

Mobile Money Networks with Tax-Incentives

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Abstract

Mobile Money (MM) is the most promising tool to enable more individuals living in rural and marginalized communities into the banking sector. Although private companies in some developing countries have transitioned most of its users over to MM, it remains unclear if government-initiated programs would be as successful. By accessing a comprehensive dataset of the first MM project to be initiated by a government, we tracked the behavior of users within the MM network. Temporal analysis of network representations of MM transactions shows how agents behave over time and how they react when given tax-incentives for the use of non-cash transactions. Tax-incentives had positive immediate effects on the economic activity of continuing users (number of transactions, mean and total value of transactions) and a marginal effect on their interconnectedness (number of partners and clustering). However, the tax-incentive distorted economic behavior and had a modest effect on the adoption and diffusion of MM over time at a high price tag. These findings offer important lessons that would be valuable to other governments and policymakers considering MM.

Keywords: mobile-money; central bank digital currency, tax-incentives; networks; Ecuador

JEL Classification: D85; E58; O33

1. Introduction

In the developing world, Mobile Money (MM) is the most promising tool to enable more individuals living in rural and marginalized communities into the banking sector than ever before. MM allows users to deposit, withdraw, and transfer money among users, perform payments for goods and services and withdraw funds through their mobile phones (via SMS and/or Data). MM has been gaining traction in various economies of the world, especially in developing countries, for almost two decades. MM use started in earnest in the mid-2000s in the Philippines and Tanzania, then saw its most prominent case in Kenya with universal coverage (1). Its widespread use across the globe continues, with Mexico likely becoming the next adopter by the end of 2019 with a government-operated platform (2). Several other countries from Latin America, as well as Canada and Sweden, are considering its adoption (3). As such, understanding optimal mechanisms and strategies for the implementation and diffusion of MM, especially in regards to how to optimally incentivize individuals to maximize their adoption and transactions, and in particular understanding their reactions to government interventions, is of timely and critical importance for countries in order to enable the successful and efficient spreading of the MM benefits.

Using the first comprehensive data set of a MM project implemented by a government, from its conception to its ending, we track the behavior of agents within the network of MM and evaluate their response to tax incentives. Specifically, MM was initiated in Ecuador at the end of 2014 by the Central Bank of Ecuador (CBE). Its objectives were to provide an alternative means of payment in a dollarized economy with a shortage of liquid assets and to include the staggering 60% of the population without access to financial services. It was the first attempt in the world to utilize a mobile phone-based e-money that was managed, provided and monitored by a central government, the first Central Bank Digital Currency (CBDC). While the project was underway, the central government tried to encourage the adoption and diffusion of MM through tax-incentives in the form of a refund into the user's MM account. By the end of the project in December 2017 the initiative only accounted for 0.002% of the total liquidity of the Ecuadorian economy, and at an expensive price (the total value of tax incentives doubled the total value of MM transactions). As a case of study for other nations seeking to implement MM, it is critically important to understand the spreading of the MM project in Ecuador, agents' transactions with other agents and their behavioral changes over time in response to tax incentives.

Our study is based on a unique dataset obtained from the CBE, covering all MM implementation from January 2015 to December 2017, and analyzes the development of different economic networks from the MM project in Ecuador. Temporal analysis is performed to understand how users behave when governments create alternative systems to increase liquidity in a small dollarized economy and give them

incentives to encourage the use of MM. In particular, we describe how agents react over time when the Ecuadorian government intervened with a new technological innovation and how agents' behavior responded to tax-incentives, and quantify the effect of these incentives on adopters who from the beginning of the project and after the incentives were continuing to use this new technology. To measure changes in the behavior of agents post incentives, and to evaluate long term effects in interconnectedness, we use economic activity measurements and network metrics in a regression framework. We also compare these results with information from the Ecuadorian economy to see whether the government fulfilled its objective. This is the first paper studying the complete set of MM transactions in a nation where all individual transactions are available.

Our data allows for the classification of agents into users, companies, and macro-agents (the distributor of MM). We found that an incentive provided by the Ecuadorian government of a 1% and 2% tax refund on non-cash transactions deposited into the MM users' account had a positive immediate effect on the economic activity but only a marginal effect on their interconnectedness among MM users. We did not find any significant effect on companies or macro-agents. Surprisingly, the policy did not generate significant long-term effects on the interconnections between agents but rather increased the frequency and value of the transactions that users were making before the tax-incentive policy was in place.

We are able to quantify the magnitude of the changes in economic activity metrics for continuing users caused by the incentive policy. These are the users who had been using the MM technology since before the tax incentives and continued using MM after the tax-incentives. For such a user, the number of transactions increased by \$4.57 (+130%) at the moment of the policy with no further growth over time. The immediate effect of the policy in the mean transaction value is an increase of \$4 (+62%) and a negative effect on the time trend. The total value of dollars transacted increased in \$120 (+200%) at the moment of the policy and did not continue growing over time after the policy.

Also, we calculated the effect of the policy in network metrics for continuing users. The incentives increased the number of partners by 1.5 agents at the time of the policy with no growing effect over time. The local clustering coefficient marginally changed by 0.013 units with the policy and had a negative effect in the time trend. All of these results evidence that the policy motivated continuing users to reap the benefits of the incentives by transacting with agents whom they were transacting before the policy rather than expanding their local network. Remarkably, we did not find any effects of the policy in economic activity metrics and network metrics for companies and macro-agents.

2. Related Research

The literature on Mobile Money (MM) has been steadily growing, especially studies on how MM contributes in the developing world, from studying its impact on finance of individuals (4), poverty and financial inclusion (5) and risk-sharing (6). The major advantages of MM as a technological innovation are that people do not have to carry cash and money can be distributed and managed across vast distances. Jack & Suri (4) demonstrate that one of the most important uses of mobile money has been peer-to-peer (P2P) remittances.

There is no consensus on what characteristics would make a MM deployment successful; characteristics of the country's economy, the role of the implementer as well as specific aspects of the implementation all play a role. For a comparison of five successful MM deployments to five less successful ones, see Lal & Sachdev (7). Some particular features about agents must be considered. Suri (8) revealed that having a widespread macro-agent network, whose cash and e-money inventories are well managed, is crucial to the success of the product.

