rate to the behavioral bias and the outperformance is unlikely sustainable in other environments. We also contribute to the literature on labor migrations and overseas remittances. (Lucas and Stark (1985), Funkhouser (1995), and Clemens and Tiongson (2017))

2. Overseas Remittance Business and FinTech

Over the last decade, overseas remittance to low- and middle-income countries has grown fast. Figure 1 reports the total amounts of overseas remittance toward low- and middle-income countries from World Bank (2019). Panel A reports that the total amounts of overseas remittance to low- and middle-income countries was about 150 billion dollars in 2004 but it reaches 500 billion dollars in 2019. Panel B reports that the amounts of overseas remittance to low- and middle-income countries excluding China starts to exceed the total amounts of foreign direct investment to these countries. The overseas remittance also takes a large part of GDP of some countries, i.e. the amounts of total remittance to Philippines was 10.2% of

the total GDP of Philippines in 2018.

Despite the fast growth, overseas remittance has been hard and expensive. Panel A of Figure 2 reports that the global average cost of sending $200 gradually reduces from 9% in 2011 to 7% in 2020 but it is still high as 7%. The cost of remittance seems to depend on the competitiveness of the industry. Panel B reports the average cost by the type of service provider from 2011 to 2020. Banks on average charge the highest with 11.55% and post offices charge the lowest with 5.25%. Money transfer operators charge 6.4% but it charges 8.66% when it has exclusive partnership arrangements with local post offices.

Naturally, we recently observe the fast growth of FinTech firms in overseas remittance business offering cheaper and easier solution for it, e.g. TransferWise or PayPal. The situation in Korea is similar. Due to the long history of strict regulations on foreign exchange transactions (the Foreign Exchange Transactions Act), overseas remittances were only served by banking institutions at a high cost. As the Ministry of Economy and Finance of Korea relaxes the regulation and makes it possible for non-bank financial firms to do overseas remittances in June 2017, few start-up firms jumped into the overseas remittance business. Our data is from one of the FinTech firm.

3. Data and Summary Statistics

We use detailed transaction-level overseas remittance data from one of the leading FinTech firms in Korea, the Sentbe, for our analysis. The firm's target consumers are mainly foreign workers working in Korea and our sample individuals are mostly from 9 different countries including Bangladesh, Indonesia, India, Cambodia, Malaysia, Philippine, Pakistan, Thailand, and Vietnam.

The key feature of our sample individuals is that they are typically low-skilled workers who need to transfer significant part of their earnings to support their families. Despite they are financially unsophisticated, the overseas remittance takes a significant part of their income

and they should exert their best efforts for the remittance decisions. We see this indirectly from the fact that the overseas remittance takes a significant part of countries' GDP in our sample. Figure 3 reports the total amounts of overseas remittance by the country of recipients in our sample and the fraction of the remittances to their GDP as of 2018. The overseas remittance takes more than 5% of countries' GDP such as Philippine, Pakistan, Vietnam, Cambodia, and Bangladesh. Detailed information on overseas remittance transactions combined with rich individual demographic information allows us to study the remittance decisions by unsophisticated individuals that have a large impact on their utility and wealth.

Table 1 reports the summary statistics of our daily individual-level data by destination country. Our sample has 25,994 individuals with 476,659 transactions from February 2016 to March 2020.[3] The largest fraction of sample individuals is from Philippine with 8,231 users (32%) who account for 244,297 number of transactions (52%) with the average transaction amounts of 497,465 Korean Won (KRW). Next largest group in our sample is from Vietnam with 7,743 users (30%), followed by the group from Indonesia with 4,994 users (19%). A large fraction of users from these three countries is not surprising since the service to these three countries started earlier than the other countries.

On average, our sample individuals make remittance transactions about 2.1 times a month with 721,912 KRW per remittance. There exists an interesting relationship between sending amounts and remittance frequency by country. Sample individuals from Philippines, Indonesia, Malaysia tend to remit smaller amounts more frequently while sample individuals from India tend to remit larger amounts less frequently. Average age of our sample individuals is about 31 but it varies from 27 to 33 across countries.

Figure 4 reports the distribution of our sample transactions by time. Panel A reports the number of remittance transactions by calendar day. The number of transactions gradually increases as the FinTech platform matures. Note that there was a 5-months period without

[3]We limit our sample to individuals whose nationality is matched with remitting currency. For example, we do not include Koreans sending money to the countries. The only exception is Cambodians since Cambodian Riel is pegged to US dollars and Cambodians send US dollars to Cambodia. There exist some users with multiple transactions within a day. We collapse them to define daily transactions.

any remittance transaction in the middle of our sample period from July 17th to December 7th in 2017. The service interruption was for acquiring a license for overseas remittance, required by the government's deregulation in July 2017.[4] In the figure, we report the days with monthly peak of transactions and we find that the days are mostly between 10th to 14th of the month.

Panel B reports the number of remittance transactions by the day of a month. As we find from the monthly peaks in Panel A, the remittance transactions are more likely to happen between 10th to 14th of the month. This period is the typical salary days in Korea and the remittance transactions from our sample individuals are highest during this period. Panel C reports the number of remittance transactions by the day of a week. We find that the remittance transactions are lower during the weekends and highest on Monday.

Panel D reports the number of remittance transactions within a day. The peak time of a day is usually around lunch time but the transactions are on average higher after the working hour. For traditional remittance transactions, individuals should visit a bank branch during the bank's working hours. 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 who need to travel significant distance to visit a bank branch, i.e. workers working in sparsely populated areas. If so, they have to pay even higher cost for remittance transactions at special bank branches exploiting the friction.[5] The FinTech allows individuals to do constraint-free remittance transactions. Note that the significant amounts of transactions during weekdays other than lunch time, i.e. non-working hours, indicate the value of the flexibility that the FinTech solution can provide to users.

For the foreign spot exchange rates, we use the spot exchange rate from the FinTech that are quoted to their consumers.[6] The spot exchange rates are the rate of foreign currency units

[4]There was another short stoppage of the service from 2018.2.15 to 2018.2.18 due to the Lunar New Year Holidays in Korea. We use entire sample period from 2016 to 2020 for our main analysis but using the sample only after 2018 does not change our main results.

[5]For the Southeast Asian workers as in our sample, there exist bank branches for weekends remittances charging even higher fee than regular bank service.

[6]We get high frequency foreign exchange spot rates by 10-minutes from the FinTech firm for our countries of

per KRW. Figure 5 plots the spot exchange rates for our sample countries during our sample period.[7]

4. Benefit of FinTech in Cost Structure

When it comes to the benefit of using FinTech, one of the major benefit would be a cheaper cost compared to traditional solutions. It would be the cost of overseas remittance in our setup. How much cost reduction can we expect by using the FinTech platform?

Traditional way of overseas remittance comes with five different layers of fee for the outbound remittances. First three is charged by local banks. First is the fixed fee per remittance (Telegraphic Charge), second is the variable fee by remittance amounts, and third is the margin on the foreign spot exchange rate. Last two are the fee by intermediary bank for using the SWIFT (Brokerage Fee) and the fee by foreign receiving bank. Here we compare 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 are using these banks as their main bank. Table 2 reports the cost structure.[8] 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 KRW (about 4 US dollars) as Telegraphic Charges. Traditional banks charge additional fee by sending amounts and charge 10,000 Korean Won (KRW) as Brokerage Fee while the FinTech firm does not charge them. Margins are about 1% but it varies by banks and by the country of destination. Panel B reports the margin by the country of destination. The FinTech firm charges 1% margin for all countries while two other banks differentiate the margins by country of destination.

interest. Their spot exchange rates come primarily from KEB-Hana Bank who specializes in foreign exchange market but also from global benchmarks such as Xe.com, or investing.com.

[7]The plot starts from 2016 for Indonesia, Philippines, and Vietnam but from 2018 for other countries since the service periods of the FinTech platform are different across countries.

[8]Here we use the cost of remittance when individuals visit bank branches to do the overseas remittance. Online platforms of the traditional banks offer cheaper solution than the branch visits. But it was not available in our early sample period and is still more expensive than the cost of FinTech.

Based on the fee structures in Table 2, Panel A of Figure 6 compares the remittance cost of the FinTech firm to the remittance cost of traditional banks by the sending amounts. The solid line reports the cost of remittance of the FinTech platform by sending amounts and the dotted line reports the cost of remittance of the traditional banks by sending amounts. The difference between two lines shows the relative cost reduction for each sending amounts. For 374,690 KRW of overseas remittance, which is the median send amounts in our dataset, the FinTech platform charges 5,000 KRW for Telegraphic Charge and 3746.9 KRW for the margins. This adds up to 8746.9 KRW which is about 2% of the sending amount. However, the traditional banks charge 6.29% for the same amount of remittance.

Note that the difference is largest in the transactions with smaller amounts. A large mass of our sample individuals are sending relatively small amounts partly due to their low income. The green bar reports the distribution of sending amounts in remittance transactions. We can compute the average cost reduction for FinTech users by using the empirical distribution of sending amounts as the weight. We find that typical consumers using the FinTech save 10.6% on remittance cost compared to the users using traditional banks. Panel B reports the similar results by the country of destination.[9] The reduction is largest among users from Indonesia with 13.1% and smallest among users from India with 4.1%.

However, FinTech may not always be a dominating solution for overseas remittance when the remittance amount is large. When the remittance amount is large, users may find the overseas remittance through traditional banks more attractive since the cost is not much different and the reliability is much better with the banks. That is, the FinTech platform seems to have comparative advantage in small but frequent overseas remittances.

[9] We only do the analysis for 7 countries excluding Bangladesh and Pakistan since both of the banks don't offer remittance service to those countries.

5. Overseas Remittance Decisions by Individuals

FinTech platform not only provide a cheaper solution for overseas remittance but also provide additional flexibility in remittance transactions. Compared to traditional banks, FinTech platform expands the users' opportunity sets by enabling them to overcome time and physical constraints. For traditional remittance transaction, individuals should visit bank branch during bank's working hour. 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 who need to travel significant distance to visit a bank branch, i.e. workers working in sparsely populated areas. FinTech allows users to execute remittance transactions regardless of time and physical location.

However, whether individuals can maximize their welfare or utility using the additional flexibility is not clear. In theory, rational agents should better off with additional flexibility in their choice sets. In the spirit of Barber and Odean (2000) who find that active trading may harm investors' wealth, individuals may worse off with additional flexibility especially when the sample individuals are financially unsophisticated. In this section, we study the determinants of individual remittance decision and the effectiveness of those determinants for optimal remittance decision.

5.1. Determinants of Remittance Transactions

Starting from our data on daily user-level transactions from February 2016 to March 2020, we fill zeros for all users without any remittance transaction from 1 month before the day of first remittance to 1 month after the last day of remittance. As a result, the dataset has 10,623,364 observations.

Table 3 reports the results from linear probability model on daily patterns of remittance transactions. The dependent variable is a dummy variable $D_\{Remittance\}_{i,t}$ that equals to 1 if an individual i transacts on day t and 0 otherwise. $D_\{Remittance\}_{i,t}$ has a mean of 0.04 indicating that users remit funds in about 4% of the days with the FinTech platform. Col-

umn (1) reports the result using dummy variables on the days of a week, $Monday$, $Tuesday$, $Wednesday$, $Thursday$, $Friday$, and $Saturday$, as independent variables. We include individual fixed effects and country-year-month fixed effects to control for potential differences in individual characteristics or the condition in foreign exchange market. All standard errors are clustered by individual and country-year-month level.

We find that remittance transactions are more likely to happen on Monday and the likelihood of remittance gradually decreases afterwards until Saturday. The likelihood of remittance is significantly lower on Saturday and Sunday. This contrasts with our expectation on remittance transactions being high during weekends if individuals had to rely on traditional banks.

In Column (2), we instead use $Weekends_t$ dummy as an independent variable. Again, we find that individuals transact 1.3% less during weekends. Since unconditional probability of remittance transaction is about 4%, the effect is about a 35% reduction (-0.013/0.04=-0.35) in the likelihood of remittance. The significant reduction in remittances during the weekends demonstrates the severity of the constraints that would have imposed to sample individuals without the FinTech service.

Column (3) reports the result using a dummy variable on $Salary\ Days_t$ as an independent variable. $Salary\ Days_t$ is a dummy variable that equals to 1 for the days between 10th to 14th of the month and 0 otherwise. We find that remittance transactions are more likely to occur during salary days. It is 40% increase (0.016/0.04=0.4) in the likelihood of remittance compared to the unconditional probability of remittance. As noted earlier, most of our sample individuals need to send money monthly for family's living and we confirm that they are more likely to send money back to home country when salary is payed.

Column (4) reports the result interacting $Salary\ Days_t$ with $Weekends_t$. We find that the likelihood of remittance during weekends is significantly lower during salary days than the other days. That is, even during the time with high demand of remittance transactions, our sample individuals are more likely to transact during weekdays which further demonstrates

the severity of the constraints discussed above.

Knowing that individuals are more likely to transact during weekdays, what are the determinants of individuals' remittance transactions that are available to individuals through the FinTech platform? First determinant is the *Cancellation* feature in the FinTech platform. The FinTech platform allows users to hold multiple remittance orders up to 24 hours and users only need to decide which orders to execute before they expire. We expect the usage of the feature would be associated with a strong motivation for remittance transactions since it shows that the users are timing the market to transact.

Since the quoted spot exchange rates do not change during weekends, the role of *Cancellation* on remittance decision is limited during weekends. We focus on the sample observations during weekdays so that our sample size reduces from 10,623,364 to 7,591,671 with 368,189 number of actual remittances.[10]

Table 4 reports the descriptive statistics on the characteristics of 368,189 transactions by the usage of *Cancellation*. The usage of *Cancellation* tends to decrease with age and increase with remittance amounts. Female tends to use it more than male and the usage varies by the nationality of individuals. About 10% of remittances by the individuals from Thailand are associated with the *Cancellation* while about 5% of remittances by the individuals from Cambodia are associated with it. Figure 7 plots the Financial Development Index of a country in 2018 from IMF and the average usage of *Cancellation* by the individuals from the country. We find that the usage of *Cancellation* is positively associated with the Financial Development Index of the country. The slope of regressing *Cancellation* on Financial Development Index is 0.06 and statistically significant at 5% level.

