The Value of Fintech for Retail Consumers

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PRELIMINARY DRAFT. PLEASE DO NOT CITE!!!

Abstract:

We measure the value for retail consumers of using a Fintech platform to send international remittance payments. The value of Fintech mostly comes through overcoming various frictions such as the high cost of sending payments or the time-constraints of transactions. Using detailed transaction-level international remittance data from a leading Fintech firm in Korea, we find that the Fintech significantly lowers the cost for low-income workers to send money home. On average, the Fintech platform lowers remittance cost by 10.6 percent, as compared to traditional commercial banks. Yet, while the Fintech enhances consumer welfare by increasing the flexibility of transactions, the flexibility offered by a cancellation feature of the Fintech product might not always lead to the optimal exchange rate timing of remittance transactions and can also harm consumers by amplifying their behavioral bias. We also construct social networks among workers in our sample using the Fintech and use this data as an identification strategy to show learning effects among these workers.

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1. Introduction

Globalization has increased labour migration and the number of international migrants reached nearly 272 million in 2019, up from 153 million in 1990 (United Nations, 2019). Many migrants are motivated by higher wages and better opportunities in foreign countries and the growth in migration has been accompanied by an increase in the value of international remittance sent back to migrants' home countries (Lucas and Stark, 1985; Funkhouser, 1995; and Clemens and Tiongson, 2017). According to World Bank estimates, remittances will total $573 billion dollars in 2019, of which US$422 billion went to developing countries that involved 250 million migrant workers. For some individual recipient countries, remittances can be as high as a third of their GDP (World Bank, 2019).

Sending international remittance can be expensive, unsafe, and difficult for workers. The global average cost of sending $200 internationally has only fallen from 9% in 2011 to 7% in 2019, which is still a financial burden for migrant workers (World Bank, 2019). Most money is sent through cash couriers, informal methods of transferring money (like Hawala), money wiring services (like Western Union), or banks. For example, according to a 2019 survey of migrant workers living in Korea, 81% of Nepali respondents informally sent money home mainly through individual brokers, known as Hundi, despite the high risk (IOM, 2019). However, the use of Financial technology (Fintech) to make international remittances has grown over the past few years with the use of mobile apps and mobile money services such as TransferWise and PayPal Zoom.

In this paper, we estimate the value of Fintech for retail consumers using transaction-level data of international remittances sent using a Fintech platform. The value of Fintech is mostly derived by relaxing various frictions such as the high cost or time (spatial) constraints of making a transaction. Our dataset allows us to study: First, the value of Fintech to reduce the costs of international remittances; second, the consequence of greater flexibility in the timing of transactions; and third, the influence of social networks on timing 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. While they find substantial value creation to innovators, they find mixed results for other financial industry participants by their willingness to adopt new technology. 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. Our paper complements this literature by focusing on additional benefits of Fintech: the reduction in cost and the flexibility in the timing of payment transactions.

We use detailed transaction-level international remittance data from ‘Sentbe’, a Korean digital money transfer operator, which sent more than USD$880 million in accumulated remittances from Korea over the 2019 calendar year.[1] Until recently, the remittance market in Korea was controlled entirely by large financial institutions—leading to high foreign transfer fees and costly delays. However, regulatory changes introduced in 2017 allowed non-bank Fintechs to offer consumer remittance services. Sentbe has drastically reduced the cost of remittance to 1.2% of the total remitted amount, while the total remittance costs of sending money through a bank remains at about 8%. Typically, money sent via Sentbe is available for family members to collect in 1-hour, as compared to 2-3 days for conventional bank services. Recipients can choose their payout option: a home delivery or cash pick-up point.

Fintech platforms provide both a cheaper solution for international remittances and additional flexibility in the timing of remittance transactions. Compared to traditional banks, Fintech platforms enable senders to overcome time and physical constraints. For example, typically, workers would need to visit a bank branch during the bank’s working hours. This constraint is especially binding for those who are tied to their jobs during the bank’s working hours, e.g. low skilled workers and workers who need to travel significant distance to visit a bank branch, such as workers living in sparsely populated areas. Fintech allows users to execute remittance transactions regardless of time and physical location.

There are several advantages of using this data to study our research questions. First, detailed information on the timing and amounts of international remittances, combined with rich demographic information about the consumers, allows us to examine individual remittance decisions. Second, we can exploit two novel features of the platform: A “cancellation” feature that allows users to cancel their order within 24 hours, for no fee. In addition, we can exploit a cash bonus for referring the product to friends to construct “social networks” of users.

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

We use this data, plus daily spot exchange rate for a window around the executed payment, to construct a measure of how well users time the exchange rate market, which we call our "optimality" score. We find that users are more likely to optimize the timing of their payment when: (i) transaction amounts are larger; (ii) the exchange rate appreciated on the previous day; and (ii) and the cancelation feature was used during the optimization period. We also show that this information is shared among social networks.

Most of our sample are foreign workers from Northeast and Southeast Asia working in Korea, who are typically low-skilled workers and need to transfer a significant part of their earnings to support their families back home.[1] Although these workers having little formal education or experience using formal financial services, international remittance are a large portion of their income and they would exert their best efforts in making remittance decisions.

Our data also shows that workers are more likely to send an international remittance payment the day after the spot exchange rate of their home country appreciates (relative to the KRW). In economic terms, for every one-standard deviation increase in spot exchange rate on the previous day, the likelihood of remittance transaction increases 4.2%. This result is robust to using the appreciation (percentage change) of spot exchange rate on the previous day. Importantly, this shows that workers respond to changes in exchange rates when deciding when to send international remittances.

We find two other features of the Fintech platform that improve the welfare of workers. First is the *Cancellation* feature that allows users to hold multiple remittance orders up to 24 hours and users can decide at any time which orders to execute before they expire. We find that workers from countries with higher levels of financial development are more likely to use this feature. Use of the *Cancellation* feature is also associated with a higher optimality score: the average spot exchange rate applied for completed remittance transactions is 1.84% higher than the average spot exchange rates of those cancelled orders associated with the completed order.

Finally, we exploit a unique feature that is associated with Fintech platforms to test whether workers learn through their social networks the optimal timing for their international

[1] Sentbe focuses on sending money to the Southeast and Northeast Asia corridors and foreign workers in our sample are from Bangladesh, China, Indonesia, India, Cambodia, Malaysia, Philippine, Pakistan, Thailand, and Vietnam.

remittance payments. Workers that use Sentbe can recommend the platform to their friends in exchange for bonus credits that can be used for future remittance transactions by the referrers. We use this referral data to construct social networks among the workers in our sample and use this data as an identification strategy to show learning effects among these workers.

2. The use of fintech for overseas remittance payments

Over the last decade, international remittance sent to low- and middle-income countries has grown fast (Figure 1). The total amounts of international remittances sent to low- and middle-income countries increased from about 150 billion dollars in 2004, to 500 billion dollars in 2019 (Panel A). Furthermore, excluding china, international remittances sent to low- and middle-income countries exceeds the total amounts of foreign direct investment to these countries (Panel B). International remittances also make large contributions to the local GDP of many countries, i.e. international remittances sent to Philippines contributed 10.2% of total GDP in 2018 and contributed more than 5% of GDP in Pakistan, Vietnam, Cambodia, and Bangladesh (Figure 3).

Despite fast growth, sending international remittance often remains difficult and expensive (Figure 2). For example, according to the World Bank, the global average cost of sending $200 is 7% of the transaction amount, a decline of only 2 percentage points from 2011 (Panel A). The cost of remittance is also sensitive to the competitiveness of the industry, as shown by the average cost, by type of service provider, from 2011 to 2020 (Panel B). Banks on average charge the highest rate (11.55%), while public post offices charge the lowest (5.25%). Money transfer operators charge, on average, 6.4%--but this charge increases to 8.66% when the money transfer operator has an exclusive partnership arrangement with the local post office.