Our work tries to characterize the MM adoption process in Ecuador. In that sense, our work is related to literature on the economic behavior of agents when they started to use MM. The most prominent case of MM adoption, as seen in Kenya with M-PESA from 2008-2014, has been documented in Jack & Suri (4,6). Using cross-sectional data in mobile banking usage, Zhoua et al (9), showed that users' adoption of mobile banking is affected not only by their perception of the technology but also by the fit between their tasks and mobile banking technology. Once adoption starts, a successful implementation will show strong network effects. The primary work documenting network effects in the adoption of MM is Fafchamps et al. (10). They used a database of mobile phone usage to study network externalities as a way to continue to reinforce adoption for Rwanda. Also, Murendo et al. (11) found that MM adoption is positively influenced by the size of the social network with which information is exchanged in Uganda.

Many of these works have reached their conclusions based on household surveys, but with the exception of Fafchamps et al. (10), none of them have been documented using real behavioral network data for MM. Our work begins to fill this gap in two ways: by using actual transaction data, which has advantages over survey data in veracity and level of detail, and by using network analysis, which enables us to observe the functioning of the whole economic system beyond aggregates of individual behavior, in particular whether network effects are important for adoption. We document structural features that evidence lack of diffusion throughout the network and show how MM usage did not reach its target levels.

3. Mobile Money Network: The case of Ecuador

The “*Electronic Money Project*” was implemented by the Central Bank of Ecuador (CBE), with a national regulation (12) that specified that e-money can only be issued by the CBE, thus creating a monopoly of MM in Ecuador. Because Ecuador lost its ability to print money in 2000 after the dollarization of the economy due to a severe economic crisis, the project was introduced in December of 2014 as an alternative means to give liquidity to the economy and to provide people a simpler, faster, and cheaper service to make financial transactions.

The system was open to natural persons (who are called *users* here) and legal entities (called *companies* here). The process to open a MM account was simple, linking their national IDs using their mobile phones. The distributors of e-money nationwide were the *macro-agents*: these were legal entities that could be private, public or mixed companies that had at least five customer service points in their commercial chain. Macro-agents can also be public institutions, financial institutions, and organizations of the popular and solidarity financial sector (i.e., the sector that embraces social organizations such as cooperatives, mutual associations, NGOs, etc.). The system was also open to other agents and was clearly defined in (12). The MM platform introduced in Ecuador allows users to deposit money into their account through macro-agents or using an ATM, transfer money to other users or to users’ banking accounts (P2P), make purchases of goods and services (B2C), and pay for services in Government institutions (G2B). MM account users could withdraw cash money from their account through a macro-agent or using an ATM. All phone to phone economic relations were using SMS technology only, unlike other settings that require smartphones.

The CBE guaranteed a sufficient stock of e-money for macro-agents. The CBE could also have direct relationships with final users. Usage charges appeared as MM account surcharges, dependent on types and amount of transactions (13). Transactions did not consume air-time balance or SMS messages from the cell phone account. The costs of operating the system with telecom companies in Ecuador were covered by the CBE.

Using official publications of Ecuador, we identified when the government put into effect tax-incentives that sought to increase the use of MM over time but affected the economic behavior of agents, specifically because this incentive brought new agents to the system. The incentives laws are described in further detail in section 3.2. The explanation of how we do graph representations of MM networks is in section 4. Our first objective is to describe over time how these incentives affect behavior as represented by four types of networks (section 5). A *Transaction Network* captures the primary economic transactions of interest (purchasing items or services of value). The *Exchange Cash-in* and the *Exchange Cash-Out Networks* describe users’ behavior of exchanging e-money for cash money and vice versa. The *Incentive Network*

records how users are collecting the tax-incentives. Then our goal is to test the effect of incentives on users, companies, and macro-agents. The estimates for this last part are presented in section 6.

3.1 Data and Agent Types

The database was provided to us by the CBE covering all transactions during the life of the project, from implementation in January 2015 to ending in December 2017. Each transaction includes the type of users and the type of transactions, including the activation of an account, balance checks, cash deposits, ATM withdraws, transfers between users, payments, incentives, and all the accounting movements between accounts to balance them. All data is de-identified, where every agent has an ID assigned by the CBE that does not link to any personal identifiable information and does not include any agent characteristics beyond its type (users, companies, and macro-agents).

3.2 Government Tax Incentives for the Adoption of MM

The enactment of the Organic Law for Equilibrium in Public Finances (OLEPF) on April 29, 2016 was created by the Ecuadorian government to encourage the adoption and diffusion of e-money to the future and includes a 2% refund of value-added tax (VAT) paid for transactions that used e-money, and a refund of 1% of VAT paid in the MM account for transactions that used debit or credit cards (14). The OLEPF not only granted tax refunds to those who used e-money in their transactions but also to those who carry out transactions with credit or debit cards. The VAT paid at that time in Ecuador was 12%. This law highlights the liquidity problem of the Ecuadorian economy and leaves financial inclusion as a secondary objective in the implementation of the MM project since by giving the benefit to those who use credit or debit cards to make payments, the incentive is excluding unbanked people, a majority of the Ecuadorian population.

On May 20, 2016, the Ecuadorian government approved the Organic Law of Solidarity for the Reconstruction and Reactivation of the Affected Zones by the Earthquake of April 16, 2016 (OLSRRAZE). This law sought funds to rebuild and reactivate the areas affected by the earthquake. The law increased the VAT from 12% to 14% for one year but kept the refund of 2% of VAT paid for transactions that used e-money (15). This measure reinforced the public interest to activate MM accounts because they had to pay a higher VAT.

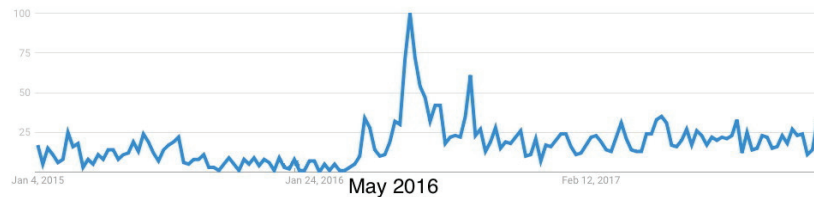
With the establishment of a new government, the Organic Law for Reactivation of the Economy (OLRE) at the end of December 2017 shut down the MM project, removed the Central Bank as the exclusive administrator of the MM system, and passed the project to the private financial system (16). The act gave agents until March 2018 to get zero balance on their MM accounts. To do so, users can consume products

in stores that accepted this type of payment, made withdrawals at ATMs, or transfer the balance to a regular bank or credit union account.