Column (1) of Table 5 reports the results using linear probability model of *Cancellation* on the likelihood of remittance. Dependent variable is a dummy variable $D_\{Remittance\}_{i,t}$ that equals to 1 if an individual i transacts on day t and 0 otherwise. We include $Salary\ Days_t$ as a control variable with individual fixed effects and country-year-month fixed effects. Main

[10]For the robustness of our results, we do our analysis including weekends observations to find that the results are qualitatively same.

independent variable is a dummy variable of $Cancellation_{i,t}$ that equals to 1 if an individual i uses $Cancellation$ for any remittance transaction on day t. We find that the likelihood of remittance transaction increases by 35% when $Cancellation$ is used.

Second determinant of daily remittance decision is the lagged percentage change in spot exchange rate of currency c, $\Delta SPOT_{c,t-1} = \log(SPOT_{c,t-1}/SPOT_{c,t-2})$. We merge the lagged daily changes in spot exchange rate of currencies to the individuals by their nationality. In Column (2), we find that the likelihood of remittance transaction increases with the appreciation in spot exchange rate on the previous day. $\Delta SPOT_{c,t-1}$ has a mean of -0.01 with standard deviation of 0.42. In economic terms, for every 1 standard deviation increase in spot exchange rate on the previous day, the likelihood of remittance transaction increases by 4.2% ((0.004*0.42)/0.04).

Similarly, we find that sample individuals are more likely to transact when the spot exchange rate appreciates on the previous day regardless of the magnitude of the change. Column (3) uses a dummy variable of $D_\{\Delta SPOT_{c,t-1} > 0\}$ that equals to 1 if $\Delta SPOT_{c,t-1}$ is positive and 0 otherwise. We find that our sample individuals are more likely to transact after the appreciation of spot exchange rate on the previous day.

What makes individuals trade more after the appreciation of spot exchange rate? One potential story is due to the behavioral bias of our sample individuals. Individuals are known to suffer the "law of small numbers" (Tversky and Kahneman (1971)) and likely to expect balanced outcome to the presumed rate. If the appreciation of spot exchange rate on the previous day makes individuals to expect a depreciation in the following day, we would expect more remittance transactions followed by the appreciations of spot exchange rate.

In Column (4), we put both $D_\{\Delta SPOT_{c,t-1} > 0\}$ and $Cancellation_{i,t}$ into the regression to find that two effects are not inter-dependent in a sense that individual effects remain same. In Columns (5)-(8), we report similar results using the amounts of remittances. Since we observe remittance amounts only if the remittance occurs, our sample size reduces to 368,189. We find that $log(SendAmount_{i,t})$ increases during $Salary\ Days_t$ and increases with

$\Delta SPOT_{c,t-1}$ and with $Cancellation_{i,t}$.

5.2. Optimality of Remittance Transactions

To investigate the performance of our sample individuals in remittance transactions, we compute a set of counterfactual amounts in receiving currency if the transaction occurs in the other days in the window of [-5, +5] around the actual transaction. Normalizing the amounts by the original amounts of remittance in receiving currency at $t = 0$, the measure equals to 1 at $t = 0$.

The measure indicates whether a transaction gets the best exchange rate in 2 weeks horizon or not. If the peak occurs at day 0, this indicates that the individual was able to pick the best day to transact within 2-weeks of time. The peak occuring before day 0 means that the individual should have done the transaction few days earlier to get the best rate. The peak being after day 0 means that the individual should have done the transaction few days later to get the best rate.

Panel A of Figure 8 plots average returns using all remittance transactions in the window of [-5,+5]. We find that the peak occurs just at day 0 although the magnitude is small. On average, our sample individuals outperform around 0.04% compared to the exchange rates in previous 5 days of the remittances and outperform around 0.02% compared to the exchange rates after 5 days of the remittances.

5.2.1. Definition of Optimality Score

The small magnitude in the outperformance is partly due to the difference in individuals' characteristics. We construct a measure of optimality to formally investigate the optimal behavior of individuals' remittance decisions. Panel A of Figure 9 shows an example of a remittance transaction by a Vietnamese user on Aug 28, 2018. The black solid line represents the spot exchange rates from -5 to +5 days of the remittance transaction relative to the spot exchange rate of the actual remittance. The relative spot exchange rate on day 0 is 1 since it

serves as a reference point. We compute the average difference between the reference point and the relative spot exchange rates to construct the *Optimality Score*$_{i,t}$ $[-5, +5]$. In this example, the *Optimality Score*$_{i,t}$ $[-5, +5]$ is 0.0083 indicating that the spot exchange rate applied to the remittance was higher than the average spot exchange rates from -5 to +5 days of the remittance by 0.8%.

But the optimality score can be vary widely across remittance transactions. We provide other examples in Panel B of Figure 9. Top-left figure being same as the one in Panel A, top-right figure reports a remittance transaction by an Indian user on Nov 16, 2018 with the *Optimality Score*$_{i,t}$ $[-5, +5]$ of 0.0028. This means that the spot exchange rate applied to the remittance was higher than the average spot exchange rates from -5 to +5 days of the remittance by 0.3%. We see that the user would get better rate if he/she transacted few days earlier.

The optimality score can be negative if the remittance transaction was not optimally done. Bottom-left figure reports a remittance transaction by an Indonesian user on Jun 26, 2018 with the *Optimality Score*$_{i,t}$ $[-5, +5]$ of -0.0018 and this indicates that the spot exchange rate for the remittance was lower than the average spot exchange rates around the remittance by 0.2%. Bottom-right figure reports a remittance transaction by a Vietnamese user on Jan 22, 2019 with the *Optimality Score*$_{i,t}$ $[-5, +5]$ of -0.0068 indicating that the spot exchange rate for the remittance was lower than the average spot exchange rates from -5 to +5 days of the remittance by 0.7%. Indeed, the remittance transaction occurs at the worst timing in 2-weeks window.

To check the robustness of the *Optimality Score*$_{i,t}$ $[-5, +5]$ measuring optimality in remittance timing, Table 6 reports the results comparing the *Optimality Score*$_{i,t}$ $[-5, +5]$ and the relative ranking of spot exchange rates within 11-days 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 of day 0, i.e. the ranking equals to 11 if the spot exchange rate of day 0 is the highest within the window period and the ranking equals to 1 if the spot exchange rate

of day 0 is the lowest. If correctly measured, *Optimality Score*$_{i,t}$ $[-5, +5]$ should be positively correlated to the probability of having higher ranking.

Panel A reports the logistic regression results using the dummy variables of the relative ranking as dependent variables. The dependent variable in Column (1) is $D_\{Rank = 11\}$ (Highest) which equals to 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 of day 0 being the best rate in the window period. Column (2) uses $D_\{Rank \geq 9\}$, which equals to 1 if the ranking of the spot exchange rate on day 0 is within top 3 and 0 otherwise, to find similar results.

Alternatively, Column (3) uses $D_\{Rank \leq 3\}$, which equals 1 if the ranking of the spot exchange rate on day 0 is within bottom 3 and 0 otherwise, to find that the *Optimality Score*$_{i,t}$ $[-5, +5]$ is negatively correlated with the probability of the spot exchange rate of day 0 being the best rate in the window period. Column (4) uses $D_\{Rank = 1\}$ (Lowest), which equals to 1 if the ranking of the spot exchange rate on day 0 is the lowest and 0 otherwise, to find that the probability of the spot exchange rate of day 0 being the lowest is lower with lower *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.

When we sort our sample individuals by the average *Optimality Score*$_{i,t}$ $[-5, +5]$, we find clearer view on the small magnitude occurring in Panel A of Figure 8. Panel B of Figure 8 plots the average returns using all remittances by the individuals with the optimality score in top 1/3. We again find that the peak occurs just at day 0 but with much larger effect. On average, our sample individuals outperform around 0.54% compared to the spot exchange rates in previous 5 days of the remittances and outperform around 0.49% compared to the spot exchange rates after 5 days of the remittances.

5.2.2. Determinants of Optimal Remittance Transactions

What explains the optimality in the timing of remittance transactions? How does the optimality in the timing of remittance transactions are related to the determinants of remittance decision?

In Table 7, we first report the average *Optimality Score*$_{i,t}$ $[-5, +5]$ by various individual characteristics. We find that the individuals in their 30s show higher optimality score than other age groups. We do not find much difference between female and male users. By country, individuals from Pakistan, Bangladesh, and India have higher average optimality score while individuals from Philippines, Cambodia, and Indonesia have lower average optimality score.

The optimality score is lower during *Salary Days* indicating that the individuals do not have much room to postpone the remittance during the *Salary Days*. Interestingly, we find that the optimality score increases from 0.02 to 0.08 when the users use *Cancellation* for their remittance transactions and it increases from -0.08 to 0.15 if the users do remittance transactions following the appreciation of spot exchange rate on previous day.

Table 8 reports the summary statistics of variables that we use for our analysis of the optimality score. $\log(SendAmount_{i,t})$ has a mean of 12.83, which is about 373,249 KRW, with standard deviation of 1.27. About 7% of our sample remittance transactions are associated with *Cancellation*, about 46% are associated with the appreciation of spot exchange rate, and about 22% are transacted on *Salary Days*$_t$. *Optimality Score*$_{i,t}$ $[-5, +5]$ has mean of 0.03 with standard deviation of 0.41.

Table 9 reports the panel regression results of the determinants of remittance decision on the optimality score. In Panel A, we use *Optimality Score*$_{i,t}$ $[-5, +5]$ as main dependent variable. Column (1) reports the effect of sending amounts on the optimality score. After controlling the individual fixed effect and country-year-month fixed effect, we find that larger sending amounts are associated with higher optimality score. A 1 standard deviation increase in $log(SentAmount_{i,t})$ increases 3% of a 1 standard deviation of the optimality score (0.011*1.27/0.41=0.03). This may indicate that individuals put extra efforts for remittances

with larger amounts when it come to picking the remittance timing.

We decompose *Optimality Score*$_{i,t}$ $[-5, +5]$ into the optimality score in pre-transaction period, *Optimality Score*$_{i,t}$ $[-5, -1]$ in Panel B, and the optimality score in post-transaction period, *Optimality Score*$_{i,t}$ $[+1, +5]$ in Panel C. We find that the sending amounts significantly increases the optimality score only in pre-transaction period. This again supports the explanation that individuals put extra efforts for the larger remittances since the effort only can affect on the optimality in pre-transaction period.

Column (2) reports the results during the *Salary Days*$_t$. In Panel A, we find that the optimality score falls during the *Salary Days*$_t$. As noted earlier, many of our sample individuals have to send money to support their families at home country and they do not have much flexibility in choosing optimal remittance timing. The inflexibility of remittance timing is more likely happening during the salary days. The effect from *Salary Days*$_t$ is 7 times larger than the effect from sending amounts. That is, the optimality score during the salary days is lower as if they are sending 7% less amounts. In Panel B and C, we find that the optimality score similarly decreases during *Salary Days*$_t$ both in the pre-transaction and the post-transaction periods.

Column (3) reports the effect of *Cancellation* on the optimality score. By using the option to hold multiple remittance orders up to 24 hours, individuals can enhance their optimal timing in remittance transactions. With the *Cancellation*, we find that individuals can increase 7% of a 1 standard deviation of the optimality score (0.029/0.41=0.07). Better performance associated with *Cancellation* is not surprising since individuals can hold multiple remittance orders and only need to pick the remittance with best exchange rate. Based on our calculation, the spot exchange rate applied for remittance transactions is higher than the spot exchange rate applied for the cancelled orders associated with the remittances by 1.84% on average.

We expect that the improvement in remittance timing should appear only in the pre-transaction period but not in the post-transaction period. In Panel B and C, we find that *Cancellation* improves the optimality score only in the pre-transaction period. We also find

similar results in Panel C of Figure 8. The optimality of remittance timing is significantly better with *Cancellation* in the pre-transaction period but not in the post transaction period.

Column (4) reports the effect of lagged percentage change in spot exchange rate on the optimality score. $\Delta SPOT_{c,t-1}$ is the log return of spot exchange rate of currency c from $t-2$ to $t-1$ and $D_\{\Delta SPOT_{c,t-1} > 0\}$ is a dummy variable that equals to 1 if $\Delta SPOT_{c,t-1}$ is positive and 0 otherwise. In Panel A, we find that the optimality score increases when individuals transact followed by the appreciation of spot exchange rate on the previous day. The appreciation of spot exchange rate increases 56% of a 1 standard deviation of the optimality score (0.228/0.41=0.56).

After controlling for the usage of *Cancellation*, we still find that $D_\{\Delta SPOT_{c,t-1} > 0\}$ significantly increases the optimality of remittance transactions (Column (5)). When we include all the independent variables in Column (6), we confirm that all the results remains same indicating that the effects are not mutually dependent. When the adjusted R^2 in Column (6) is 0.136, the adjusted R^2 only with $D_\{\Delta SPOT_{c,t-1} > 0\}$ is high as 0.131 and this indicates the dominant role of $D_\{\Delta SPOT_{c,t-1} > 0\}$ in explaining the optimal remittance timing.

Earlier in Table 5, we find that our sample individuals are more likely to make remittance transactions after the appreciation of spot exchange rate. If the behavior is purely due to the behavioral bias, we would expect to find negative performance when individuals follow the behavioral bias. However, we find significant improvement in optimal remittance timing when individuals follow the appreciation of spot exchange rate. How should we understand the results?

We examine the short-term behavior of foreign spot exchange rates. Since our sample individuals are not the professional traders in foreign exchange market nor the individual traders who aim trading profit from the foreign exchange market, they are likely to have a narrow time window for remittance due to the nature of their remittance needs, i.e. monthly remittance for family's living, and the behavior of short-term changes in spot exchange rates are particularly important for the sample individuals.