To address the challenges to workers sending money home, there has been a global surge in the creation and growth of Fintech firms servicing international remittance payments. These Fintech solutions offer cheaper and easier solutions, e.g. TransferWise or PayPal. In Korea, a long history of strict regulations on foreign exchange transactions (the Foreign Exchange Transactions Act), limited formal international remittance payments to regulated banking institutions, who charged high prices with limited competition. In June, 2017, the Ministry of Economy and Finance of Korea relaxed the regulation and allowed non-bank financial firms to compete in the international remittance market. Our data is from one of the Fintech firms who entered the market.

3. Data and summary statistics

We use detailed transaction-level international remittance data and individual-level demographic data from one of the leading Fintech firms in Korea, the Sentbe, for our analysis. The firm's target customers are mainly foreign workers in Korea and includes individuals mostly from nine Asian countries: Bangladesh, Indonesia, India, Cambodia, Malaysia, Philippine, Pakistan, Thailand, and Vietnam. A key feature of our data is that it includes low-skilled workers who send a significant portion of their earnings back home to support their families. Although these workers are financially unsophisticated, they exert their best efforts in making remittance decisions, which have a large impact on their utility and wealth.

The average age of our sample individuals is about 31 but it varies from 27 to 33 across countries, etc. Table 1 reports summary statistics of our daily individual-level data, by destination country. Our sample has 25,994 individuals who make 476,659 payment transactions from February 2016 to March 2020.[1] The largest percent of workers in our sample are from the Philippines with 8,231 users (32%) who account for 244,297 transactions (52%) with the average transaction amounts of 497,465 KRW, about USD$415. The next largest country represented in our sample is Vietnam, with 7,743 users (30%), followed by workers from Indonesia with 4,994 users (19%).

Workers in our sample send international remittance payments, on average, about 2.1 times a month with 721,912 KRW, about USD$600, per remittance. There are notable patterns between sending amounts and remittance frequency by country: Workers from the Philippines, Indonesia, Malaysia tend to remit more frequent, smaller denomination payments, while workers from India tend to remit less frequent, larger denomination payments.

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

Finally, for the foreign spot exchange rates (foreign currency units per KRW), we use the spot exchange rate that Sentbe quoted within their app to their consumers.[1] Figure 5 plots the spot exchange rates for our sample countries during our sample period.[2]

4. Measuring the benefits of fintech

In this section we estimate the cost savings of using a Fintech, relative to traditional banking products. Banks charge five different layers of fees for international remittances: The first is a fixed fee per remittance ('Telegraphic Charge'), the second is the variable fee as a percentage of the remittance amount, and the third is the margin on the foreign spot exchange rate. Additional fees are charged by the intermediary bank for using SWIFT (Brokerage Fee), and the foreign receiving bank.

To compare fees, we use the list fees for two major banks in Korea, IBK bank and Woori Bank, which are commonly used by workers to send international remittances. Table 2 reports the cost structure.[3] 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 USD$4) as Telegraphic Charges. Only the traditional banks charge a Brokerage fee of about 10,000 KRW (USD$8). Exchange rate margins are about 1% of the amount sent, but varies by bank and destination country (as shown in Panel B.) The Fintech firm charges a fixed rate 1% margin for all countries.

Based on the fee structures in Table 2, Figure 6, Panel A compares the remittance cost of the Fintech firm to the remittance cost of traditional banks for a sample of 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 green bar reports the distribution of sending amounts of remittance transactions, which we use

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[1] Sentbe shows users high frequency foreign exchange spot rates, updated every 10-minutes. This information is provided primarily from KEB-Hana Bank, who specializes in the foreign exchange market, and also from global benchmarks such as Xe.com and investing.com.

[2] Sentbe introduced international remittance services to most countries in 2018, except for Indonesia, Philippines, and Vietnam which were introduced to the platform in 2016.

[3] We use the cost for workers to send international remittances at a bank branch. Some banks now offer online apps with cheaper solutions, but these were not available during our early sample period and are still more expensive than the cost of using a Fintech solution.

as a weight to compute the average cost reduction for Fintech users across the distribution. The difference between two lines shows the relative cost reduction for each sending amounts. For example, the fees for sending the median international remittance payment amount in our sample, 374,690 KRW (USD $314), the Fintech platform charges 5,000 KRW (USD $4) for Telegraphic Charge and 3747 KRW (USD $3) for the exchange rate margin. This adds up to 8747 KRW (USD $7), which is approximately 2% of the sending amount. However, traditional banks charge 6.3% for the same amount of remittance.

We find that the Fintech solution charges are on average 10.6 percent lower than traditional banks. This sizable effect is largely because Fintech's have a relative advantage in sending smaller denomination payments, typical in our sample: Workers send on average about USD$600 (721,906 Korean Won (KRW)) per month. Note that the difference is largest in transactions with smaller amounts. A large number of workers in our sample earn a low-income and send low-denomination payments—that incur the highest fees (as a percent of amount sent).

Panel B reports the similar results by the country of destination.[1] The reduction is largest among workers from Indonesia (13.1 percentage points) and smallest among workers from India (4.1 percentage points).

However, using a Fintech may not always be the preferable means to send international remittances: When the remitted amount is large, workers may prefer to send their payment through a traditional bank, since the cost is similar, and the reputation of safety and reliability is higher. In general, Fintech platforms appear to have a comparative advantage for low-denomination, high-frequency international remittance payments.

We also find that a large number of payments are made on the weekend and outside of typical bank operating hours. Since workers using traditional bank services can only transact during lunch breaks during the week or on weekends[2], this finding suggests a severe constraint that may be imposed on individual workers if a Fintech option did not exist.

[1] We do this analysis for seven countries, excluding Bangladesh and Pakistan since neither bank offers remittance service to these two countries.
[2] Weekend service is available at banks for a significant additional fee.

5. Timing international remittance payments

Fintech platforms not only provide a cheaper solution for international remittance payments, but also provide additional flexibility in the timing of remittance transactions. Compared to traditional banks, Fintech platform enable workers to overcome time and physical constraints. To send an international remittance payment using a bank, workers are required to travel, in-person, to a bank branch during its opening hours. This constraint is particularly challenging for workers who are tied to their jobs during the bank's working hours, e.g. low skilled workers, or those who need to travel significant distance to visit a bank branch, e.g. workers in sparsely populated areas. The only alternative to banking during working hours was to pay even higher fees at special bank branches exploiting this friction. [1] In comparison, workers can send international remittances using a Fintech app on their phone any time of day or night, weekday or weekend, from the comfort of their home.

Figure 4 shows the distribution of our sample of transactions over time. Panel A reports the number of remittance transactions by calendar day and shows that the number of transactions gradually increases as the Fintech platform matures.[2] We find that the calendar days with the highest number of transactions are between the 10th-14th of the month, which are the typical salary days in Korea. Panel B reports the number of remittance transactions by the day of a month. As seen in the monthly peaks in Panel A, remittance transactions are more likely to occur between the 10th-14th of the month. 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 Sebtbe remittance transactions, averaged over time by the time-of-day (in 10-minute intervals). Although the greatest number of transactions are during

[1] To service Southeast Asian workers, special bank branches open on the weekend to send international remittances at a higher fee.

[2] Service was suspended from July 17th-December 7th 2017, while Sendbe acquired a license for overseas remittance, required by the government's deregulation in July 2017.There was another short stoppage of the service from February 15th-February 18th 2018 due to the Lunar New Year Holidays in Korea. We use the complete sample period from 2016-2020 for our main analysis, but including only the post-2018 period does not change our main results.

lunchtime (12:30), we find a high number of transactions done in the evening, after traditional bank working hours.