All these laws were made within economic policy decisions that were not expected by society. The OLEPF was a project that sought to develop incentive mechanisms to encourage the use of non-cash payments (i.e. MM, credit and debit cards). The OLSRRAZE was a response to an earthquake of great magnitude that affected a large part of Ecuador and the OLRE was a policy that reversed what was done by the previous government.

The interest generated by these decrees and the search for information about electronic money in Ecuador are positively related. The Google trend for searches in Ecuador that were made with the phrase “dinero electronico”, or electronic money, provides evidence of the effect of these laws on the general interest in this topic over time. Figure 1 (obtained from trends.google.com) shows that after the OLEPF in May 2016, the search for information about electronic money was at its highest peak.

Figure 1: Google Trend for “*Dinero Electronico*” in Ecuador



4. Methods

Network representations of the data have the advantage that structural metrics can be computed, showing not only what typical agents are doing in isolation but also how they are connected to each other. Temporal analysis of the MM data illustrates how agent behavior changes over time from the perspective of different types of networks. In addition, time is a very important variable to consider in adoption process of new technologies where trial and error is not only a process of assimilation of users but also for the supplier of the new technology. The diffusion of a new technology among agents is reinforced with positive time trends of adoption and usage. In this section, we construct networks that will be used in the following Sections to understand the development of MM in Ecuador. In Section 5, we study metrics on the networks constructed in 30-day time slices, plotting and examining metric trends over time and in relation to significant events, and interpret trends in terms of the economic behavior of users. We also compare these results with data from the Ecuadorian economy to see if the final objective of the tax-incentive policy was met. Then, in Section 6, we evaluate the impact of the policy using a model to estimate the effects of the

policy on continuing users and in all agents that have been using the MM tool. This gives us the magnitude of change in behavior over time.

4.1 Graph Representations of Mobile Money Networks

Our network representations are constructed with agents (a.k.a. actors) as nodes (vertices) and transactions as links (edges). We begin with a multi-graph representation, with a directed link for each transaction that takes place. Each link is annotated with the dollar amount of transaction, date of transaction, and a description of the transaction type.

We study four important networks in our analysis derived from the data set of MM in Ecuador: The *Transaction Network*, the *Exchanges Cash-in Network*, the *Exchanges Cash-out Network*, and the *Incentives Network*. The *Transaction Network*, constructed from payments between agents or charges in exchange for goods or services, represents the economic activity that MM was intended to support. The *Cash-in Network* consists of transactions in which users load e-money with cash. The *Cash-out Network* consists of transactions where users withdraw cash money from their MM accounts. The comparison of cash-in and cash-out networks may give an indication of when users intend to move their primary economic activity to one or the other medium. The *Incentives Network* consists solely of government incentive refunds to MM accounts received for using non-cash payment. This network can be used to gauge the extent to which users are motivated by incentives to participate.

Each of these networks is represented as two kinds of graphs. In the *multi-graph* representation, there is a distinct edge for each transaction that takes place. This means that there may be many parallel edges between any two given nodes. The *multi-graph* enables metrics that are on a per-transaction basis (e.g., average value in dollars per transaction, or number of transactions a typical agent engages in). Then the *multi-graph* is transformed into a *simple-graph* representation, where all the edges between each pair of nodes are collapsed into one, summing the transaction values. The *simple-graph* enables metrics that are on a per-agent basis (e.g., average dollar value exchanged per agent). Both representations are used to compute various network-level (structural) metrics. Some of the metrics we compute do not require networks, but all can be computed using the network representations, so we use networks throughout for simplicity.

4.2 Temporal Analysis

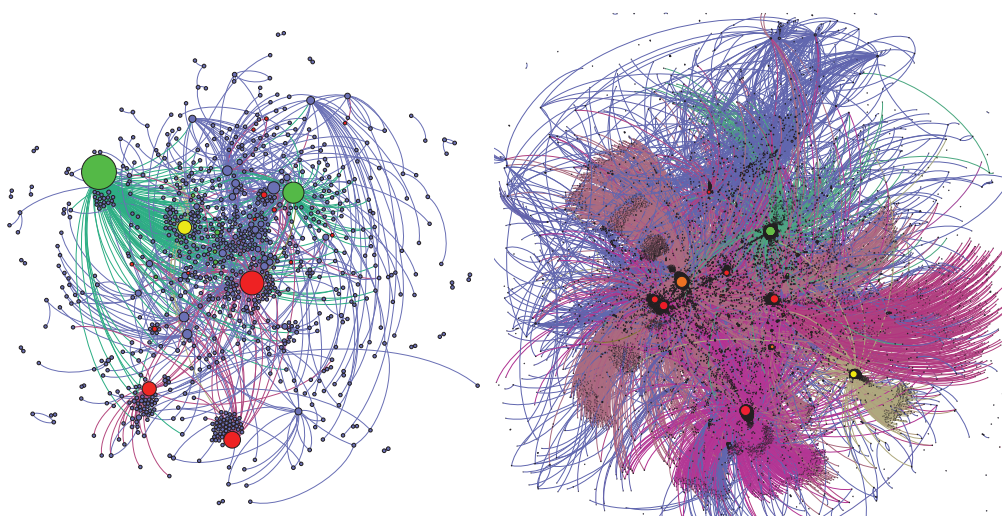
Transaction dates on the edges were used to construct time spans, which are graphs of the same type as discussed above but limited to transactions (edges) within a given time period (17). For this part, we chose 30-day spans as the temporal unit of analysis, because is convenient to interpret, long enough to accumulate

sufficient economic activity to construct graphs large enough for the metric algorithms to apply, and short enough to characterize how activity changed over time. Also, a 30-day window lets us localize the spike in agents doing economic activities, especially after the incentives laws. We define time span 0 to include the enactment of the laws: the OLEPF date (04-29-2016) and the OLSRRAZE date (05-20-2016). Timespan 0 extends from 04-25-2016 to 05-24-2016, chosen to place the above events in the middle of the time span with a 4-day buffer on either side. Further, we determine "before" as the time spans, -1, -2, etc. working back in time in 30-day increments, and "after" as the time spans 1, 2, etc. working forward in 30-day increments. In this fashion, we are able to construct 30-day span network graphs.