Main dependent variables in Table 10 are the cumulative changes in spot exchange rates from $t-1$ to $t+s$ for $s = 0, 1, 2, 3$ and 4. In Panel A, we use $\Delta SPOT_{c,t-1}$ as main independent variable and we control for country-year-month fixed effects. When the spot exchange rate appreciates from $t-2$ to $t-1$, we find that the cumulative return from the spot exchange rate in following days are negative. In economic terms, for every 1 standard deviation increase in spot exchange rate from $t-2$ to $t-1$, the cumulative return of the spot exchange rate from $t-1$ to $t+s$ decreases about 0.09 to 0.22 standard deviations. We uses $D_{-}\{\Delta SPOT_{c,t-1} > 0\}$ as main independent variable in Panel B and find that the appreciation of spot exchange rate from $t-2$ to $t-1$ significantly reduces the cumulative return of spot exchange rate in the following days.

If the improvement in remittance timing of individuals comes through the mean-reverting tendency of spot exchange rates in short-term period, we should find a strong effect of $D_{-}\{\Delta SPOT_{c,t-1} > 0\}$ on the post-transaction optimality score. Panel C of Table 9 reports the results using *Optimality Score*$_{i,t}$ $[+1, +5]$ to find that the appreciation of spot exchange rate indeed explains the post-transaction optimality.

The results related to $D_{-}\{\Delta SPOT_{c,t-1} > 0\}$ indicates that the appreciation in spot exchange on the previous day leads to a reversal in spot exchange rate in a near future. As a result, the remittance decisions by the sample individuals following $D_{-}\{\Delta SPOT_{c,t-1} > 0\}$ (as in Table 5) could be resulted in higher optimality in remittance timing (as in Table 9). We then arrive at two alternative explanations for the results. First is the case when our sample individuals understand the short-term mean-reverting behavior of spot exchange rate and follow the signal for their remittance transactions. Second is the case when our sample individuals suffer the behavioral bias believing the mean reversion in spot exchange rates but the spot exchange rates turned out to be favorable to them. To distinguish the two alternative hypothesis, we use the social networks among sample individuals in the FinTech platform to examine the learning effects of these determinants in the social networks.

6. Learning effect through social network

Social network has been an important factor to explain various phenomena including the learning effect through the network.(Hirshleifer (2020), Munshi (2003)) One of the key feature of FinTech platforms is the social network that are associated with the platforms. Many of the FinTech firms take advantage of social network for their expansion. Naturally, it provides an ideal environment to test the learning effect through the social network. As other FinTech platforms, individuals can recommend the Sentbe service to their friends in exchange of bonus credits that can be used for future remittance transactions by the referrers. We are able to construct social networks among our sample individuals by the referral data.

We report an example of a social network among Indonesian users in our sample. Panel A of Table 11 shows 11 Indonesian users with registration date, area of residence, and type of occupation. We label users in an alphabetical order by the time of registration to the system. We find that they are similar to each others in the residence area and the type of occupation. Figure 10 reports the referral relationship between 11 users. User A recommends the service to other users (B, C, D, and H). The user C recommends it again to other users (K, J, and E) and the user E again recommends it to other users (F and I). Lastly, the user F recommends it to user G. We define this group of 11 individuals as a social network.

We report the summary statistics of the social networks in our sample in Table 12. Panel A reports the size distribution of the social networks. We define those networks with more than 4 members as social networks[11] and identify 361 social networks in our sample with average number of users of 6.78. Panel B reports the summary statistics of variables related to social networks. Among 24,687 sample individuals, about 11% of them are associated with some social networks. On average, individuals use *Cancellation* at 65% point in the length of their usage periods. For example, if an individual uses *Cancellation* in his 10th remittance transaction and the total number of remittance transactions of him is 20, then *Time to 1st*

[11] Our results on social networks are robust with any cutoff for the network size from 2 to 4 but the number of social network decreases as we increase the cutoff.

Cancellation is 0.5. *Credit Balance* of individuals has mean of KRW 2,924 with standard deviation of KRW 4,773.

In Panel C, we find that the individuals in social networks have higher number of remittance transactions than the individuals without any social network. The individuals in social networks also use *Cancellation* significantly earlier in their total usage period. The fraction of members of social network being in a same area is higher than unconditional fraction of individuals with same nationality in the area. *Credit Balance* also seems to be higher among the individuals in social networks.

We report additional result validating our social network measure in Panel D. Among the individuals with social networks, we find that the individuals with larger *Credit Balance* amounts are likely to be located at the central nodes in the networks by the measures of $Centrality_d$ and $Centrality_e$ from Banerjee et al. (2013).

6.1. Clustering of remittance transactions within social network

With the identified social networks, we first test whether the remittance transactions within a social network are clustered. Panel B of Table 11 shows an example of the time stamps of remittance transactions occurred in the social network in Panel A on Feb 25th, 2020. Followed by the user B who submitted the remittance order at 16:16, different users sequentially submitted remittance orders on the same day.

To further examine the clustered remittance transactions within a social network, for each social network, we form a hypothetical matching group with the same number of individuals who are individually matched to individuals in the social network in terms of nationality, total number of remittance, and the average amounts of remittance in that month. Figure 11 compares the daily number of remittances in February 2020 between the social network in Figure 10 and its matching group of individuals. 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 matching group. We find that the remittance transactions seem to be

more clustered in the social network.

We compute the Herfindahl-Hirschman index (HHI) of the remittance transactions in social network and its matching group for each trading months. For example, the HHI of the remittance transactions of the month in Figure 11 is 0.0089 for the social network and 0.0035 for the matching group. When we calculate the average HHI for all social networks in all trading months, the average HHI of social networks is 0.0123 while the average HHI of the matching groups is 0.0082 so that the average HHI of social networks is 50% higher than the average HHI of the matching groups with t-statistics of 3.65.

6.2. Learning the determinants through social network

We use the learning effect through the social network to distinguish the hypothesis we discussed in the earlier section. We find that two determinants, the usage of *Cancellation* and the appreciation of spot exchange rate on the previous day, increase the likelihood of remittance transaction and the optimality of the remittance timing.

While *Cancellation* is unarguably a feature that helps users to improve their remittance timing, the role of the appreciation of spot exchange rate is less clear since the result can be driven by the realization of favorable behaviors in spot exchange rates to individuals' behavioral bias. If individuals recognize the determinants as valuable signals for remittance transactions, we would expect a learning occurring in the social networks. By testing whether the determinants are learnt through the social network or not, we can intepret the meaning of the determinants.

Table 13 reports the learning of *Cancellation* in the social network. Dependent variable is a dummy variable of $Cancellation_{i,t}$ which equals to 1 if an individual i uses *Cancellation* on day t and 0 otherwise. In Column (1), main independent variable is a dummy variable of $I_SocialNetwork_{i,t}$ which equals to 1 if an individual i is affiliated to any social network at day t and 0 otherwise. We control a dummy variable for the appreciation of lagged spot exchange rate ($D_\{\Delta SPOT_{c,t-1} > 0\}$), $log(SendAmount_{i,t})$, a dummy variable for $Salary\ Days_t$ with

country-year-month fixed effects. We find that being in a social network does not change the likelihood of using *Cancellation*. We also find that younger females are more likely to use *Cancellation* and the remittance transactions with larger amounts are more likely associated with *Cancellation*.

In Column (2), we use $CancellationHistory_IN_{i,t}$, the ratio of the cumulative number of cancellations to the cumulative number of remittance transactions up to day t by individual i, as independent variable. We find that individuals use *Cancellation* more when they have more experience with it. For minimizing look-ahead bias due to the individual fixed effects, we do not include individual fixed effects but include individual characteristics as control variables.

In Column (3), we use $CancellationHistory_SN_{i,t}$, the ratio of the cumulative number of cancellations to the cumulative number of remittance transactions up to day t by all individuals in the social network s that individual i belongs to excluding the individual i's own cancellations and remittances, as independent variable. We find that being in a social network actually lowers the likelihood of using *Cancellation*. But only when the social network has cumulative experience among users using *Cancellation*, individuals tends to use *Cancellation* more. The result indicates that individuals are learning about *Cancellation* through their social networks. Column (4) include both $CancellationHistory_IN_{i,t}$ and $CancellationHistory_SN_{i,t}$ to find that both effects are still significant. We find that the effect from the social network experience is similar to the effect from individual experience.

In Table 14, we investigate the learning through social network on the appreciation of spot exchange rate on the previous day. The dependent variable is a dummy variable of $D_\{Remittance\}_{i,t}$ which equals to 1 if an individual i transacts on day t and 0 otherwise. The result in Column (1) uses the regression specification that is similar to Table 5 except we exclude individual fixed effects but include individual control variables and additional variable on the learning. The main independent variable is $SpotHistory_IN_{i,t}$, the ratio of the cumulative number of remittances on the following day with the appreciation in spot rate change to the total number of remittance transactions by day t.

As in Table 5, the likelihood of remittance transaction increases with $D_\{\Delta SPOT_{c,t-1} > 0\}$, $Cancellation_{i,t}$, and *Salary Days*. We also find that the likelihood of remittance transactions increase with $SpotHistory_IN_{i,t}$. That is, an individual is more likely to do remittance transactions as he has more experience of remittance transactions associated with the appreciation of spot exchange rate on the previous day. This may be due to individuals' overconfidence through their superior past performances. The individuals with more experience of remittance transactions when the spot exchange rate appreciates have higher optimality score due to the mean-reverting behavior of spot exchange rate in our sample.

Column (2) includes the interaction term between $SpotHistory_IN_{i,t}$ and $D_\{\Delta SPOT_{c,t-1} > 0\}$. We find that the interaction is not significant. That is, individuals who tend to do remittance transactions when the spot exchange rate appreciate on the previous day do not show higher probability of remittance transaction when the appreciation actually occurs. This indicates that the individuals are not taking the appreciation of spot exchange rate as a signal for remittance decisions. It seems to be a behavioral response to the appreciation of spot exchange rate given a positive coefficient on $D_\{\Delta SPOT_{c,t-1} > 0\}$.

Column (3) use $SpotHistory_SN_{i,t}$, the ratio of the cumulative number of remittance transactions on the following day with the appreciation in spot rate change to the total number of remittances before day t by all individuals in the social network s excluding the individual i's own remittances, are main independent variable. While $SpotHistory_SN_{i,t}$ increases the likelihood of remittance, the interaction term between $SpotHistory_SN_{i,t}$ and $D_\{\Delta SPOT_{c,t-1} > 0\}$ does not show significant effect in Column (4). This indicates that individuals in a social network did not learn about the usage of $D_\{\Delta SPOT_{c,t-1} > 0\}$ as a signal for remittance timing through the network.

What does this imply to the value of FinTech to retail consumers? Additional flexibility in FinTech platform can allow users to improve their financial decisions though constraint-free transactions with some unique features in the technology such as *Cancellation* in our case. And the information can be spread out through the social networks to improve the decisions

of other consumers in the networks. However, the additional flexibility can exacerbate the effect of the behavioral bias of retail consumers on their optimal decisions. Considering the general consensus of unpredictable short-term foreign exchange rate from a large body of empirical literature (i.e. Meese and Rogoff (1983)), the flexibility of remittance transactions may harm consumers' welfare when the short-term behaviors of spot exchange rate change but the consumers remain overconfident on their ability of optimal decisions.

7. Conclusion

We study the value of FinTech for retail consumers from individual overseas remittances on a FinTech platform. The value of FinTech mostly comes through overcoming various frictions such as high cost or time/spatial constraints of transaction. Using detailed transaction-level overseas remittance data from a leading FinTech firm in Korea, we find that the FinTech platform lowers remittance cost by 10.6% on average compared to traditional commercial banks. However, we find mixed results regarding the time/spatial flexibility provided by the FinTech platform that it may not always lead to the optimal timing of remittance transactions. While the FinTech platform can enhance consumer welfare by allowing constraint-free transactions with some advanced features in the platform, the flexibilities can also harm consumers by amplifying their behavioral bias.

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Table 1: Individual Remittance Transactions by Nationality

We report the summary statistics of individual remittance transactions by users' nationality. Our sample includes individuals-transactions from February 2016 to March 2020 for the remittances to 9 Southeast Asian Countries including Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, Philippine, Thailand, and Vietnam. We report the number of sample users, their number of remittance transactions, average sending amounts in Korean Won (KRW), and average age by users' nationality. We also report average number of remittance transactions per month.