5.1 Day and time of day

Our analysis uses daily individual-level transactions from February 2016 to March 2020. We construct a balanced sample by replacing missing observations for 1 month before the day of first remittance to 1 month after the day of the last remittance payment with zero. The final dataset has 10,623,364 observations.

Table 3 reports the results from a linear probability model estimating daily remittance transaction patterns. The dependent variable is a dummy variable $D\{Remittance\}_{i,t}$ that equals one 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 using the Fintech platform on about 4% of sample days. Column (1) shows result using dummy variables for the days of a week, i.e. *Monday*, *Tuesday*, *Wednesday*, *Thursday*, *Friday*, and *Saturday* are included as independent variables. We include individual fixed effects and country-year-month fixed effects to control for potential differences in individual characteristics and fluctuations in the 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 remittances gradually decreases daily through the week. The likelihood of remittance is significantly lower on Saturday and Sunday. This is contrary to our expectations that digital remittance transactions would be more convenient—and more commonly used—during non-working days/hours.

Column (3) adds a dummy variable $Salary\ Days_t$ that is equal to 1 for the 10^{th}-14^{th} days of the month, and 0 otherwise. We find that remittance transactions are 40% more likely to occur during salary days, as compared to the unconditional probability of remittance. Many workers are supporting families back home and are likely to send money home soon after their salary is paid.

5.2 Exchange rate appreciation

Next, we examine the relationship between the daily remittance decision and the lagged appreciation (percentage change) in spot exchange rate of currency *c*: [$\Delta SPOT_{c,t-1} = \log(SPOT_{c,t-1}/SPOT_{c,t-2})$]. In Column (2), we find that the likelihood of making a 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 workers are more likely to transact after the appreciation of spot exchange rate 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.

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 reversion to the mean, i.e. that an appreciation of the spot rate on the previous day will be followed by a depreciation of the spot rate on the following day. In this case, we would expect more remittance transactions following the appreciations of spot exchange rate.

5.3 Cancellation feature

Next we examine a unique features of the Fintech platform, which are not available to workers making bank payments: the *Cancellation* feature, which allows users to hold multiple remittance orders up to 24 hours and users can decide which orders to execute before they expire. Since spot exchange rate quotes do not change over the weekend, the importance of the *Cancellation* feature 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.[1]

Table 4 reports the descriptive statistics on the characteristics of 368,189 transactions by the use of *Cancellation*. The *Cancellation* feature is more typically used by women, young workers,

[1] For robustness we include weekends observations and find no qualitative differences.

and for larger remittance amounts. Usage varies by the nationality of individuals: about 10% of remittances by Thai workers use the cancellation feature, as compared to about 5% of remittances by workers from Cambodia. To help explain these trends, 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 use of the *Cancellation* feature is positively correlated with the Financial Development Index of the home/receiving country. The slope of regressing *Cancellation* on Financial Development Index is 6% and statistically significant at 5% level.

Table 5, Column (1) reports our results using a linear probability model of *Cancellation* on the likelihood of a remittance payment. The dependent variable is a dummy variable $D\{Remittance\}_{i,t}$ that is 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. Our main independent variable of interest is a dummy variable $Cancellation_{i,t}$ 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.

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 greater payment amounts are associated with larger payment amounts, following spot exchange rate appreciations, and with the use of the cancellation feature.

6 Optimizing remittance transactions

Next, we analyze whether workers in our study optimize the timing of their remittance payments by using daily exchange rates to compute a set of counterfactual amounts, assuming the transaction occurs on another day within the window of [-5, +5] around the actual transaction. We normalize the amount of the original remittance, in *receiving* currency, to that at t = 0, the amount is equal to 1.

The measure indicates whether a remitted payment receives the optimal exchange rate within a 2 week horizon, or not. If the highest value occurs at day 0, this indicates that the worker was able to pick the best day to transact within a 2-week window. If the peak occurs prior to day 0, this implies that the worker should have sent the transaction earlier and a peak following day 0 suggests that the worker should have made the transaction few days later in order to optimize the exchange rate.

Figure 8, Panel A plots average returns using all remittance transactions in the window of [-5,+5]. We find that the peak generally occurs 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.

6.1 Definition of Optimality Score

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.

Why do workers make more transactions after the appreciation of spot exchange rate? One possible reason is behavioral biases: For example, individuals are susceptible to the "law of small numbers" (Tversky and Kahneman, 1971), that is, they tend to generalize from small amounts of data. In this case, the appreciation of spot exchange rate on the previous day would cause workers to expect the spot rate to continue to appreciate (and their wages to depreciate). However, if the home-country's exchange rate recovers (depreciates), workers could lose money.

When a new technology arrives and relaxes pre-existing constraints on consumers, is it always beneficial to consumers? In theory, rational agents should be better off with additional flexibility in their choice set. However, Barber and Odean (2000) find that individual investors who hold common stocks directly pay a tremendous performance penalty for active trading because of overconfidence in their timing of the market. Similarly, workers with additional flexibility on the timing of international remittance payments—and greater exposure to exchange rate fluctuations— may be worse off, particularly when the workers have low financial capability.

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 vary widely across remittance transactions. We provide other examples in Panel B of Figure 9. The 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* ≥ 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* ≤ 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.

6.2 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 relate 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.

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 make a remittance payment following the appreciation of spot exchange rate on previous day. In other words, a higher optimality score is correlated with workers that used the cancelation option in prior transactions, suggesting that canceling orders helps workers better time the exchange rate market.

Table 8 reports the summary statistics of variables that we use for our analysis of the optimality score. Our variable log(*SendAmount*$_{i,t}$) has a mean of 12.83, which is about 373,249 KRW (USD

\$313), with a standard deviation of 1.27. About 7% of our sample remittance transactions included a *Cancellation* option, 46% are associated with the appreciation of spot exchange rate on the previous day, 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 one 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 effort to time larger payments.

We decompose *Optimality Score*$_{i,t}$ [−5,+5] into the optimality score in the 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 amount of the payment is significantly related to a higher optimality score only in the 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 (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* option, 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.

Consistent with our expectations, we find that improvements in the timing of payments occurs 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 following the appreciation of the 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 remain 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 found that workers in our sample 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 workers in our sample are not professional traders in foreign exchange markets nor individual traders who aim to profit from the trading foreign exchange contracts, 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 use $D\ \{\Delta SPOT_{c,t-1} > 0\}$ 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.

7 Learning effect through social network

Social networks have been a key factor to explain various phenomena, including the effect of learning through network behavior (Hirshleifer, 2020; Munshi, 2003). One of the key features of Fintech platforms is the social network that are associated with growth of the services. Like many Fintechs, Sentbe offers cash incentives (1,500 Won, or about $4.20) for users to ‘recommend’ the service to their friends in exchange for bonus credits that can be used to pay for future remittance payments. We use this referral data to construct social networks among our sample of workers.

First, we report an example of a social network among Indonesian users in our sample. Table 11, Panel A shows 11 Indonesian users with registration date, area of residence, and type of occupation. We label users in alphabetical order by the time of registration in the system. We find that this network of workers live in a similar residential area and report a similar occupation. Figure 10 reports the referral relationship between 11 users. User A recommends the service to other users (B, C, D, and H); next, user C recommends the service to additional users (K, J, and E); followed by user E recommending it to other users (F and I). Lastly, 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[1] and identify 361 social networks in our sample with an average number of seven users in the social network. Panel B reports summary statistics of variables related to social networks. Among the 24,687 workers in our sample, about 11% are associated with some social network.