The 30-day analyses constructed a new graph for each 30-day window. We then deleted isolated nodes, those that had no incident edges in each given 30-day graph. The resulting graph most accurately represents what transpired in a 30-day span, as it has only nodes for active agents and edges for transactions that occurred, but plots over time must be interpreted keeping in mind that the number and identity of nodes each 30-day span is changing.

Visualizations of the transactions simple-graph for typical spans in the pre-incentives period (span -5) and in the incentives period (span 15) are shown in Figure 2. Node size represents degree, and color represents agent type: blue for users, green for companies, red for macro-agents, and black for the central bank. In the figure, many users are directly related to macro-agents or companies. In addition, it is clear that the degree of macro-agents and companies is much greater than users. We can also see that there are peripheral users that only made transactions with one other user (isolates were removed).

Figure 2: Example Transaction Networks



a. Span -5: 873 agents, 1117 transactions

b. Span 15: 20387 agents, 23886 transactions

5. Results of Temporal Analysis

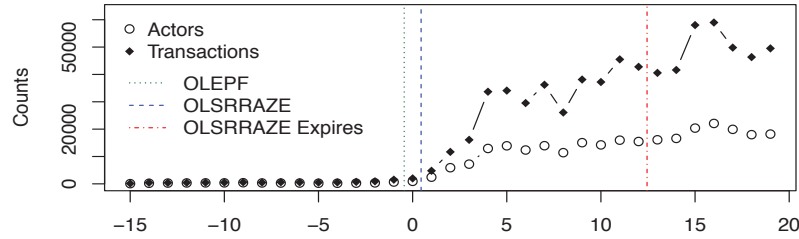
Figures 3-14 show the temporal progression of various metrics. The plot for each metric shows the metric value on the y-axis, organized by 30-day spans on the x-axis. The x-axis is labeled numerically, where 0 is the time span that include the tax incentive laws, “before” includes the time spans -1, -2, -3, etc. and “after” includes the time spans 1, 2, 3, etc. Major economic events are marked with vertical lines in time span 0: the OLEPF and the OLSRRAZE, also the OLSRRAZE expiration line is presented.

5.1 Transaction Network

Figure 3 shows that every 30 days more actors (circles, Figure 3) were part of the real economics transaction network once the OLEPF and OLSRRAZE were effective at time 0. This graph has a peak of 22,106 agents in time 16 (August 2017). After a new government came into power and the discontinuation of the MM project was made public, more agents appear in our graph and started to make economic transactions. Possibly these are agents who had other means of payment such as debit or credit cards and activated MM accounts due to the incentives. They were accumulating e-money in their MM accounts and at the end of the project, they have to use what they had left in their accounts (e.g. spending in stores). That is why we see more agents appear at the end of the time line. The number of actors in the MM project who made real transactions is modest given that the economically active population in Ecuador is approximately 8 million (18) and the ratio of people with mobile phones is approximately 60% in 2016 (19).

Before the incentive laws, few transactions were made (diamonds, Figure 3), and there was an increase in the number of real transactions after the laws. The network goes from almost no transactions to over 40,000 transactions per 30-day span in the last 10 time spans, peaking at 60,572 transactions in time 16. When the balance of users’ MM accounts falls below the minimum that can be withdrawn from an ATM, users may be finding other ways to use the e-money such as small purchases in stores. Agents that were removed as inactive from networks in prior 30-day spans become active as they conduct these small transactions, leading to the peak seen in Figure 3. This shows that incentives motivated agents and transactions; however, it will be important to compare this result with the mean number and value of transactions per agent.

Figure 3: Agents and Total Number of Transaction



The mean number of transactions per agent (diamonds, Figure 4) was increasing before the tax-incentive laws, reaching about 5.2 transactions per agent. This coincided with an expansion on the number of companies entering the network, so there were more places where people can use their MM. After the first year of life of the project, the mean number of transactions per agent starts to decrease, and then, with the incentives, there is a new increasing trend that stabilized at around 5 transactions per agent per 30-day.

Figure 4: Mean Number of Partners and Mean Transactions per Agent

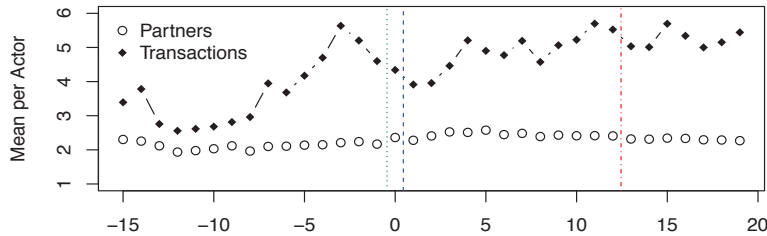
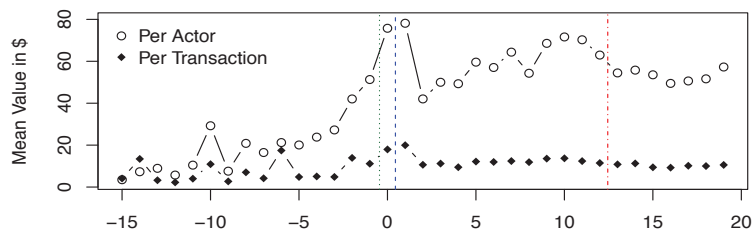


Figure 4 (circles) also shows the mean number of partners with which an agent is doing transactions. The number of partners is small, on average around 2.4 before and after the laws. Agents do transactions with few other agents. Thus, the incentives did not have an effect on the number of new connections that an agent had. This is something that we are going to explore in more detail in our regression model when we will see the effect of the policy for different types of agents.