		Number of Total		Sending Amounts (KRW)		# of Remittances	
Country	Data Starts	Users	Remittances	Mean	Median	per Month	Age
Bangladesh	Jun-18	530	3,583	874,835	418,770	1.57	31
Cambodia	Jul-18	500	5,041	656,564	455,430	1.99	28
India	Jul-18	1,765	17,498	1,459,941	1,077,860	1.61	33
Indonesia	Sep-16	4,994	91,149	723,133	340,540	2.13	30
Malaysia	Jul-18	167	2,233	816,842	465,000	2.55	27
Pakistan	Jul-18	1,290	12,346	972,833	627,314	1.70	32
Philippines	Feb-16	8,231	244,297	497,465	266,320	2.31	32
Thailand	Apr-18	1,074	15,182	1,257,479	1,000,000	2.03	32
Vietnam	Jun-16	7,443	85,330	1,075,212	700,000	1.72	28
Total	Feb-16	25,994	476,659	721,912	374,690	2.08	31

Table 2: Cost Structure of Commercial Banks and FinTech

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

Panel A: Cost Structure

	Amounts (KRW)		
Type of Cost	IBK	Woori	Sentbe
Telegraphic Charges	5,000	5,000	5,000
Sending Amount Fees			
up to $500	5,000	5,000	
from $500 to $2,000	10,000	10,000	
from $2,000	15,000	15,000	
Margin (%)	0.94	0.97	1.00
Brokerage Fees	10,000	10,000	

Panel B: Margin by Country of Destination

Margin (%)	IBK	Woori	Sentbe
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	0.95	0.97	1.00
Vietnam		0.83	1.00
Average	0.94	0.97	1.00

Table 3: Daily Remittance Decisions

We report the panel regression results of individual daily remittance decisions. Starting from our data on daily user-level transactions from February 2016 to March 2020, we fill zeros for all users without any remittance transaction from 1 month before the day of first remittance to 1 month after the last day of remittance. As a result, the dataset has 10,623,364 observations. The dependent variable is a dummy variable $D_\{Remittance_{i,t}\}$ which equals to 1 if an individual i transacts on day t and 0 otherwise. Column (1) reports the result using dummy variables of $Monday$, $Tuesday$, $Wednesday$, $Thursday$, $Friday$, and $Saturday$ as independent variables. We include individual fixed effects and country-year-month fixed effects. Column (2) reports the result using a dummy variable of $Weekends_t$ as an independent variable. Column (3) reports the result using a dummy variable of $Salary\ Days_t$ as an independent variable. Column (4) reports the result using $Weekends_t$, $Salary\ Days_t$, and the interaction of $Weekends_t$ and $Salary\ Days_t$ as independent variables. All the standard errors are clustered at the individual and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)
Variables		$D_\{Remittance_{i,t}\}$		
$Monday$	0.021***			
	(18.38)			
$Tuesday$	0.013***			
	(12.40)			
$Wednesday$	0.010***			
	(9.74)			
$Thursday$	0.007***			
	(7.06)			
$Friday$	0.005***			
	(5.51)			
$Saturday$	-0.004***			
	(-7.67)			
$Weekends_t$		-0.013***		-0.012***
		(-15.23)		(-13.48)
$Salary\ Days_t$			0.016***	0.017***
			(12.33)	(10.89)
$Weekends_t \times Salary\ Days_t$				-0.006***
				(-3.75)
Observations	10,623,364	10,623,364	10,623,364	10,623,364
Adjusted R^2	0.023	0.023	0.023	0.023
Individual FE	Yes	Yes	Yes	Yes
Country-Year-Month FE	Yes	Yes	Yes	Yes

Table 4: Descriptive Statistics of Cancellation Usage

We report the descriptive statistics of the usage of *Cancellation* by different characteristics of individual users. We report the average usage of *Cancellation* by age, sending amounts, gender, and nationality. We divide the sample by age into three groups of Below 30s, 30s, and Above 30s. We divide the sample by sending amounts into three groups of below 30th quantile (Below Q30), between 30th to 70th quantile (Q30-Q70), and above 70th quantile (Above Q70).

	Average Usage		Number of		
Group	Mean	Std. Dev.	Users	Cancellations	Remittances
Age					
Below 30s	0.067	0.250	12,542	10,776	160,496
30s	0.065	0.247	10,450	11,388	173,917
Above 30s	0.060	0.237	1,695	2,012	33,776
Sending Amounts					
Below Q30	0.049	0.216	6,987	5,414	110,456
Above Q70	0.085	0.278	8,919	9,347	110,455
Q30-Q70	0.064	0.245	8,781	9,415	147,278
Gender					
Female	0.077	0.267	6,357	8,457	109,133
Male	0.061	0.239	18,267	15,683	258,748
Nationality					
Bangladesh	0.077	0.267	442	206	2,659
Cambodia	0.050	0.219	453	181	3,597
India	0.088	0.283	1,708	1,370	15,587
Indonesia	0.057	0.232	4,686	3,832	66,906
Malaysia	0.095	0.293	155	167	1,764
Pakistan	0.078	0.269	1,218	805	10,294
Philippines	0.059	0.235	7,914	10,732	182,447
Thailand	0.104	0.305	1,035	1,345	12,995
Vietnam	0.077	0.267	7,076	5,538	71,940
Total	0.066	0.248	24,687	24,176	368,189

Table 5: Determinants of Individual Remittance Decisions

We report the panel regression results of determinants of individual remittance decision. In Columns (1)-(4), dependent variable is the dummy variable of $D_\{Remittance_{i,t}\}$ that equals to 1 if individual i remits currency c on day t and 0 otherwise. Column (1) reports the result using $Cancellation_{i,t}$ as the main independent variable. $Cancellation_{i,t}$ is a dummy variable that equals to 1 if individual i uses the *Cancellation* for the remittance transaction on day t. We include *Salary Days*$_t$ as a control variable with individual fixed effects and country-year-month fixed effects. Column (2) reports the result using $\Delta SPOT_{c,t-1}$ (%) as the main independent variable. $\Delta SPOT_{c,t-1}$ is the lagged change of spot exchange rate of currency c from $t-2$ to $t-1$. Column (3) reports the result using a dummy variable of $D_\{\Delta SPOT_{c,t-1} > 0\}$ that equals to 1 if $\Delta SPOT_{c,t-1}$ is positive and 0 otherwise. Column (4) reports the result including $Cancellation_{i,t}$ and $D_\{\Delta SPOT_{c,t-1} > 0\}$ as independent variables. In Columns (5)-(8), we use $\log(SendAmount_{i,t})$ as dependent variable. All the standard errors are clustered at the individual and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$D_\{Remittance_{i,t}\}$				$\log(SendAmount_{i,t})$			
$Cancellation_{i,t}$	0.353***			0.353***	0.221***			0.221***
	(67.80)			(67.83)	(28.19)			(28.35)
$\Delta SPOT_{c,t-1}$ (%)		0.004***				0.045***		
		(3.78)				(5.00)		
$D_\{\Delta SPOT_{c,t-1} > 0\}$			0.003***	0.003***			0.034***	0.034***
			(3.87)	(3.42)			(4.44)	(4.43)
Salary Days$_t$	0.016***	0.017***	0.017***	0.016***	0.164***	0.167***	0.166***	0.165***
	(10.91)	(10.95)	(10.83)	(11.00)	(12.84)	(13.15)	(12.98)	(13.01)
Observations	7,591,671	7,591,671	7,591,671	7,591,671	368,189	368,189	368,189	368,189
Adjusted R^2	0.048	0.024	0.024	0.048	0.351	0.349	0.349	0.351
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Validity of Optimality Score

We report the results of logistic regression and Pearson correlation between the optimality score and the rank of spot exchange rate in 2-weeks window. Panel A reports the logistic regression results using the dummy variables of the relative ranking as dependent variables. The dependent variable in Column (1) is $D_\{Rank_{c,t} = 11\}$ (Highest) that equals to 1 if the spot exchange rate of day 0 is the highest in the window and 0 otherwise. Main independent variable is *Optimality Score*$_{c,t}$ $[-5, +5]$ which is the optimality score of the day t of 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 to 1 if the ranking of the spot exchange rate in day 0 is within 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 bottom 3 in the window and 0 otherwise. Column (4) uses $D_\{Rank_{c,t} = 1\}$ (Lowest) that equals to 1 if the ranking of the spot exchange rate in 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*$_{i,t}$ $[-5, +5]$. We report the p-value of the Pearson correlation in angular bracket. All standard errors in 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

Table 7: Descriptive 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, gender, nationality, and sending amounts. We divide the sample by age into three groups of Below 30s, 30s, and Above 30s. We divide the sample by sending amounts into three groups of below 30th quantile (Below Q30), between 30th to 70th quantile (Q30-Q70), and above 70th quantile (Above Q70). We also report the average optimality score by the determinants of remittance decisions such as *SalaryDays*, the usage of *Cancellation*, and the sign of $\Delta SPOT_{c,t-1}$.

	Average Optimality Score				Number of	
Group	Mean	Std. Dev.	10th Perc.	90th Perc.	Users	Remittances
Age						
Below 30s	0.026	0.450	-0.485	0.533	12,542	160,496
30s	0.030	0.455	-0.481	0.537	10,450	173,917
Above 30s	0.017	0.455	-0.481	0.509	1,695	33,776
Gender						
Female	0.028	0.423	-0.478	0.521	6,357	109,133
Male	0.027	0.464	-0.492	0.531	18,267	258,748
Nationality						
Bangladesh	0.079	0.494	-0.529	0.645	442	2,659
Cambodia	0.013	0.445	-0.538	0.572	453	3,597
India	0.071	0.498	-0.438	0.608	1,708	15,587
Indonesia	0.016	0.480	-0.461	0.466	4,686	66,906
Malaysia	0.027	0.378	-0.411	0.468	155	1,764
Pakistan	0.109	0.761	-0.637	0.792	1,218	10,294
Philippines	0.010	0.418	-0.487	0.509	7,914	182,447
Thailand	0.054	0.367	-0.409	0.496	1,035	12,995
Vietnam	0.054	0.454	-0.491	0.588	7,076	71,940
Sending Amounts						
Below Q30	0.003	0.438	-0.490	0.494	6,987	110,456
Q30-Q70	0.011	0.448	-0.496	0.516	8,781	147,278
Above Q70	0.073	0.470	-0.455	0.585	8,919	110,455
Salary Days						
No	0.042	0.455	-0.454	0.542	19,442	287,624
Yes	-0.027	0.440	-0.562	0.507	5,245	80,565
Usage of *Cancellation*						
No	0.023	0.450	-0.485	0.527	22,256	344,013
Yes	0.081	0.488	-0.452	0.601	2,431	24,176
$\Delta SPOT_{c,t-1}$						
≤ 0	-0.080	0.436	-0.584	0.447	13,112	197,675
> 0	0.151	0.440	-0.306	0.617	11,575	170,514
Total	0.027	0.453	-0.483	0.533	24,687	368,189

Table 8: Summary Statistics of Individual Daily Remittances

We report the summary statistics of individual daily remittances. $\log(SendAmount_{i,t})$ is the log of sending amounts (KRW) of an individual i at day t. $Cancellation_{i,t}$ is a dummy variable that equals to 1 if an individual i use the *Cancellation* for the remittance on day t and 0 otherwise. $\Delta SPOT_{c,t-1}$ is lagged daily change of spot rate of currency c from $t-2$ to $t-1$. $D_\{\Delta SPOT_{c,t-1} > 0\}$ is a dummy variable that equals to 1 if $\Delta SPOT_{c,t-1} > 0$ and 0 otherwise. *Salary Days*$_t$ is a dummy variable that equals to 1 for days between 10th and 14th of each month and 0 otherwise. *Optimality Score*$_{i,t}$ $[-5,+5]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the 2-weeks window of [-5, +5]. Similarly, *Optimality Score*$_{i,t}$ $[-5,-1]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the window of [-5, -1] and *Optimality Score*$_{i,t}$ $[+1,+5]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the window of [+1, +5]. Financial Development Index is the IMF financial development index by country and we match it to individuals by their nationality. We winsorize $\log(SendAmount_{i,t})$, $\Delta SPOT_{c,t-1}$, *Optimality Score*$_{i,t}$ $[-5,+5]$, *Optimality Score*$_{i,t}$ $[-5,-1]$, *Optimality Score*$_{i,t}$ $[+1,+5]$, and Age at 1% and 99% level.

Variable	Observations	Mean	Std.Dev.	10th Perc.	90th Perc.
$\log(SendAmount_{i,t})$	368,189	12.83	1.27	11.00	14.51
$Cancellation_{i,t}$	368,189	0.07	0.25	0	0
$\Delta SPOT_{c,t-1}$ (%)	368,189	0.01	0.43	-0.52	0.51
$D_\{\Delta SPOT_{c,t-1}\}$	368,189	0.46	0.50	0	1
Salary Days$_t$	368,189	0.22	0.41	0	1
Optimality Score$_{i,t}$ $[-5,+5]$ (%)	368,189	0.03	0.41	-0.48	0.53
Optimality Score$_{i,t}$ $[-5,-1]$ (%)	368,189	0.03	0.54	-0.61	0.68
Optimality Score$_{i,t}$ $[+1,+5]$ (%)	368,189	0.02	0.54	-0.62	0.67
Financial Development Index	368,189	0.37	0.08	0.29	0.39
Age	368,189	31.09	5.92	24	39

Table 9: Determinants of Optimal Remittance Timing

We report the panel regression results of the determinants of optimal remittance timing. Panel A use *Optimality Score*$_{i,t}$ $[-5,+5]$ as main dependent variable. *Optimality Score*$_{i,t}$ $[-5,+5]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the 2-weeks window of [-5, +5]. Column (1) reports the result using $\log(SendAmount_{i,t})$ as independent variable where $\log(SendAmount_{i,t})$ is the log of sending amounts (KRW) of an individual i at day t. We include individual fixed effects and country-year-month fixed effects. Column (2) reports the result using $SalaryDays_t$, a dummy variable that equals to 1 for days between 10th and 14th of each month and 0 otherwise, as independent variable. Column (3) reports the result using $Cancellation_{i,t}$, a dummy variable that equals to 1 if an individual i use the $Cancellation$ for the remittance on day t and 0 otherwise, as independent variable. Column (4) report the result using $D_\{\Delta SPOT_{c,t-1} > 0\}$, a dummy variable that equals to 1 if $\Delta SPOT_{c,t-1} > 0$ and 0 otherwise, as independent variable. Column (5) include both $Cancellation_{i,t}$ and $D_\{\Delta SPOT_{c,t-1} > 0\}$ as independent variables. Column (6) includes all the covariates. Panel B use *Optimality Score*$_{i,t}$ $[-5,-1]$ as main dependent variable. *Optimality Score*$_{i,t}$ $[-5,-1]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the window of [-5, -1]. Panel C use *Optimality Score*$_{i,t}$ $[+1,+5]$ as main dependent variable. *Optimality Score*$_{i,t}$ $[+1,+5]$ is the average percentage difference between actual spot rate charged on a remittance at day t and the spot rates in the window of [+1, +5]. All standard errors in panel regressions are clustered at individual and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: Determinants of Optimality Score in the Window of [-5, +5]

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Optimality Score*$_{i,t}$ $[-5,+5]$ (%)					
$\log(SendAmount_{i,t})$	0.011***					0.010***
	(5.13)					(6.41)
Salary Days$_t$		-0.074**				-0.070**
		(-2.07)				(-2.07)
$Cancellation_{i,t}$			0.029***		0.028***	0.026***
			(7.10)		(7.05)	(7.01)
$D_\{\Delta SPOT_{c,t-1} > 0\}$				0.228***	0.228***	0.227***
				(14.90)	(14.90)	(15.21)
Observations	368,189	368,189	368,189	368,189	368,189	368,189
Adjusted R^2	0.059	0.063	0.059	0.131	0.132	0.136
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9 Continues