As discussed earlier, on average, workers use the *Cancellation* feature at 65% point in the length of their usage periods. For example, if an individual use *Cancellation* in his 10th remittance transaction and the total number of remittance transactions of him is 20, then *Time to 1st Cancellation* is 0.5. *Credit Balance* of individuals has mean of KRW 2,924 (USD $2.5) with a standard deviation of KRW 4,773 (USD $4.0).

In Panel C, we find that individuals in social networks make a larger number of transactions than workers not in social networks. Workers in social networks are also more likely to use the *Cancellation* feature significantly earlier. 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. Panel D shows that among workers in social networks, workers with larger *Credit Balances* are located at the

[1] 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.

central nodes in the networks, using measures of $Centrality_d$ and $Centrality_e$ from Banerjee et al. (2013).

7.2 Clustering of remittance transactions within social network

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

To further examine the clustered remittance transactions within a social network, we construct for each social network 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 remittances 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.

7.3 Learning through social network

We use the learning effect through the social network to distinguish hypothesis discussed earlier. 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 interpret the meaning of the determinants.

Table 13 reports the learning of *Cancellation* by members of a social network. The dependent variable is a dummy variable, $Cancellation_{i,t}$, which equals 1 if an individual *i* uses *Cancellation* on day *t* and 0 otherwise. In Column (1), the 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 include a dummy variable to control for the appreciation of lagged spot exchange rate ($D\ \{\Delta SPOT_{c,t-1} > 0\}$), $log(SendAmount_{i,t})$, a dummy variable for $Salary\ Days_t$, and country-year-month fixed effects. We find that being in a social network does not change the likelihood of using *Cancellation*. We continue to also find that the use of *Cancellation* is associated with younger users, women, and large transaction amounts.

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 the 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 when the social network has cumulative experience among users of using the *Cancellation* feature, social network members use *Cancellation* more. This result suggests 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 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 an additional variable to proxy for 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 increases 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 make remittance transactions when the spot exchange rate appreciates on the previous day do not show a higher probability of making a remittance transaction when the appreciation actually occurs. This indicates that 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) uses as the independent variable *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. While *SpotHistory SN*$_{i,t}$ increases the likelihood of making a remittance payment, the interaction term between *SpotHistory SN*$_{i,t}$ and *D* {$\Delta SPOT_{c,t-1} > 0$} does not show a significant effect in Column (4). This indicates that individuals in social networks do 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 rates shown in a large body of empirical literature (i.e. Meese and Rogoff, 1983), the flexibility of remittance payments may harm consumers' welfare when the short-term behavior of spot exchange rate changes, but workers remain overconfident on their ability of optimal decisions.

8 Conclusion

We study the value of Fintechs for retail consumers using transaction-level data of low-income workers in Korea sending international remittances through a Fintech platform. We find that the value of Fintech is mostly derived from overcoming various frictions, such as high cost or time/spatial constraints of bank/brick-and-mortar transactions. We find that the Fintech platform lowers remittance cost by 10.6%, on average, as 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 customers' nationality. Our sample includes individuals-transactions from February 2016 to March 2020 for the remittances to 9 Southeast and Northeast Asian Countries including Bangladesh, Cambodia, India, Indonesia, Malaysia, Pakistan, Philippine, Thailand, and Vietnam. We report the number of sample customers, their number of remittance transactions, average sending amounts per transaction in USD, and average age by customers' nationality. We also report average number of remittance transactions per month.

Country	Date of 1st transaction	Number of Customers	Number of Remittance payments	Transaction Amount (USD): *Mean*	*Median*	Average Number of Monthly Remittances	Average age of Sender
Bangladesh	Jun-18	530	3,583	552	383	1.57	31
Cambodia	Jul-18	500	5,041	1,226	905	1.99	28
India	Jul-18	1,765	17,498	607	286	1.61	33
Indonesia	Sep-16	4,994	91,149	686	391	2.13	30
Malaysia	Jul-18	167	2,233	817	527	2.55	27
Pakistan	Jul-18	1,290	12,346	418	224	1.70	32
Philippines	Feb-16	8,231	244,297	1,056	840	2.31	32
Thailand	Apr-18	1,074	15,182	903	588	2.03	32
Vietnam	Jun-16	7,443	85,330	552	383	1.72	28
Total	Feb-16	25,994	476,659	1,226	905	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 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 KRW (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: Transaction, Product & Market Features Associated with Optimality of 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. Depende nt variables are $\Delta SPOT_{c,t-1\rightarrow t+s}$ 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 $\Delta SPOT_{c,t-1\rightarrow t}$, Column (2) uses $\Delta SPOT_{c,t-1\rightarrow t+1}$, Column (3) uses $\Delta SPOT_{c,t-1\rightarrow t+2}$, Column (4) uses $\Delta SPOT_{c,t-1\rightarrow t+3}$, and Column (5) uses $\Delta SPOT_{c,t-1\rightarrow t+4}$. 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: ıvior of Forei

	(1)	(2)	(3)	(4)	(5)
			$\Delta SPOT_{c,t-1\rightarrow t+s}$		
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)
			$\Delta SPOT_{c,t-1\rightarrow t+s}$		
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, $(\sum_{\tau<t} Cancellation_{i,\tau}) \,/\, (\sum_{\tau<t} D\_\{Remittance_{i,\tau}\})$. 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

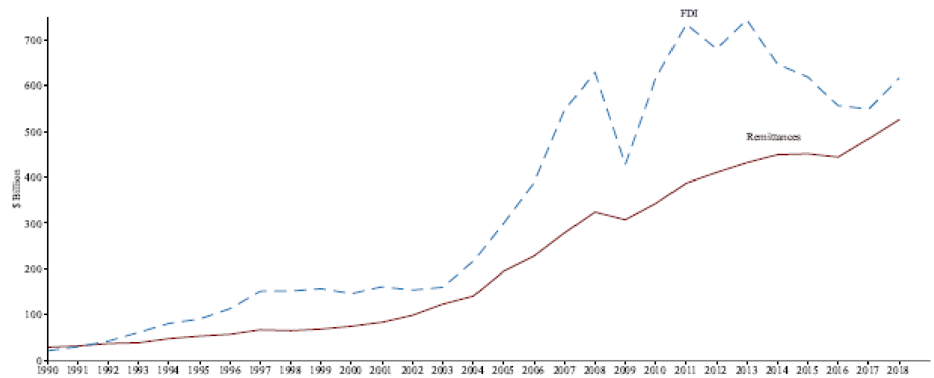
We report the panel regression results of the history of transactions with the appreciation in the spot exchange rate on individuals' remittance decision with the appreciation in the spot exchange rate. The dependent variable is D {$Remittance_{i,t}$}, which is a dummy variable that equals to 1 if an 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