After the incentive laws, the mean of each transaction is \$11.3 in time spans 5-20 (diamonds, Figure 5). With 5.2 mean transactions per agent per 30-day after the laws and \$11.3 as the mean transaction value after the laws, the mean value of dollars exchanged in each transaction by those agents who are active in any given 30-day span is around \$58.6 after incentives, as seen in Figure 5 (circles). If we compare this value with cost of the basic consumption bundle in Ecuador that is around \$700 per month in 2017, we can say that actors who used this innovation did not even cover 10% of the cost of the consumer basket, not achieving the Government objective that MM will be used on a daily basis for Ecuadorian consumption

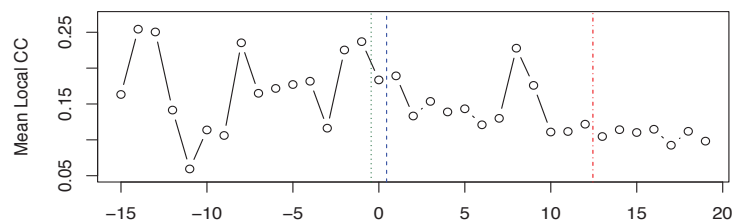
transactions. Figure 3 showed that in this network the number of actors and transactions increased, but Figure 5 shows that economic activity in the network never grew enough to occupy a large proportion of the total transactions of the economy.

Figure 5: Mean Transaction Values



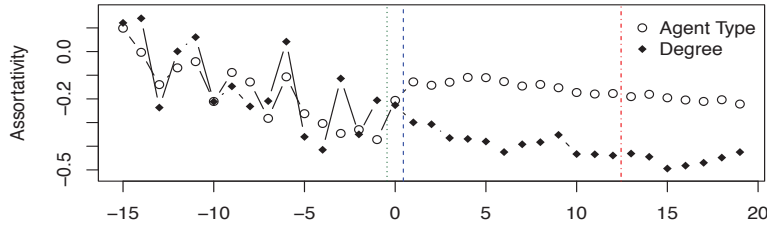
Turning to structural metrics, Figure 6 tells us that the mean local clustering coefficient¹ is moderate and decreases with time. (Although the clustering coefficient is expected to be *very* small in random graphs, most anthropogenic networks have values orders of magnitude higher: see Table 8.1 and section 12.8 of (20)). Users are connected only with macro-agents and are less focused on each other, as seen in the dense collections around hubs in Figure 2. If the incentives had increased adoption of MM by users who are mutually transactive outside of MM, then we would see an increase in the clustering coefficient, corresponding to mutual (Simmelian) ties that reinforce the group use of MM (21). However, few triangles have formed between users, so we lack evidence that clusters of mutual groups of economic actors have also adopted the use of MM and are reinforcing their mutual use.

Figure 6: Mean Local Clustering Coefficient



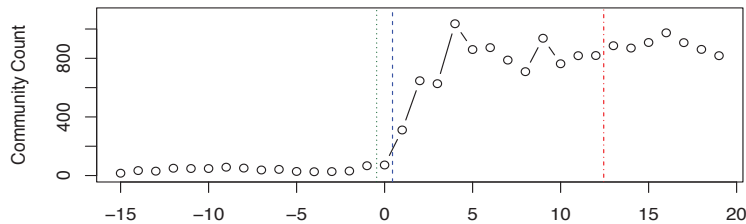
¹ Mean local clustering coefficient measures what proportion of a node's neighbors are connected to each other. This indicates the extent to which agents are clustered in mutually transactive groups, from the point of view of the typical agent.

Figure 7: Assortativity by Agent Degree and Type



We use two types of assortativity to illustrate the type of connections that agents had². Degree assortativity (diamonds in Figure 7) shows that early on there was no clear preference of attachment by degree, but then assortativity becomes negative as low degree nodes, typically representing individual users, prefer to attach to high degree nodes such as companies and macro-agents. This trend stabilizes after enactment of the incentive laws. Individual actors connect primarily to hubs rather than to each other, reinforcing the conclusion from the clustering coefficient that networks of “small” agents are not a significant structural feature. Our second measure is nominal assortativity on agent type, represented in the same figure as circles. This measure illustrates that agents connect to other agents of various types, with a tendency for natural persons to be connected to companies and macro-agents.

Figure 8: Community Count by Louvain Method



Our work also studies a measure of community structure based on the Louvain method of partitioning (22). Given a partition of the network, modularity indicates the extent to which edges connect within partitions greater than expected at random (20). The Louvain method is a heuristic approximation of the best possible partitioning under this metric. A high value on modularity indicates that there is more “community structure”: nodes are connected in cohesive sub-clusters. The modularity of the partition by

² We first use undirected *degree* assortativity, a metric that ranges from 1 to -1, and is mathematically related to the Pearson correlation. Positive values mean that high degree nodes connect to high degree nodes and low degree to low degree. Negative values are common in social and economic networks where high degree nodes connect to low degree nodes. Our second measure of assortativity is the undirected *nominal* assortativity on agent types. This is mathematically equivalent to the above, except that the correlation is on categorical (nominal) data. Positive assortativity indicates that (for example) macro-agents connect to macro-agents, users to users, etc Negative assortativity indicates that macro-agents connect to users.

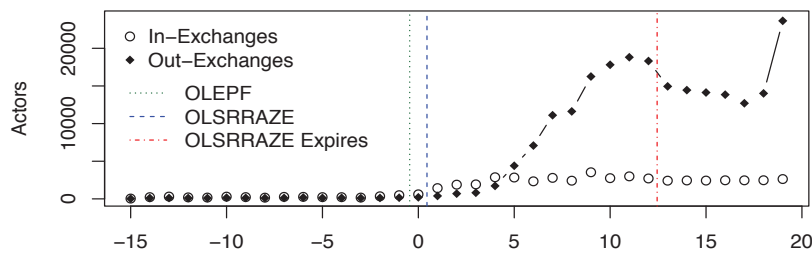
the Louvain method stabilizes after the incentive laws around 0.81, which tells us that there is a strong community structure, also visible in Figure 2. After the incentives, there are 852 monthly communities on average (Figure 8). Although most actors are involved in a small number of communities centered on large agents (Figure 2), the vast majority of these “communities” are pairs or small clusters of users. The large community count reflects the large number of agents with only one or two MM partners in a 30 day period, not formation of significant communities of MM users.

5.2 Exchanges Networks

Exchange networks record agents putting money into and taking money out of the MM platform, explicitly going to a macro-agent or through an ATM. We constructed an Exchange Network for Cash-in and an Exchange Network for Cash-out.