Panel B: Determinants of Optimality Score in the Window of [-5, -1]						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Optimality Score*$_{i,t}$ $[-5,-1]$ (%)					
$\log(SendAmount_{i,t})$	0.018***					0.016***
	(7.34)					(8.45)
Salary Days$_t$		-0.063				-0.056
		(-1.41)				(-1.40)
$Cancellation_{i,t}$			0.046***		0.045***	0.042***
			(8.43)		(8.41)	(8.36)
$D_\{\Delta SPOT_{c,t-1} > 0\}$				0.363***	0.363***	0.362***
				(18.53)	(18.53)	(18.84)
Observations	368,189	368,189	368,189	368,189	368,189	368,189
Adjusted R^2	0.240	0.241	0.240	0.348	0.348	0.351
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Determinants of Optimality Score in the Window of [+1, +5]						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*Optimality Score*$_{i,t}$ $[+1,+5]$ (%)					
$\log(SendAmount_{i,t})$	0.002					0.003
	(0.68)					(1.53)
Salary Days$_t$		-0.069				-0.068
		(-1.59)				(-1.58)
$Cancellation_{i,t}$			0.004		0.004	0.004
			(0.89)		(0.87)	(0.93)
$D_\{\Delta SPOT_{c,t-1} > 0\}$				0.049**	0.049**	0.048**
				(2.53)	(2.53)	(2.50)
Observations	368,189	368,189	368,189	368,189	368,189	368,189
Adjusted R^2	0.221	0.224	0.221	0.223	0.223	0.225
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Short-term Behavior of Foreign Exchange Rate

We report the panel regression results of short-term behavior of foreign exchange rates. We use the exchange rates of 9 countries that Sentbe is servicing. The foreign exchange rate is expressed as foreign currency unit per KRW. Dependent variables are $\Delta SPOT_{c,t-1\to t+s}$ for $s = 0, 1, 2, 3, 4$, which are the log ratio of spot exchange rates between day $t-1$ and $t+s$ ($\log(SPOT_{c,t+s}/SPOT_{c,t-1})$). Column (1) uses $\Delta SPOT_{c,t-1\to t}$, Column (2) uses $\Delta SPOT_{c,t-1\to t+1}$, Column (3) uses $\Delta SPOT_{c,t-1\to t+2}$, Column (4) uses $\Delta SPOT_{c,t-1\to t+3}$, and Column (5) uses $\Delta SPOT_{c,t-1\to t+4}$. In Panel A, main independent variable is $\Delta SPOT_{c,t-1}$, which is the log ratio of spot exchange rate between day $t-2$ and $t-1$. We also include country-year-month fixed effects. In Panel B, main independent variable is $D_\{\Delta SPOT_{c,t-1} > 0\}$, which is a dummy variable that equals to 1 if $\Delta SPOT_{c,t-1} > 0$ and 0 otherwise. All the standard errors are clustered at the country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: Short-term Behavior of Foreign Exchange Rate

	(1)	(2)	(3)	(4)	(5)
			$\Delta SPOT_{c,t-1\to t+s}$		
Variable	$s = 0$	1	2	3	4
$\Delta SPOT_{c,t-1}$	-0.117***	-0.086***	-0.140***	-0.171***	-0.215***
	(-5.82)	(-4.16)	(-5.84)	(-6.93)	(-8.93)
Observations	6,657	6,657	6,657	6,657	6,657
Adjusted R^2	0.017	0.059	0.100	0.138	0.173
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes

Panel B: Short-term Behavior of Foreign Exchange Rate When It Appreciates

	(1)	(2)	(3)	(4)	(5)
			$\Delta SPOT_{c,t-1\to t+s}$		
Variable	$s = 0$	1	2	3	4
$D_\{\Delta SPOT_{c,t-1} > 0\}$	-0.070***	-0.086***	-0.119***	-0.152***	-0.168***
	(-6.09)	(-5.65)	(-5.97)	(-6.42)	(-6.39)
Observations	6,657	6,657	6,657	6,657	6,657
Adjusted R^2	0.008	0.059	0.098	0.136	0.169
Country-Year-Month FE	Yes	Yes	Yes	Yes	Yes

Table 11: An Example of Social Network

We report a real example of social network among Indonesian users with the list of users and the clustering behavior in users' remittance within the network. In Panel A, we report the list of users in the network. We label the users by the order of users' registration date. We report the area of residence and occupation type for the users. Panel B reports an example of the remittance transactions by the users in the network on February 25th, 2020.

Panel A: List of Users in a Social Network

User	Registration Date	Area of Residence	Occupation Type
A	2018-05-24	Gyeongju-si, Gyeongsangbuk-do	
B	2018-05-31	Gyeongju-si, Gyeongsangbuk-do	
C	2018-06-10	Gyeongju-si, Gyeongsangbuk-do	
D	2018-10-28	Gyeongju-si, Gyeongsangbuk-do	
E	2018-12-06	Jeju-si, Jeju-do	Wage Worker
F	2018-12-07	Jeju-si, Jeju-do	Wage Worker
G	2018-12-07	Jeju-si, Jeju-do	Wage Worker
H	2019-02-10	Gyeongju-si, Gyeongsangbuk-do	
I	2019-03-23	Jeju-si, Jeju-do	Wage Worker
J	2019-06-07		
K	2019-10-14		Wage Worker

Panel B: Clustering in Remittance Transaction, Example of February 25th, 2020

User	Remittance Time	Area of Residence	Occupation Type
B	2020-02-25 16:16	Gyeongju-si, Gyeongsangbuk-do	
J	2020-02-25 16:22		
G	2020-02-25 18:33	Jeju-si, Jeju-do	Wage Worker
E	2020-02-25 20:24	Jeju-si, Jeju-do	Wage Worker
I	2020-02-25 20:27	Jeju-si, Jeju-do	Wage Worker

Table 12: Descriptive Statistics of Social Networks

We report the descriptive statistics of social networks and the characteristics of social networks. Panel A reports the summary statistics of the number of users in the social networks. We limit our definition of social network for those networks with more than 4 users in it. Panel B reports the summary statistics of individual-level variables that are related to the social networks. *I_SocialNetwork* is a dummy variable that equals to 1 if the individual is in any of the social networks and 0 otherwise. *Number of Remittances* is the total number of remittances by individuals in our sample. *Time to 1st Cancellation* is the relative time of the first usage of *Cancellation* to the total number of remittances by individuals. *% of Users in Same Area* is the fraction of users in the social network who has same area of residence. For those without social network, we use the fraction of the users in the same area of residence with same nationality. *Credit Balance* is the average credit amounts of users. $Centrality_d$ and $Centrality_e$ are the measures of the centrality of an individual in the network from Banerjee et al. (2013). These measures are only defined for users in any social network. $Centrality_d$ measures the degree centrality of individuals in social networks and $Centrality_e$ measures the eigenvector centrality of individuals in social networks. Panel C reports cross-sectional regression results of individual characteristics with social networks. The dependent variables are *Number of Remittances* in Column (1), *Time to 1st Cancellation* in Column (2), *% of Users in Same Area* in Column (3), and *Credit Balance* in Column (4). Panel D reports the Pearson correlation between *Credit Balance*, $Centrality_d$ and $Centrality_e$. ***, **, * denotes 1%, 5%, and 10% statistical significance.

Panel A: Distribution of the Number of Users in the Social Networks

	Observations	Mean	Std. Dev.	10th Perc.	90th Perc.
Number of Users	361	6.78	9.49	4	11

Panel B: Summary Statistics

	Observations	Mean	Std. Dev.	10th Perc.	90th Perc.
I_SocialNetwork	24,687	0.11	0.31	0	1
Number of Remittances	24,687	14.91	16.29	2	34
Time to 1st Cancellation	24,687	0.65	0.40	0	1
% of Users in Same Area	18,984	0.10	0.20	0.01	0.25
Credit Balance	24,323	2,924	4,773	1,000	5,000
$Centrality_d$	2,615	1.80	3.07	1	3
$Centrality_e$	2,615	0.31	0.19	0.07	0.65

Panel C: Individual Characteristics with Social Networks

	(1) *Number of Remittances*	(2) *Time to 1st Cancellation*	(3) *% of Users in Same Area*	(4) *Credit Balance*
I_SocialNetwork	4.388***	-0.056***	0.516***	1,815.331***
	(13.16)	(-6.76)	(176.27)	(18.63)
Constant	14.442***	0.651***	0.045***	2,726.076***
	(132.05)	(241.47)	(47.10)	(84.66)
Observations	24,687	24,687	18,984	24,323
Adjusted R^2	0.007	0.002	0.621	0.014

Panel D: Correlation between Credit Balance and Network Centrality

	Credit Balance	$Centrality_d$	$Centrality_e$
Credit Balance	1		
$Centrality_d$	0.74***	1	
$Centrality_e$	0.18***	0.38***	1

Table 13: Learning About the Usage of Cancellation

We report the panel regression results of the usage of *Cancellation* in a social network on the individual usage of the *Cancellation*. The dependent variable is $Cancellation_{i,t}$, which is a dummy variable that equals to 1 if an individual i use the *Cancellation* for the remittance on day t and 0 otherwise. Column (1) reports the result using $I_SocialNetwork_{i,t}$ as main independent variable. We control $D_\{\Delta SPOT_{c,t-1} > 0\}$, $\log(SendAmount_{i,t})$, $Salary\ Days_t$, Age, and $Male$ with country-year-month fixed effects. Column (2) reports the result using $CancellationHistory_IN_{i,t}$ as main independent variable. $CancellationHistory_IN_{i,t}$ is the ratio of the cumulative number of remittances involving cancellations before day t to the total number of remittances before day t, $\left(\sum_{\tau<t} Cancellation_{i,\tau}\right) / \left(\sum_{\tau<t} D_\{Remittance_{i,\tau}\}\right)$. We also control $I_SocialNetwork_{i,t}$. Column (3) reports the result using $CancellationHistory_SN_{i,t}$ as main independent variable. $CancellationHistory_SN_{i,t}$ is the ratio of the cumulative number of remittances involving cancellations before day t in a social network where the individual i is in to the total number of remittances before day t in the social network excluding the individual i's own cancellations and remittances, $\left(\sum_{\tau<t, j\in s} Cancellation_{j,\tau}\right) / \left(\sum_{\tau<t, j\in s} D_\{Remittance_{j,c,s,\tau}\}\right)$. Column (4) reports the result using both $CancellationHistory_IN_{i,t}$ and $CancellationHistory_SN_{i,t}$. All standard errors in panel regressions are clustered at individual and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)
Variables		$Cancellation_{i,t}$		
$I_SocialNetwork_{i,t}$	0.003	0.002	-0.010**	-0.008**
	(1.46)	(1.28)	(-2.59)	(-2.41)
$CancellationHistory_IN_{i,t}$		0.189***		0.189***
		(19.83)		(19.77)
$CancellationHistory_SN_{i,t}$			0.198***	0.155***
			(4.12)	(3.77)
$D_\{\Delta SPOT_{c,t-1} > 0\}$	0.002*	0.001	0.002*	0.001
	(1.85)	(1.56)	(1.84)	(1.55)
$\log(SendAmount_{i,t})$	0.011***	0.011***	0.011***	0.011***
	(16.43)	(17.66)	(16.45)	(17.67)
$Salary\ Days_t$	0.001	0.001	0.001	0.001
	(0.33)	(0.57)	(0.33)	(0.57)
Age	-0.000***	-0.000***	-0.000***	-0.000***
	(-4.22)	(-4.05)	(-4.20)	(-4.04)
$Male$	-0.021***	-0.019***	-0.021***	-0.019***
	(-11.77)	(-12.07)	(-11.77)	(-12.06)
Observations	368,189	368,189	368,189	368,189
Adjusted R^2	0.010	0.020	0.011	0.020
Country-Year-Month FE	Yes	Yes	Yes	Yes

Table 14: Learning About the Short-Term Behavior of Spot Exchange Rate

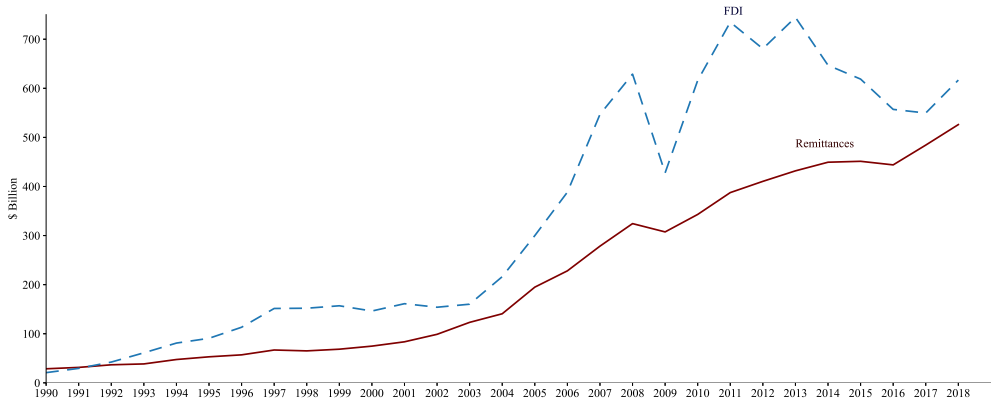
We report the panel regression results of the history of transactions with the appreciation in the spot exchange rate on individuals' remittance decision with the appreciation in the spot exchange rate. The dependent variable is $D_\{Remittance_{i,t}\}$, which is a dummy variable that equals to 1 if an individual i transacts on day t and 0 otherwise. Column (1) reports the result using $SpotHistory_IN_{i,t}$ as the main independent variable. $SpotHistory_IN_{i,t}$ is the ratio of the cumulative number of remittances with the appreciation of spot exchange rate on the previous day to the total number of remittances before day t, $\left(\sum_{\tau<t} D_\{\Delta SPOT_{c,\tau-1} > 0\}\right) / \left(\sum_{\tau<t} D_\{Remittance_{i,\tau}\}\right)$. We control $D_\{\Delta SPOT_{c,t-1} > 0\}$, $Cancellation_{i,t}$, $Salary\ Days_t$, Age, and $Male$ with country-year-month fixed effects. Column (2) reports the result using the interaction term of $D_\{\Delta SPOT_{c,t-1} > 0\}$ and $SpotHistory_IN_{i,t}$. Column (3) reports the result using $SpotHistory_SN_{i,t}$ as the main independent variable. $SpotHistory_SN_{i,t}$ is the ratio of the cumulative number of remittance with the appreciation of spot exchange rate on the previous days to the total number of remittances before day t in a social network s where the individual i is in excluding the individual i's own remittances, $\left(\sum_{\tau<t,j\in s} D_\{\Delta SPOT_{c,\tau-1} > 0\}\right) / \left(\sum_{\tau<t,j\in s} D_\{Remittance_{j,s,\tau}\}\right)$. Column (4) reports the result using the interaction term of $D_\{\Delta SPOT_{c,t-1} > 0\}$ and $SpotHistory_SN_{i,t}$. All standard errors in panel regressions are clustered at individual and country-year-month level. ***, **, * denotes 1%, 5%, and 10% statistical significance.