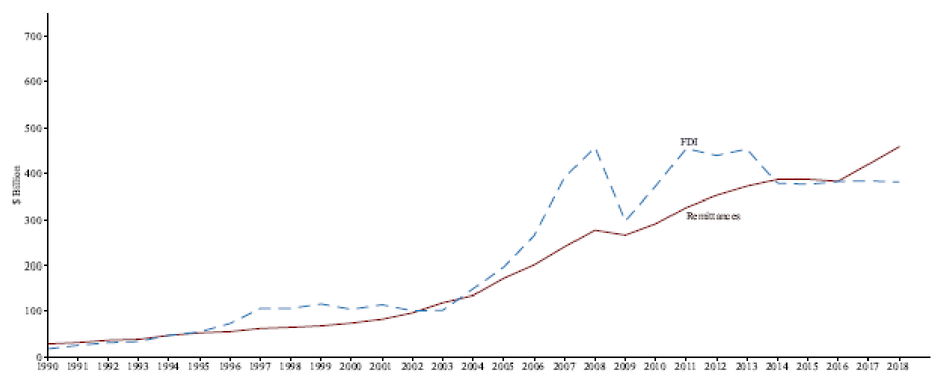
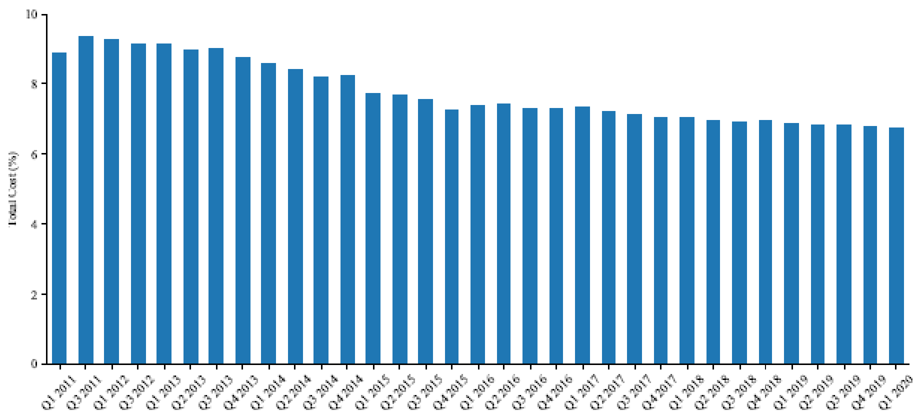


Figure 2: Cost of Overseas Remittance

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

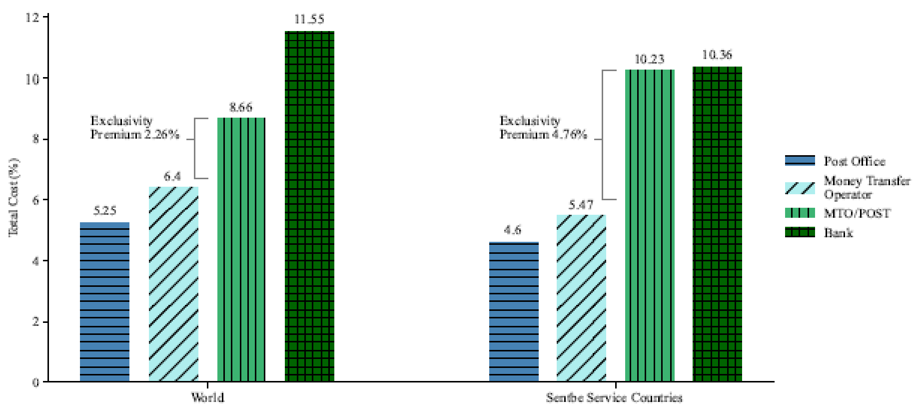


Figure 3: Importance of the Overseas Remittance in east Asian Region

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.

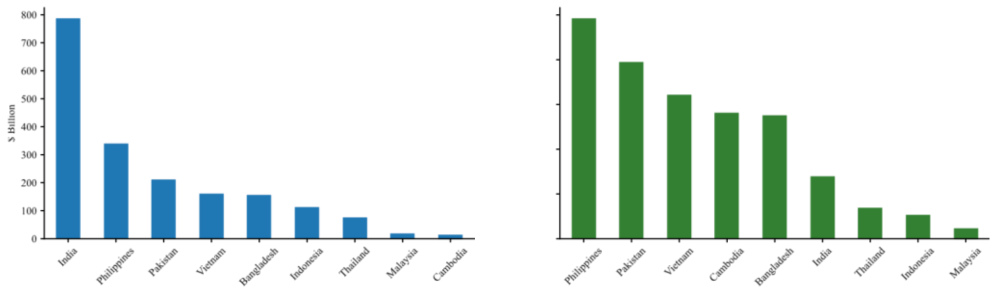
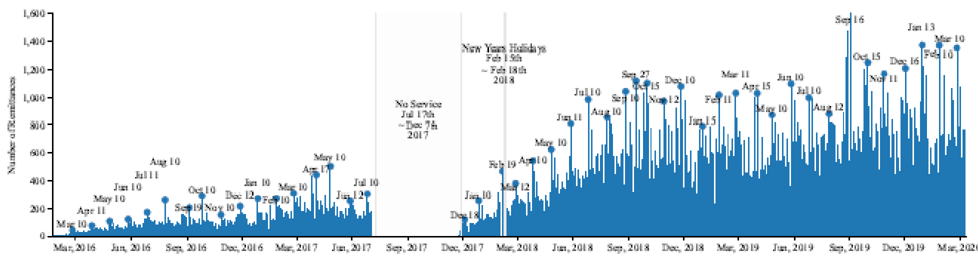


Figure 4: Time-Series of Individual Remittance Transactions

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

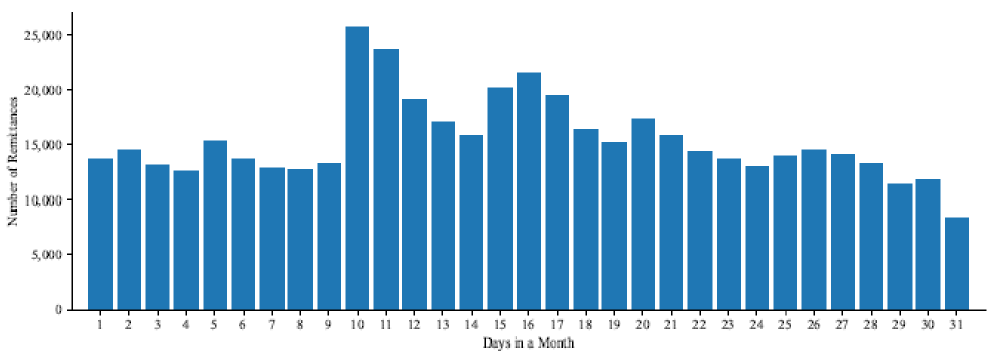
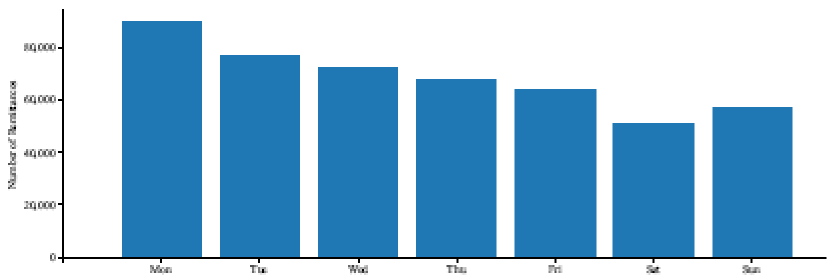


Figure 4 Continues

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



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

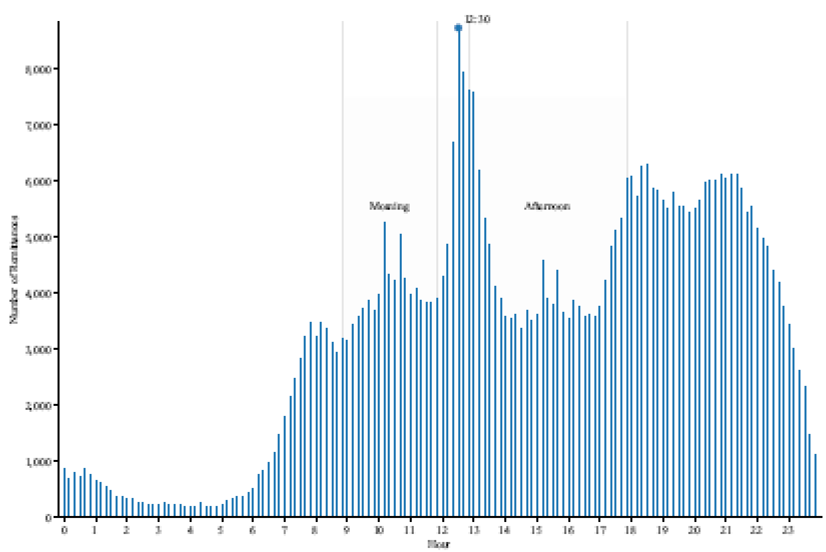


Figure 5: Spot Exchange Rates

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.