Figure 9 shows that the number of actors cashing in (circles) goes up slightly after the incentives are in place but remains moderate, indicating a low commitment to the MM system, and starts to go down before the expiration of the OLSRRAZE. By that time users know that the MM project will no longer will in place. Figure 9 (diamonds) also shows that there is a rapid increase in actors cashing out after the incentives, and reaches its highest value in ten 30-day spans, well above the earlier time spans of the project when incentives were not present. Then, exchanges start to decrease when OLSRRAZE expires in span 12. Probably at this time many agents already have zero balance in their MM accounts. The spike at the end of the project likely represents the remaining group of users who wanted to cash-out before the project termination.

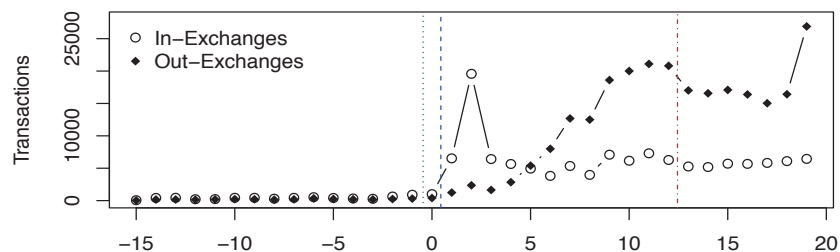
Figure 9: In and Out Exchanges Actor Counts



The average number of agents that appear in each network is consistently different: there are 2,657 agents who cash-in every 30-day span from time 5-20, after the incentives law, a modest number compared to an average of 13,070 during the same period (peaking at 24,682) who cash-out. This indicates a primary interest in the withdrawal of funds.

The cost to join the system is minuscule: one only needs to send a text message. However, if we use the Jack & Suri (4,6) results and consider that in this kind of project, initial adopters are educated people with a high level of income, for the Ecuadorian case adopters would be banked people. These are people who already have other means of payment such as credit or debit cards, and are entering into this network to get the benefits of the incentives and accumulate e-money in their MM accounts to then cash-out dollars.

Figure 10: In and Out Exchanges Counts



For the total number of cash-in transactions per 30-day, we can see in Figure 10 (circles) that the number stabilizes around 5700 transactions per 30-day after the peak. The spike in Figure 10 represents the massive reaction that agents have after the announcement of tax-incentives, possibly when users create the MM account with a minimum amount of dollars. However, for the number of cash-out transactions, a positive trend is always present during OLSRRAZE's life, reaching more than 27,000 transactions (diamonds, Figure 10) and closely mirroring actor counts (Figure 9).

After the spike of activity in time 4, for the 2,657 agents that are cashing in on average, the mean number of transactions is around 4.3; and for the 13,070 that are cashing out their accounts, the mean number of transactions is about 2.4 (plots omitted due to space limitations). To see how much money actors are cashing in per span, see Figures 11-12. From the 2,657 people conducting in-exchanges, the mean value after the incentive laws is around \$64 (circles, Figure 11). Since they are making 4.3 transactions per 30-day, the total value exchanged per actor (circles, Figure 12) is around \$276 and is growing over time.

Figure 11: Mean Value per Exchange Transaction

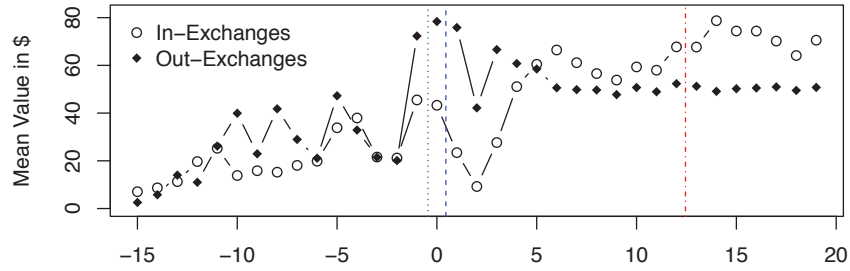
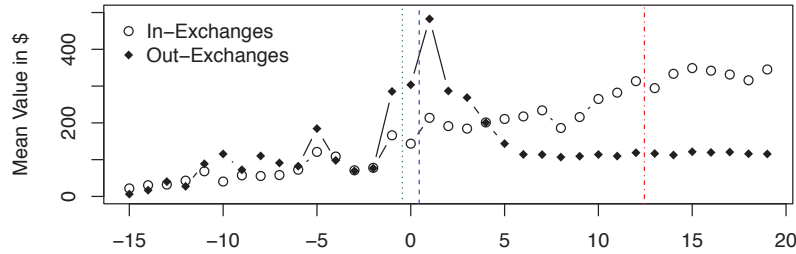


Figure 12: Mean Value Exchanged per Actor



In Figures 11-12, we can see that the 13,070 active agents were withdrawing \$52 on average after the incentive laws (diamonds month 20 onwards, Figure 11) in 2.4 transactions per 30-day, so the total value exchanged per actor every month is \$128 (diamonds, Figure 12), a value that makes sense for the size of the Ecuadorian economy. If most of these people are getting the government transfer because of the law, they expect to accumulate e-money in their MM accounts until they have approximately \$50 value to convert into cash money and they are doing these cash-outs two to three times every 30 days. Comparing this amount to the mean transaction value of \$11 that we found in the Transaction Network, it is clear that the incentives distort the economic behavior: new users were there to collect the incentive as opposed to utilizing the electronic tool.

5.3 Incentives Network

This last network captures transactions in which the Government gives agents money back because of their usage of non-cash payments (e.g., MM, debit card or credit card). Nodes in this network are macro-agents, companies, users and the Government and the Central Bank. We analyze this network after 2016-04 (span 0) because there were no incentives to users before OLEPF.

Figure 13 shows that the system was transferring money to more users over time. This reaches 164,441 accounts per span, 62% of the 265,240 agents in the incentives network. This graph is consistent with what already shown: many people are in the network just to cash-out.