	(1)	(2)	(3)	(4)
Variables		$D_\{Remittance_{i,t}\}$		
$SpotHistory_IN_{i,t}$	0.008***	0.008***		
	(8.63)	(8.21)		
$D_\{\Delta SPOT_{c,t-1} > 0\} \times SpotHistory_IN_{i,t}$		0.000		
		(0.55)		
$SpotHistory_SN_{i,t}$			0.008***	0.008***
			(5.28)	(4.83)
$D_\{\Delta SPOT_{c,t-1} > 0\} \times SpotHistory_SN_{i,t}$				0.001
				(0.51)
$D_\{\Delta SPOT_{c,t-1} > 0\}$	0.003***	0.002***	0.003***	0.003***
	(3.44)	(3.06)	(3.39)	(3.45)
$Cancellation_{i,t}$	0.360***	0.360***	0.360***	0.360***
	(67.32)	(67.32)	(67.33)	(67.33)
$Salary\ Days_t$	0.016***	0.016***	0.016***	0.016***
	(11.04)	(11.04)	(11.04)	(11.04)
Age	0.000***	0.000***	0.000***	0.000***
	(6.38)	(6.38)	(6.50)	(6.50)
$Male$	-0.009***	-0.009***	-0.009***	-0.009***
	(-7.21)	(-7.21)	(-7.30)	(-7.30)
Observations	7,591,671	7,591,671	7,591,671	7,591,671
Adjusted R^2	0.031	0.031	0.031	0.031
Country-Year-Month FE	Yes	Yes	Yes	Yes

Figure 1: Overseas Remittance toward Low- and Middle-Income Countries

We plot the overseas remittance toward low- and middle-income countries. The sample period is from 1990 to 2018. Panel A plots the aggregated amounts of remittance flows to the full sample of low- and middle-income countries and Panel B plots the aggregated amounts excluding China. We also plot the amounts of Foreign Direct Investment (FDI) for comparison. The data is from World Bank (2019).

Panel A: Remittance Flows and Foreign Direct Investment



Panel B: Remittance Flows and Foreign Direct Investment Excluding China

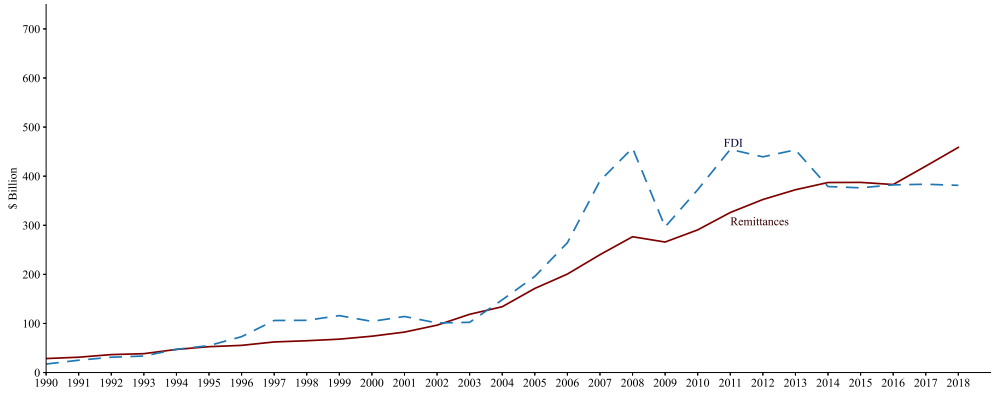
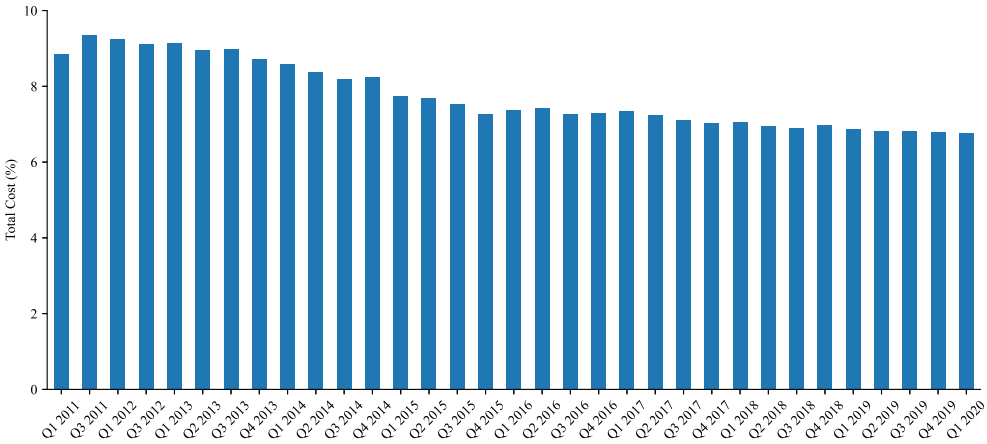


Figure 2: Cost of Overseas Remittance

We plot the cost of overseas remittance using the quarterly data from 2011 Q1 to 2020 Q1. Panel A shows the time-series plot of the global average cost of sending $200. Panel B plots the average costs of remitting $200 by type of provider. The left Panel reports the average cost of worldwide full sample including 48 countries and the right panel reports the average cost of 9 countries with the remittance service provided by our FinTech platform, Sentbe, such as Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, Philippine, Thailand, and Vietnam. The data is from World Bank (2019).

Panel A: Global Average Cost of Sending $200, from 2011 Q1 to 2020 Q1



Panel B: Average Costs of Remitting $200 by Type of Provider, from 2011 Q1 to 2020 Q1

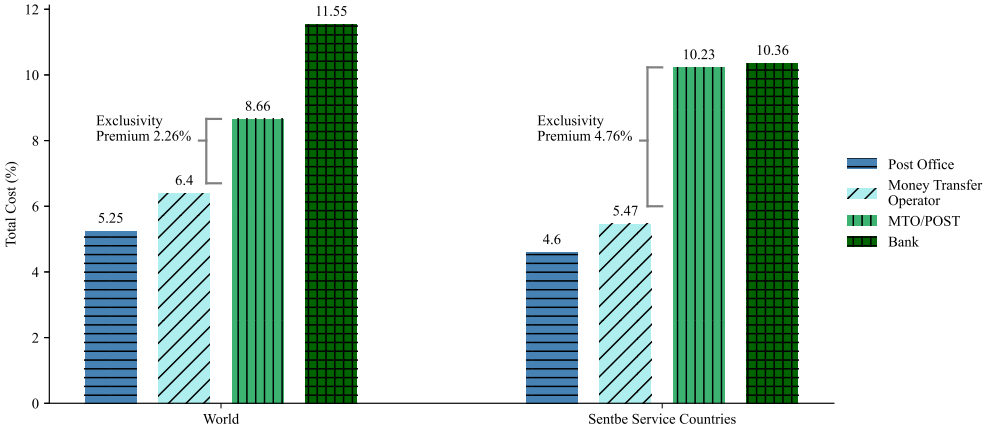


Figure 3: Importance of the Overseas Remittance in Southeast Asian Region

We plot the total remittance amounts in 2018 and the percentage of remittance amounts in the countries' GDP in 2018 for the countries with the FinTech remittance service such as Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, Philippine, Thailand, and Vietnam. The left panel plots the total amounts of remittance in 2018, and the right panel plots the percentage of remittance amounts in the countries' GDP.

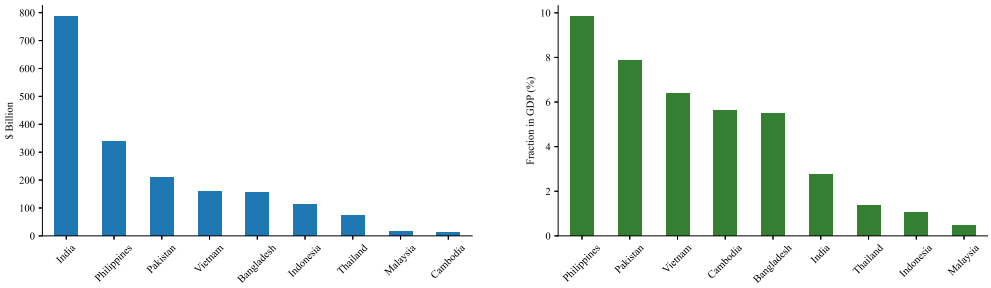
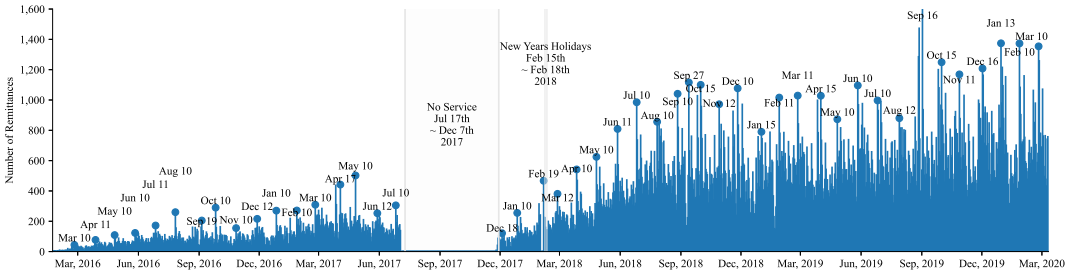


Figure 4: Time-Series of Individual Remittance Transactions

We plot the time-series of the number of individual remittances. Panel A plots the daily number of remittances in our sample period. The circle markers indicate the days with monthly peak of remittance transactions. The FinTech service was not available 2 times in our sample period. The first is from July 17th to December 7th of 2017, and the second is from February 15th to 18th of 2018. Panel B plots the number of remittances in each day of a month. Panel C plots the number of remittances in each day of a week. Panel D plots the number of remittances in each 10 minutes in a day. The marker indicates 12:30PM when the maximum number of remittances in a day occurs.

Panel A: Number of Daily Remittances in Our Sample Period



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

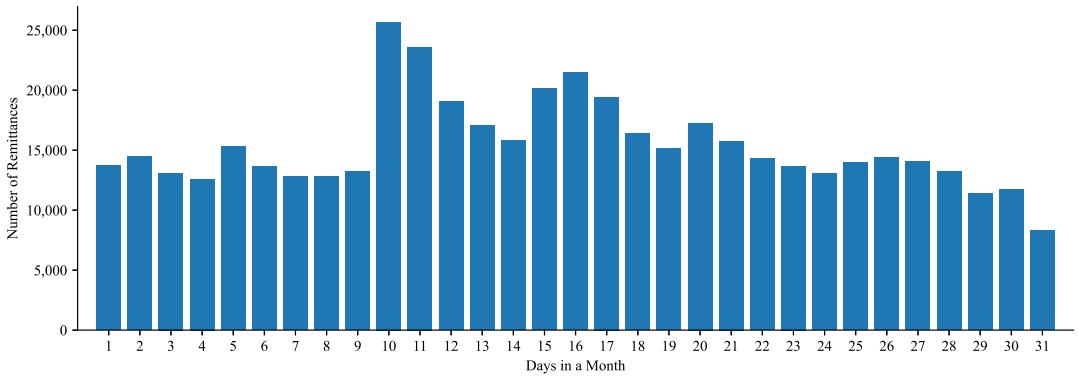
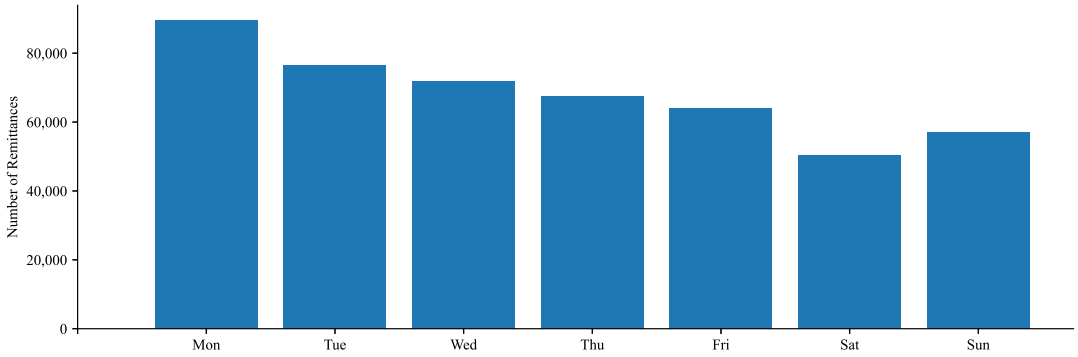