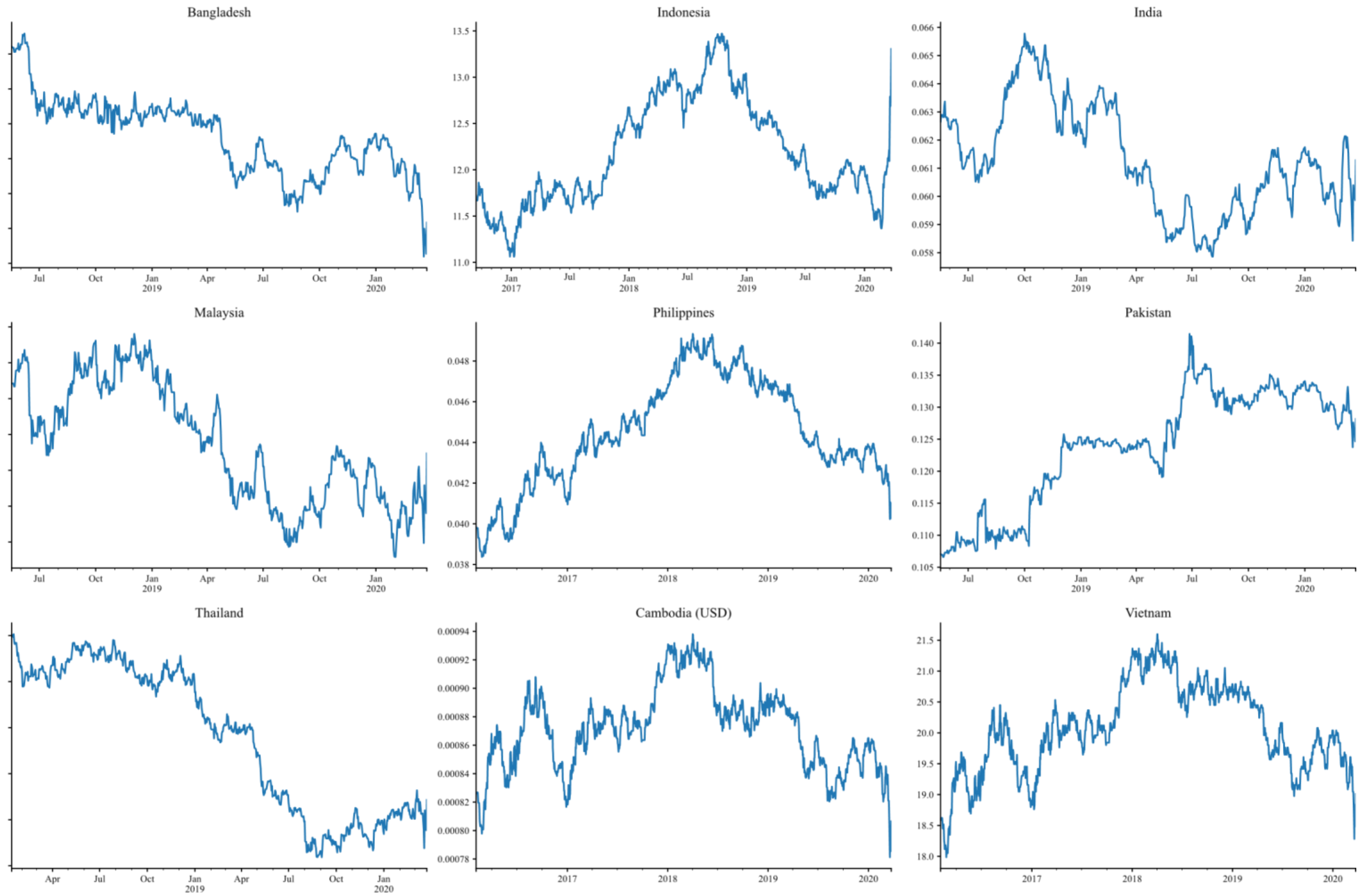


Figure 6: Comparison of Remittance Cost between Fintech and Commercial Banks

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 KRW. 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