Figure 13: Incentives Actor Count

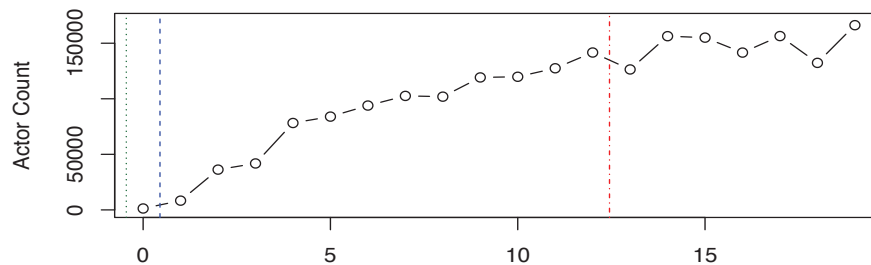
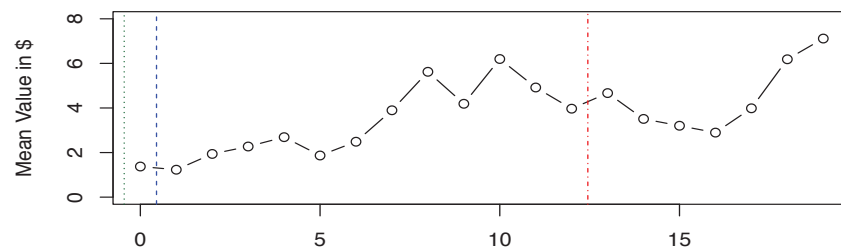


Figure 14: Incentives Mean Transaction Value



For more and more users, the Government increasingly is giving e-money back, until the law expires in time 12. Figure 14 shows the mean value of incentives transactions that agents are getting for using non-cash payments. The value was increasing over time, and we can understand this as the 1% or 2% refund that most of these users are getting because of the incentives.

If we compare the average primary transaction value (such as purchasing goods or services) per person in the after-law period to the average incentives received per person, we find that the government had to pay \$66 to get people to engage in \$97 of primary economic activity. Note that 83,523 actors engaged in primary economic activity after-laws, while 247,379 got incentives. Therefore, the government paid \$16 million for a system that supported transactions that accounted for only \$8 million.

6. Testing Changes in Behavior over Time

In this section we show that incentives had an immediately positive effect on the behavior of users and a negative effect on the time trend, slowing down the diffusion of the new technological tool in the economy. In particular, we test whether incentives had a significant effect on heterogeneous agents, especially on those who had been using the MM tool since the beginning of the project and continued using MM after the incentives, called *continuing users*. In the last part of this section, we evaluate the changes in behavior when we considered *all* agents over time.

Our analysis focuses on five measures that come from the transaction network described in the temporal analysis. Our explained variables will be *number of transactions*, *average value of the transactions*, *total value of transactions*, *average degree of agents*, and *local clustering coefficient (transitivity)*. The first three metrics relate to the expansion in economic activity for agents using MM. The last two serve as a guide to understanding whether agents interacted with more peers after the policy.

As in our previous analysis, time is our main variable since we are looking to the adoption process of MM over time. In order to do that, we consider again time spans of 30 days, centered on time span 0 defined to include the enactment of the laws. According to what we analyzed in the temporal analysis, it is not unexpected for some nodes to have no activity in this new monetary system over a period of 30 days, and also users who did not join until later will lead with a lot of zeros in the metrics that we are utilizing. Therefore, to obtain more data per actor, we assembled graphs with 90-day windows sliding 30 days, and graphs with 150-day windows sliding 30 days. With these windows, we can count more actors and transactions in every time span delivering fewer zeros in our explained metrics.

Now we need to identify agents in time: *Early* are agents with a transaction before the OLEPF date; *Late* are agents with a transaction after the OLSRRAZE date, *Continuing* agents are the intersection of *Early* and *Late*, and *Total* agents are the union of *Early* and *Late*. Unlike the temporal analysis where the number of nodes each 30-day is changing, here, the number of nodes is fixed, including every agent under analysis in all-time spans regardless of whether they had activity in a given time span.

The specification that we use to evaluate the impact of the tax-incentive policy on each type of agent is:

$$y_{it} = \alpha + \beta t + \gamma After_t + \delta After_t * t + \epsilon_{it}$$

where y_{it} is the outcome measure for each of the five metrics discussed above, for node i at time span t . For the term βt , the coefficient β provides the time-trend before the incentive policy. $\gamma After_t$ is a term with a dummy variable $After_t$ for before and after the policy where the coefficient γ captures a change in

level immediately after the tax-incentive policy. Finally, the term $\delta After_t * t$ describes the interaction of the policy with time: this is the time trend changes or changes in growth rate over time for the explained variable. The magnitude δ describes the new direction of the trend after the policy when compared to β .

To overcome serial correlation and heteroscedasticity in the error terms, we did the regressions using Newey-West robust standard errors. We describe below the results for 90-day time spans, where each column is a separate regression for each agent type (users, companies, and macro-agents). We leave the 30-day and 150-day time spans regressions for the supplementary information section as robustness checks. We note that the results of the estimators are consistent across the three different time spans (30-day, 90-day, 150-day).

Result 1: *The policy had a significant immediate effect on the behavior of continuing users. In particular, there is a significant positive change in the number of transactions, the average value of the transactions, and the total value of transactions.*

This result can be seen by looking at the estimates for the variable $After_t$ in Tables 1-3 (Users column). We also note that this result is robust across the three specified time spans. While this policy had a significant immediate effect at the discontinuity in all the metrics, there is no change in the trend after the policy. Furthermore, for some metrics, the benefits of the policy on users' behavior slowly disappeared over time, as we discuss in detail below.

While this policy was specifically targeting users' behavior, we show that no externalities are seen for companies and macro-agents on either of the metrics.

Result 2: *The policy had no effects on the behavior of continuing companies and macro-agents for any of the five metrics, both for changes in level and time trend.*

This result can be seen by looking at the estimates for the variables $After_t$ and $After_t * t$ in Tables 1-5 (Companies and Macro-Agents column). We also note that this result is robust across the three specified time spans.

We now provide the specific magnitudes of changes to each of the six metrics derived by the estimation.

Table 1
Number of transactions – 90-day spans

	Users	Companies	Macro-Agents
Time	0.131*** (0.027)	8.031** (3.927)	2.136 (3.177)
After	4.676*** (1.098)	375.544 (896.562)	1,074.087 (981.929)
(After)(Time)	-0.157 (0.108)	271.885 (171.160)	50.788 (118.751)
Constant	2.653*** (0.272)	88.995** (41.655)	73.641 (43.540)
Observations	37,521	627	198

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table 1 shows that the tax-incentive policy had a permanent change in the average number of transactions per user. This amounts to an average increase of 4.68 transactions per user, a 130% increase over the 90-days before the policy. The time trend remains statistically constant over time, as the change in the trend of transactions is not statistically different than zero.