Figure 4 Continues

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



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

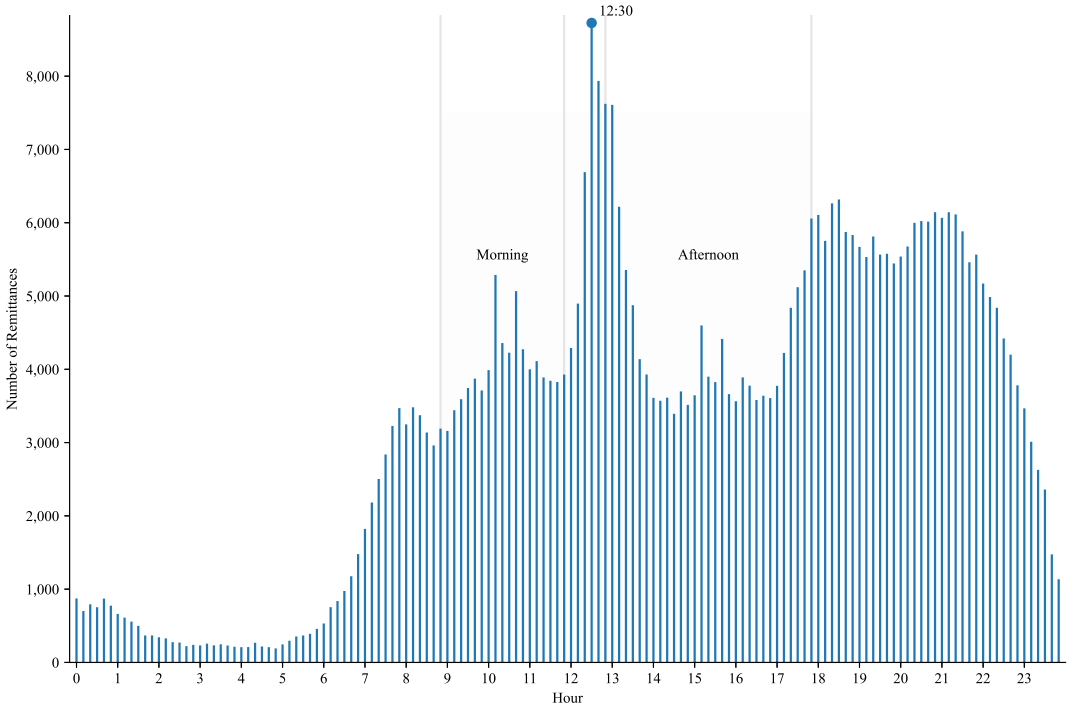


Figure 5: Spot Exchange Rates

We plot the spot exchange rates of the currencies for 9 countries in our sample. The sample period is from February 2016 to March 2020. Countries may have different starting dates due to the different starts of the FinTech service for those countries.

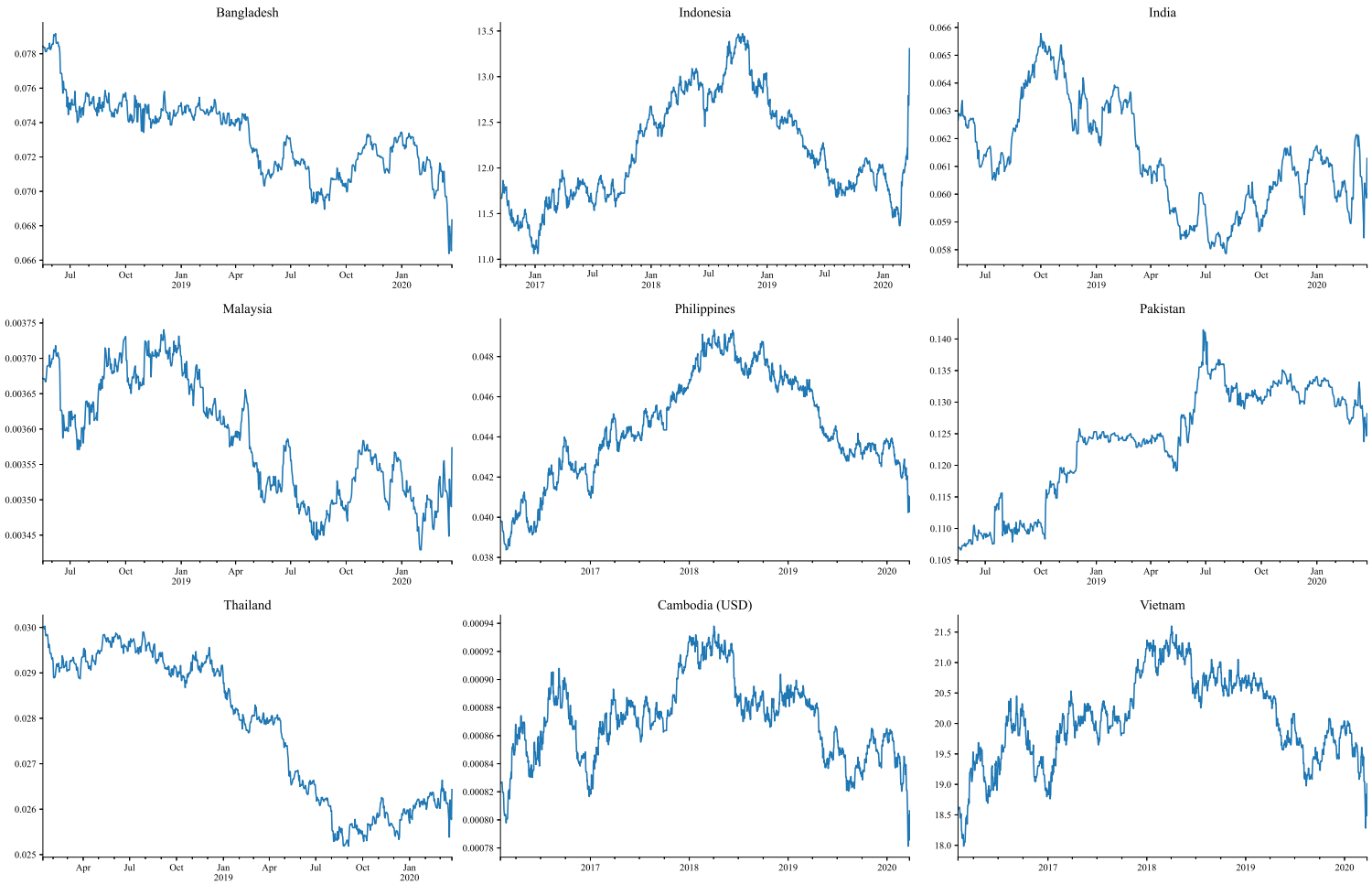


Figure 6: Comparison of Remittance Cost between FinTech and Commercial Banks

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 sending amounts in x-axis and the cost of remittance for the amounts in y-axis. Solid line reports the remittance cost associated with the sending amounts using FinTech Platform and dotted line reports the remittance cost associated with the sending amounts using commercial banks. The difference between two lines is the difference in remittance cost for the amounts. We also report the remittance transactions in our data by the bins of 10,000 Korean Won. We compute and report the transaction-weighted difference between two lines for the average benefit from cost reduction using FinTech. Panel B plots the similar results by country.

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

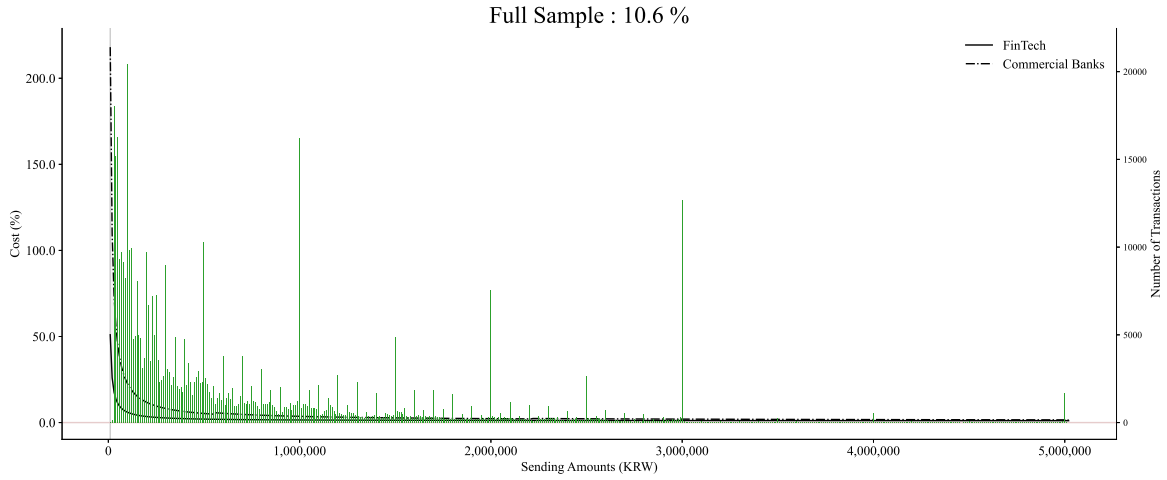


Figure 6 Continues

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

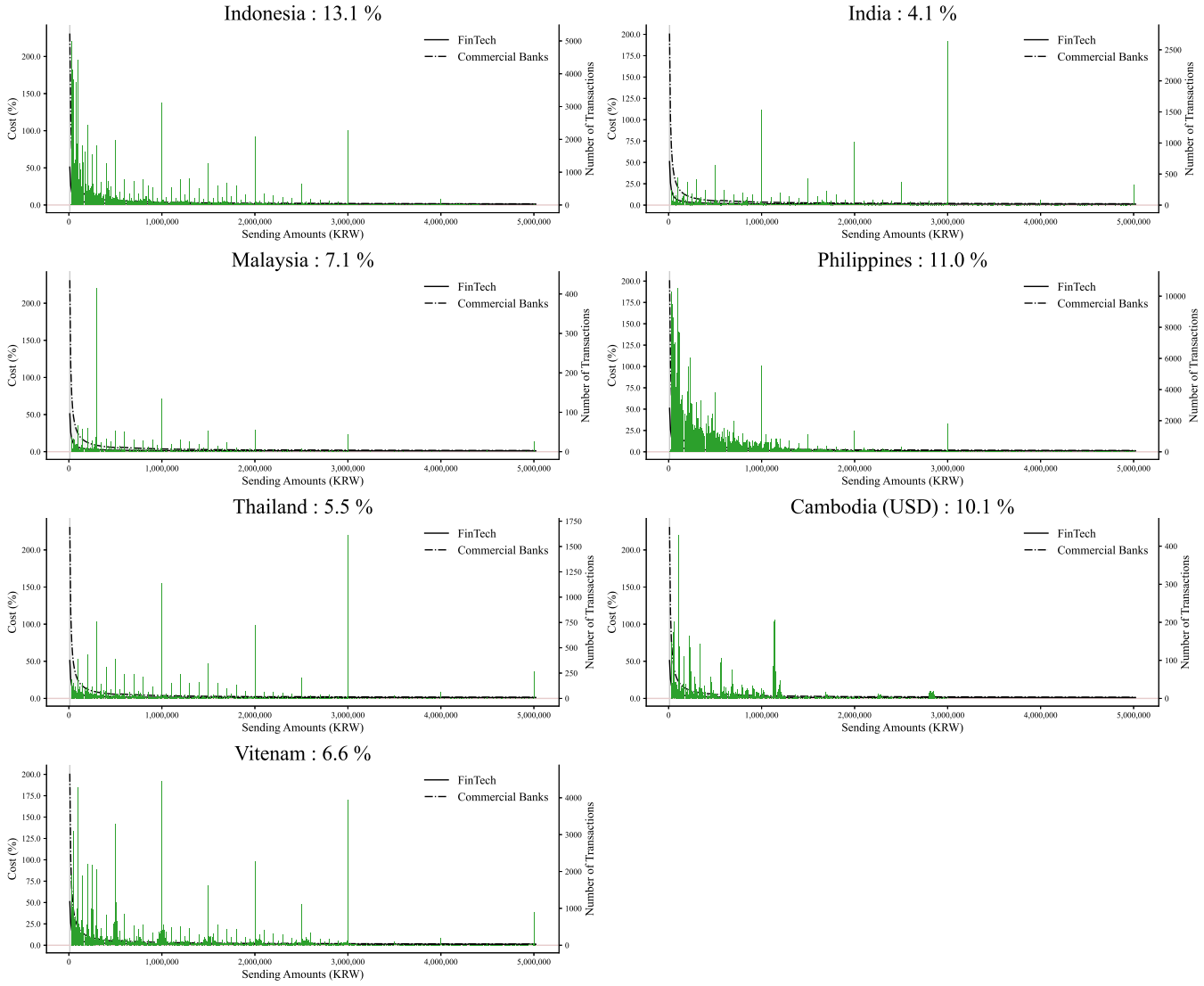


Figure 7: Financial Development Index and the usage of *Cancellation*

We plot the financial development index and the probability of using the *Cancellation* feature in the FinTech platform. The x-axis is the Financial Development Index in 2018 from IMF. The y-axis is the average probability of using *Cancellation* by the individuals from the country. We include the linear-fitted line.

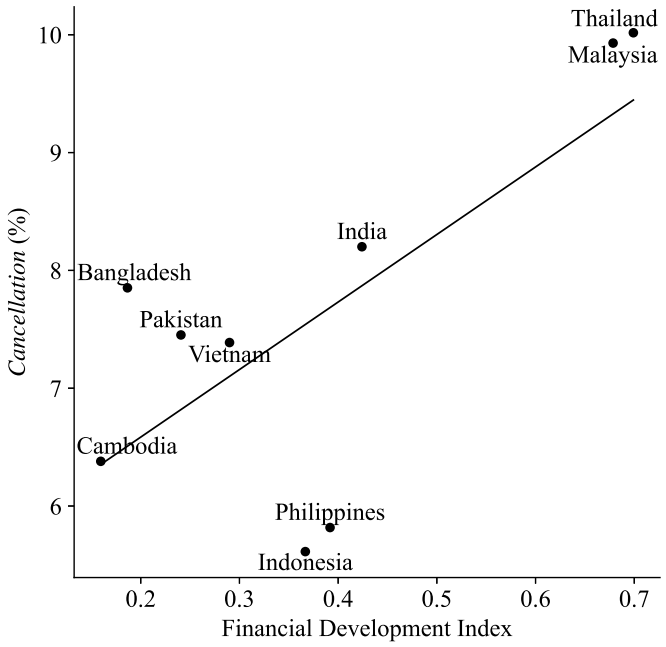


Figure 8: Optimality in Remittance Timing

We plot the average optimality of remittance transactions. For each remittance transaction, we compute hypothetical remittance amounts in 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 receiving currency on day 0. Panel A reports the average relative spot exchange rate using full sample. We report the 95% confidence interval around the line. Instead of using full sample, Panel B only use the sample individuals in top 1/3 among all sample individuals in terms of the optimality. The box plots report 10th, 25th, 50th, 75th, and 90th of the distribution. Panel C plots the average optimality of remittance transactions with the usage of *Cancellation*. The solid line reports the relative spot exchange rate of users with *Cancellation* and the dashed line reports the relative spot exchange rate of users without *Cancellation*. We report 95% confidence intervals associated with the two lines. All the standard errors are clustered at the individual, and currency-year-month level.