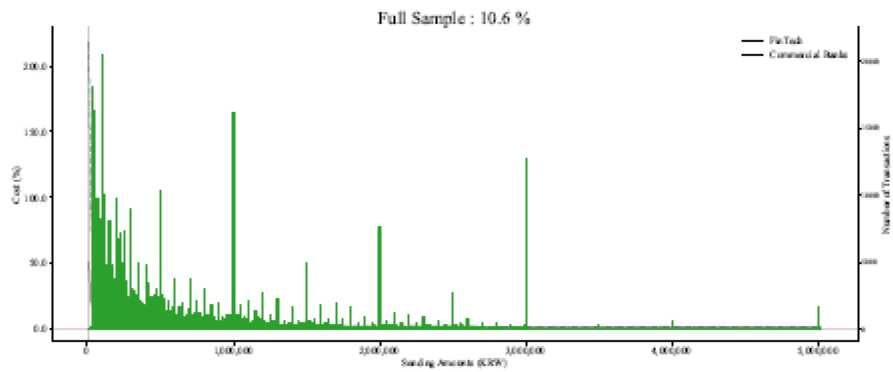


Figure 6 Continues

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

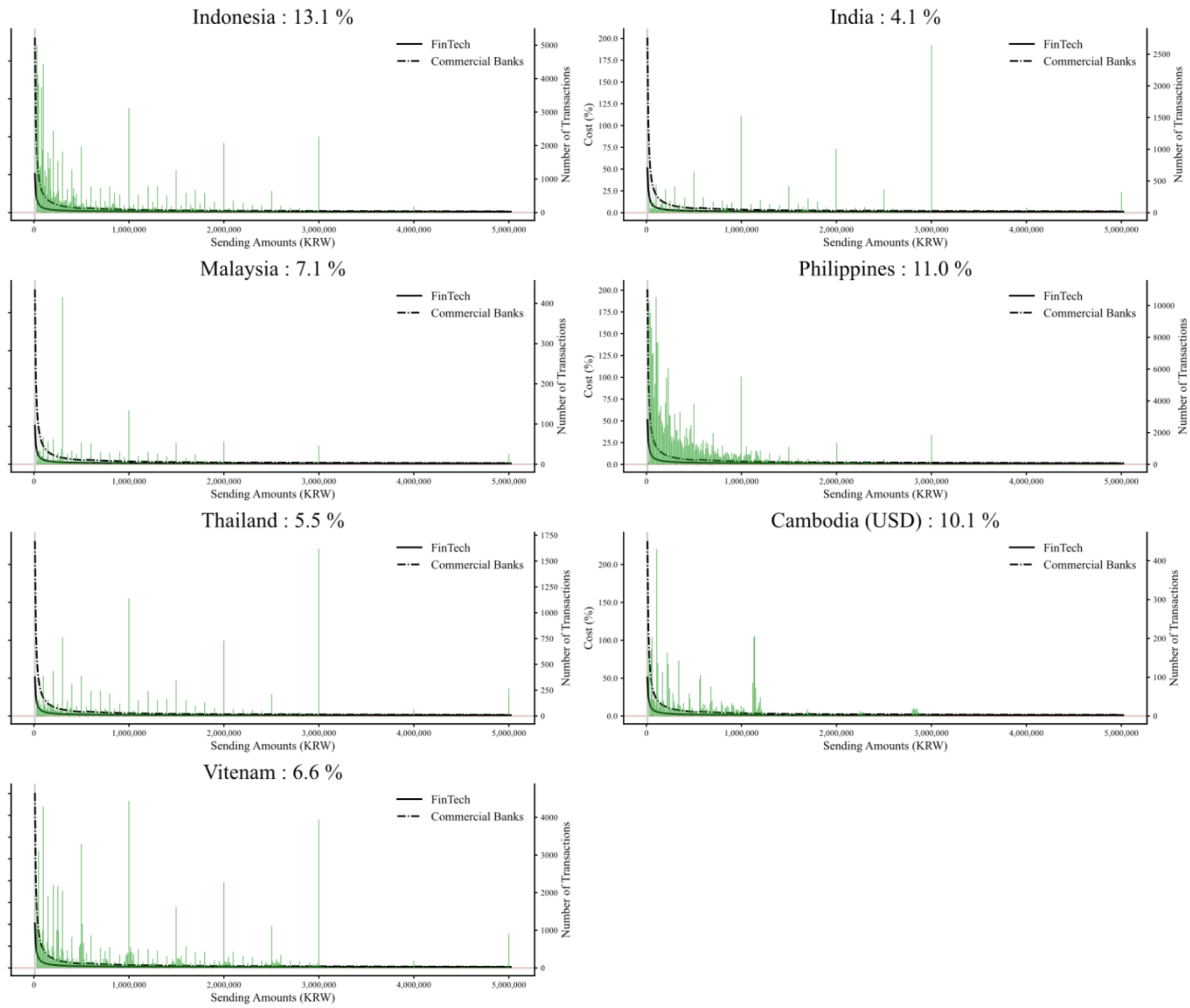


Figure 7: Financial Development Index and the usage of *Cancellation*

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.

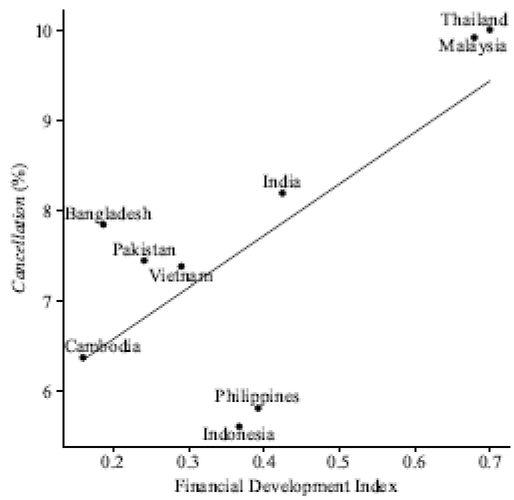


Figure 8: Optimality in Remittance Timing

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

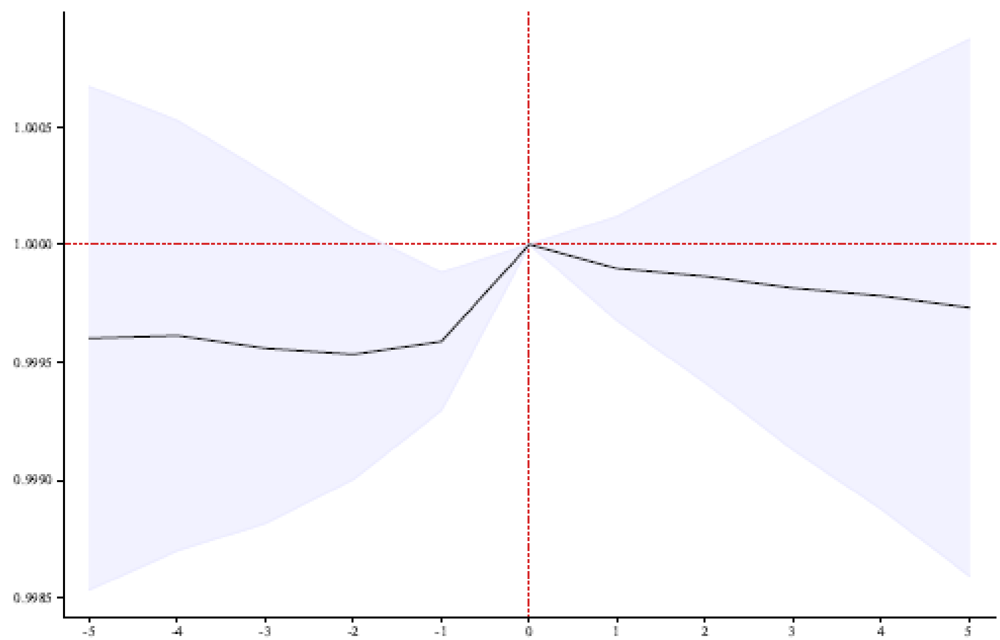
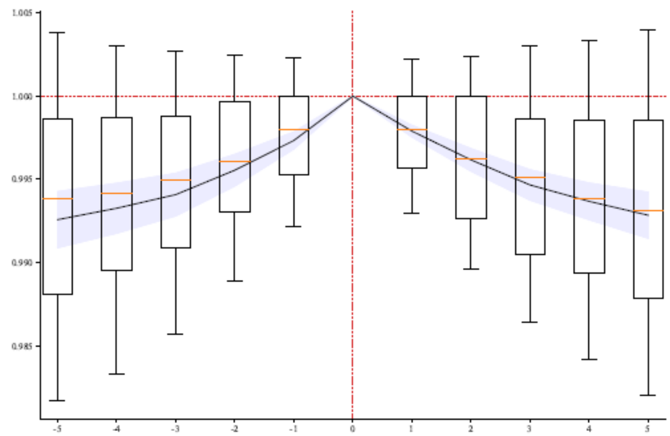


Figure 8 Continues

Panel B: Average Optimality Score of Top 1/3



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

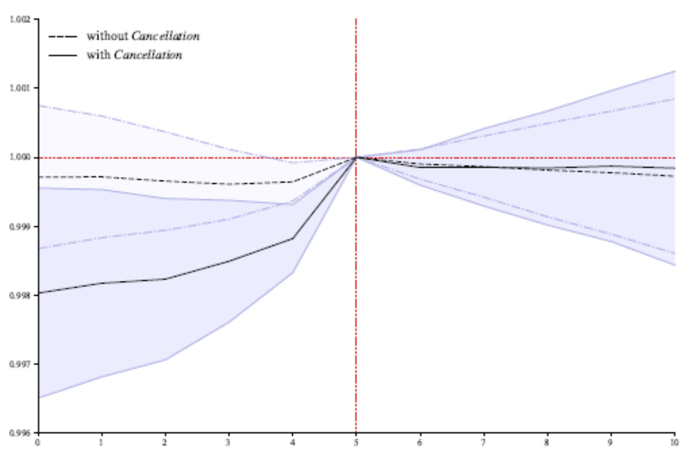


Figure 9: Measure of Optimal Remittance Timing

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

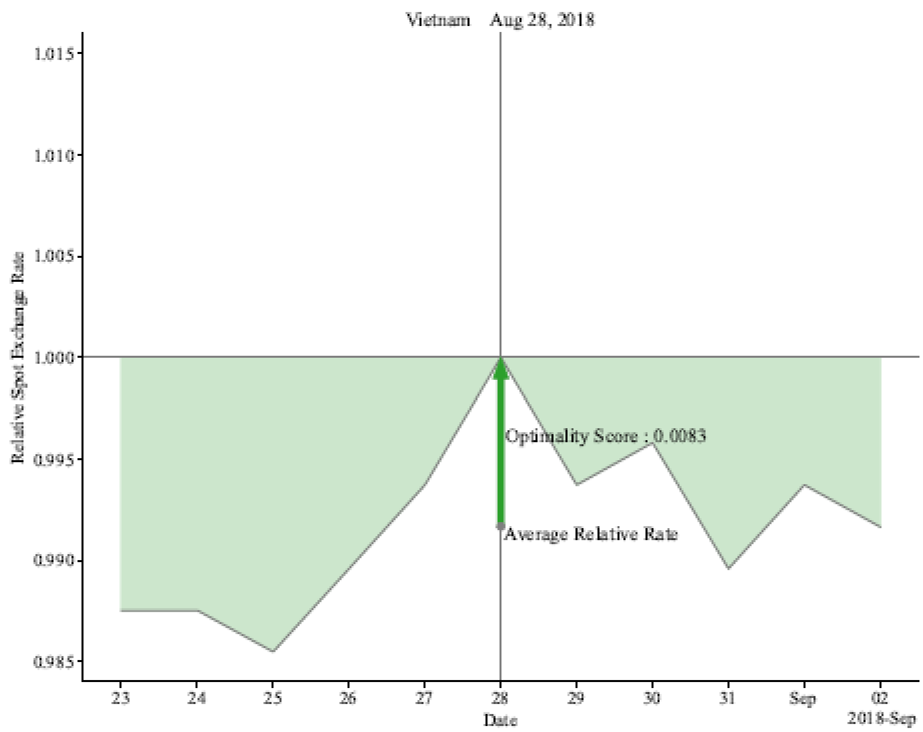


Figure 9 Continues

Panel B: Other Examples

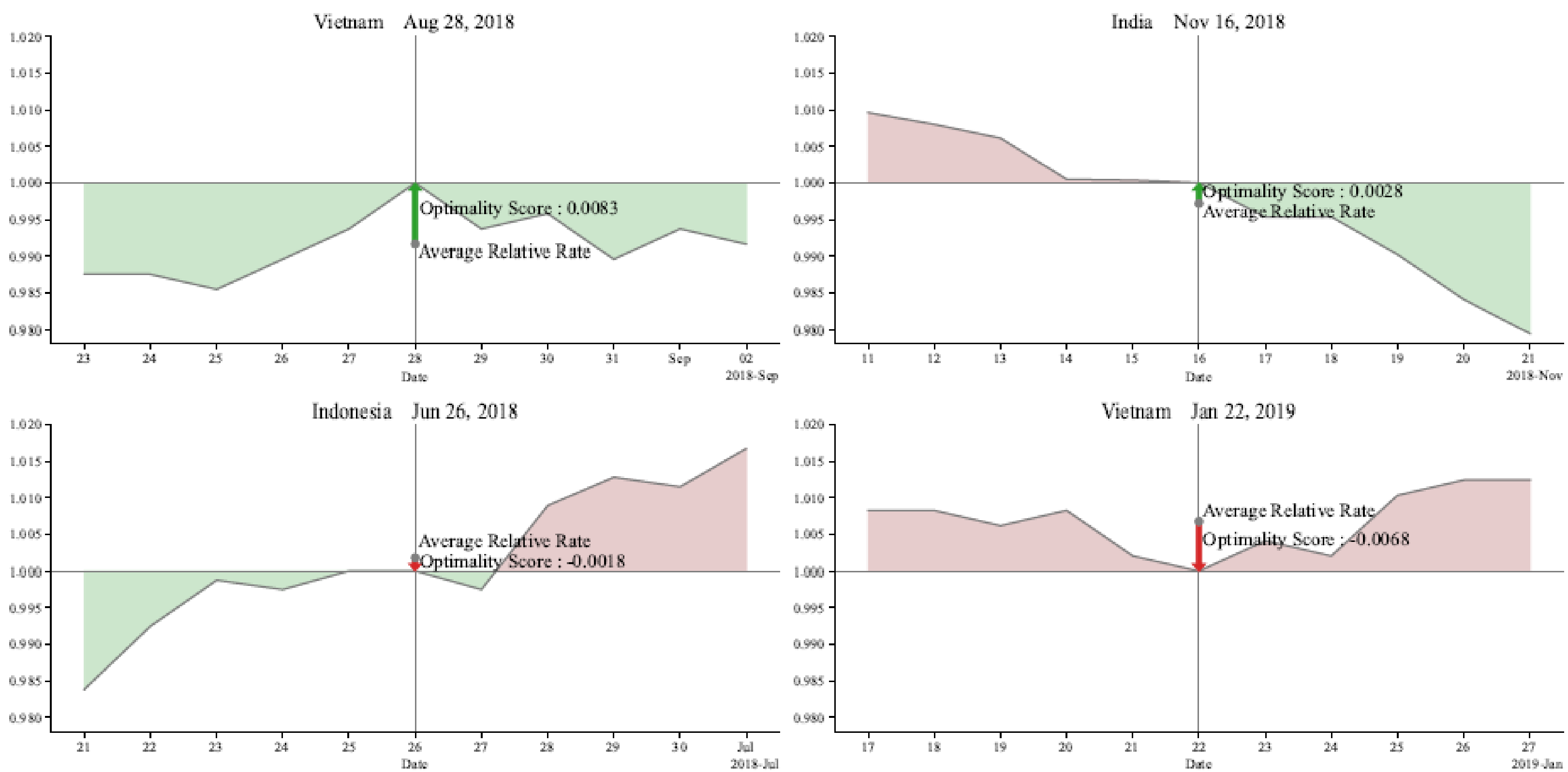


Figure 10: An Example of Social Network

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.

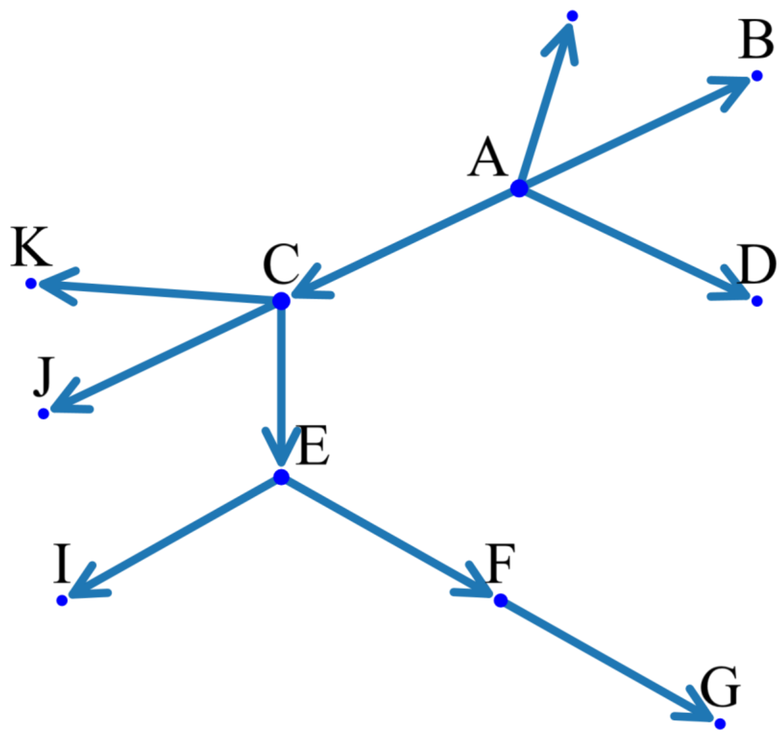


Figure 11: Clustered Remittance Transactions within a Social Network

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 KRW.