Panel A: Average Optimality Score in Full Sample

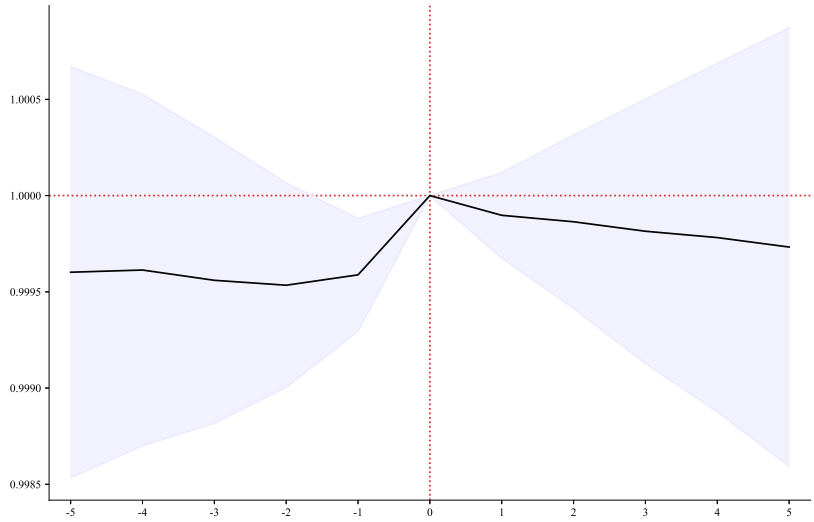
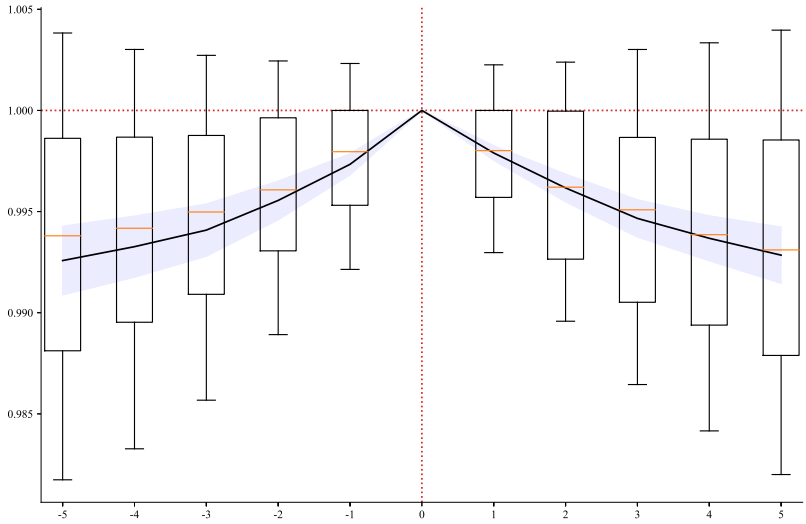


Figure 8 Continues

Panel B: Average Optimality Score of Top 1/3



Panel C: Average Optimality Score with the Usage of *Cancellation*.

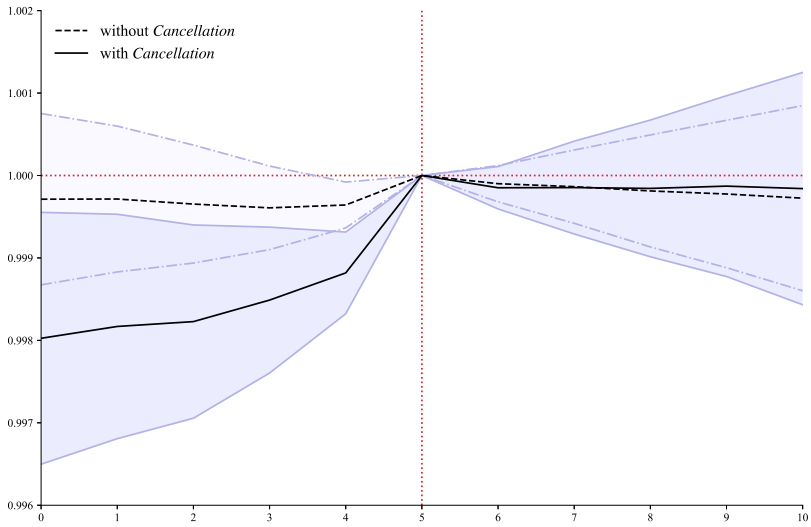


Figure 9: Measure of Optimal Remittance Timing

We report some examples of calculating optimality score using real examples in the data. In Panel A, we plot the spot exchange rate in the window of [-5, +5] relative to the spot exchange rate of day 0 using an example of a Vietnamese user on August 28th, 2018. The difference of 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 score. While top-left figure reports the same example as in Panel A, we report other examples with various optimalities in remittance timings.

Panel A: Example of Optimal Remittance Timing

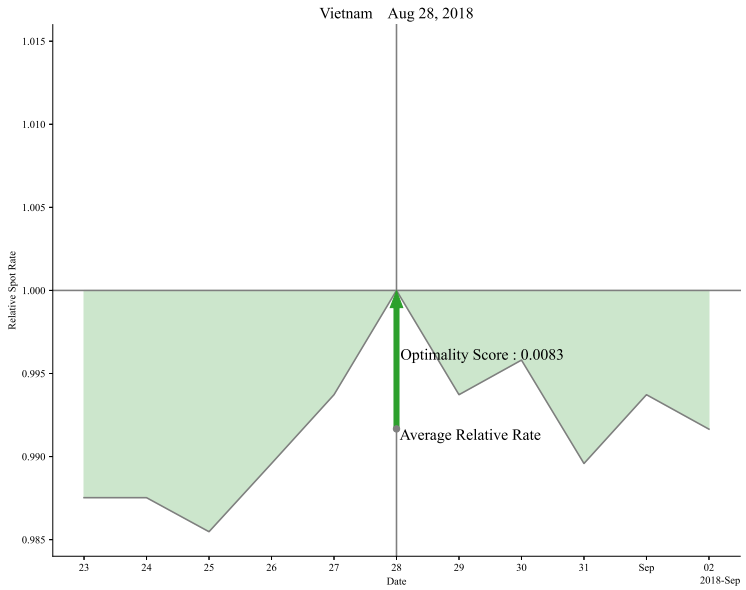


Figure 9 Continues

Panel B: Other Examples

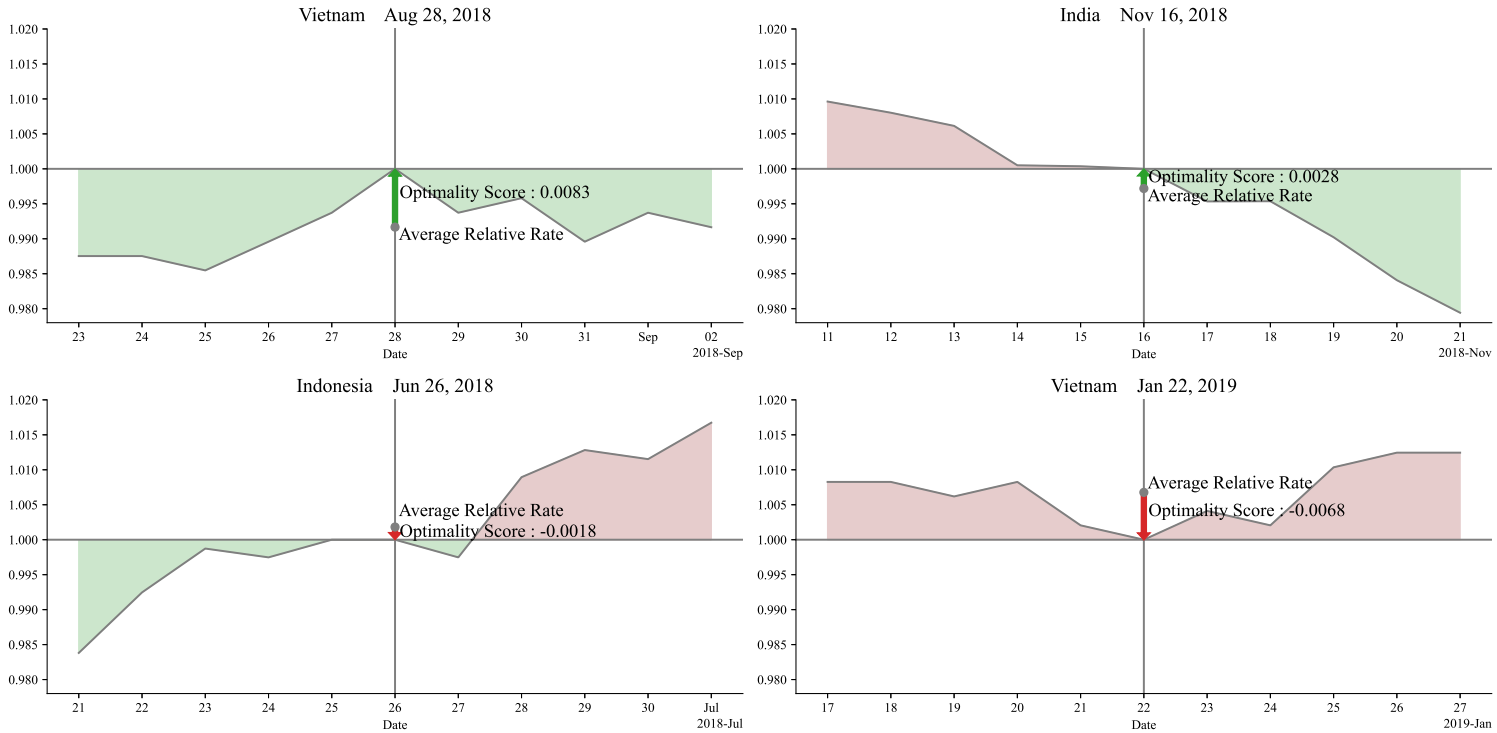


Figure 10: An Example of Social Network

We report an example of a social network among Indonesian users. We label the users by the order of their registration dates to the FinTech platform. In this example, user A recommends the platform to B, C, D, and H. The user C recommends it to E, J, and K and the user E recommends it to F and I. And the user F recommend it to G.

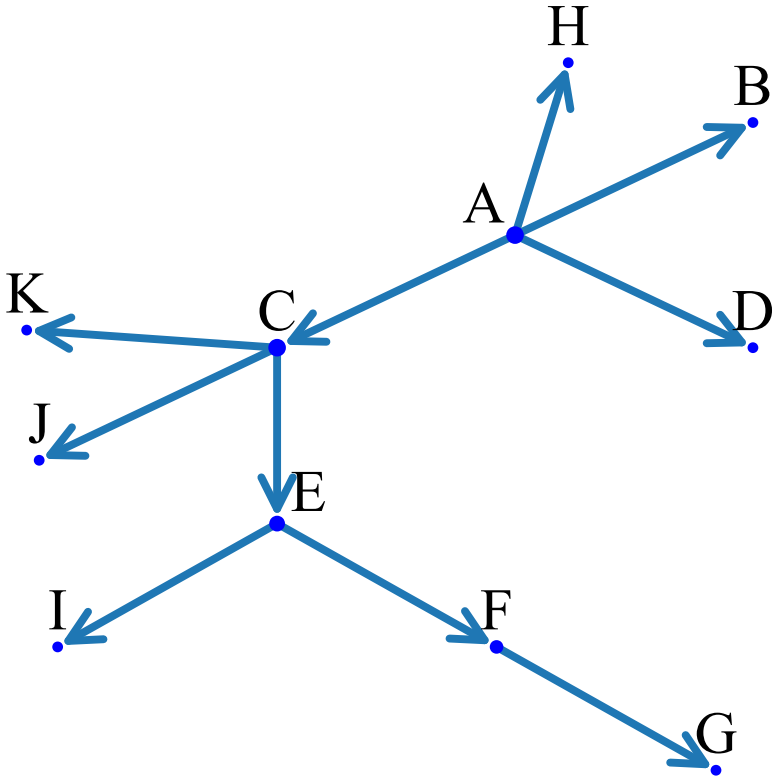
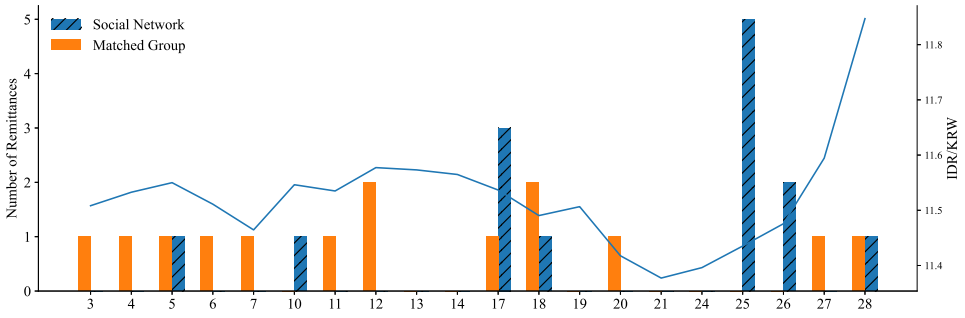


Figure 11: Clustered Remittance Transactions within a Social Network

We plot an example of clustered remittance transactions within the social network in Figure 10 in February 2020. We plot the daily aggregated number of remittance transaction by the users in the social network (blue dash bar) and their matching sample without social network (orange solid bar). We also plot the spot exchange rate of Indonesian Rupiah in the unit of 1 Korean Won.