It is remarkable that despite the large growth on the amounts of tax-incentives returned to users (See Figure 13 and 14), the average number of transactions per person did not increase over time.

Table 2
Mean transaction value – 90-day spans

	Users	Companies	Macro-Agents
Time	0.298*** (0.060)	0.511 (0.323)	0.566 (0.915)
After	4.078*** (1.064)	-0.885 (5.222)	-1.269 (9.176)
(After)(Time)	-0.336*** (0.116)	-0.504 (0.366)	-0.676 (1.123)
Constant	4.424*** (0.582)	7.898 (4.714)	14.210 (8.877)
Observations	37,521	627	198

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

While on average every user increases their spending of \$4 per user with the tax-incentive, (62% increase) at the time of the policy, the benefits did not persist. In particular, we observe a strong negative change in the trend of 0.34, Table 2. The benefits of the policy on the mean transaction per user are basically dissipated by the time in which the project ended.

Table 3
Total value of transactions – 90-day spans

	Users	Companies	Macro-Agents
Time	2.054*** (0.537)	62.516 (34.267)	134.566 (170.683)
After	119.539** (55.440)	4,170.653 (8,663.990)	23,572.866 (17,422.425)
(After)(Time)	-4.931 (2.589)	1,888.970 (1,514.242)	178.777 (1,953.199)
Constant	26.317*** (5.406)	665.960 (357.073)	2,371.327 (2,047.710)
Observations	37,521	627	198

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Results in Table 3 show that for the total value of transactions per agent per 90 days, there is a positive jump of \$120 caused by the policy, more than 200% increase over their previous value. While the new trend is negative, it is not statistically significant. The total value of transactions at best remained constant or even decreased after the incentives. This is consistent with the temporal analysis observed in Figure 5, where the total amount of dollar exchanged in transaction per agent is around \$58.6 after incentives in 30-day spans. Therefore, again we see that MM was never a significant component of the economic activities of agents in Ecuador.

While we have shown that tax-incentive policy resulted in a temporary level effect for the three metrics of economic activity, their growth at best remains constant or decreased, potentially making their effect disappear by the end of the project. We now focus on two additional network metrics that relate to the interconnectedness of agents of continuing individuals.

Result 3: *The policy increased the number of partners with marginal effects on the interconnections between them over time.*

According to Table 4, the incentives increased the average number of partners by 1.6 agents (114% increase with respect to previous period). This trend remained constant with almost zero growth over time. Therefore, the policy did not incentivize agents to continue searching for new partners with time. This is consistent with our temporal analysis when we showed that the average number of partners for all the agents remained basically constant at 2.4 partners; thus, newly entered nodes had less than 2.4 partners throughout the life of the project.

Table 4
Number of partners per agent – 90-day spans

	Users	Companies	Macro-Agents
Time	0.018 (0.010)	2.151** (0.995)	0.176 (1.501)
After	1.556*** (0.255)	111.088 (204.442)	442.837 (465.035)
(After)(Time)	-0.044 (0.026)	52.443 (35.782)	37.958 (63.431)
Constant	0.942*** (0.083)	24.062** (10.526)	29.723 (19.113)
Observations	37,521	627	198

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table 5
Local clustering coefficient – 90-day spans

	Users	Companies	Macro-Agents
Time	0.001661*** (0.000385)	-0.003905 (0.002684)	-0.001262 (0.001209)
After	0.013826*** (0.004835)	0.046472 (0.026533)	0.006509 (0.011533)
(After)(Time)	-0.001833*** (0.000557)	0.001319 (0.003105)	0.001232 (0.001310)
Constant	0.033016*** (0.003783)	-0.006969 (0.014155)	0.000732 (0.007942)
Observations	37,521	627	198

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

The local clustering coefficient changed for continuing users by 0.013 units in the time of the policy. The increase was 34% with respect to the previous coefficient, evidencing the lack of clusters before and after the policy was implemented (Table 5). The clustering was actually marginally increasing with time before the policy to become almost zero after the policy. The combination of Table 4 and 5 evidence the effect of the tax-incentive on the topology of the network of users: an increase in the number of partners, but a lack of interconnections between them. This result reinforces what we obtained in the previous section where we describe that users were motivated by the policy to try to obtain the benefits of the incentives rather than perform more interaction with peers.

Definitively, for agents that we could identify as continuing users, the tax-incentives surprised them by giving them the opportunity to receive an extra benefit for continuing using the new tool, making them “jump” instantaneously at the moment of the policy in partners and transactions, but didn't incentive them

to expand the contacts with time. Therefore, the MM did not occupy a large space of their economic activities, and never found a real possibility of expansion over time.

Finally, we want to see the effect of the policy when we do not distinguish between different types of agents, that is when we include All Continuing agents (users, companies, and macro-agents). We perform a Newey-West robust standard errors regression employing the same model as before, but now, we are using collapsed samples for average values of the metrics in each time span in the 90-day window. Therefore, we only work with 33 observations. The result of the regression is presented in Table 6.

Table 6
Number of transactions, Mean transaction value, Total value, Number of partners and Local clustering coefficient – 90-day spans

	Number Transact.	Mean Transact. Value	Total Value	Number of Partner	Local Clustering Coefficient
Time	0.275*** (0.056)	0.302*** (0.067)	3.726*** (1.051)	0.055*** (0.016)	0.00154*** (0.00025)
After	16.111*** (4.537)	3.954** (0.920)	306.184*** (89.165)	5.718*** (1.243)	0.01463** (0.00236)
(After)(Time)	4.937*** (0.396)	-0.338*** (0.067)	27.701*** (7.860)	1.106*** (0.108)	-0.00177*** (0.00023)
Const.	4.495*** (0.480)	4.522*** (0.595)	48.897*** (8.716)	1.493*** (0.146)	0.03208*** (0.00186)
Observ.	33	33	33	33	33

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01. Each column reports a separated regression, conducted for all agents.

Here, we have some similar results to the case of continuing users. The tax-incentive policy generated an immediate positive level effect in number of transactions, mean transaction value, total value, number of partner and local clustering coefficient metrics. Also, for the metrics: mean transaction value and local clustering coefficient, a negative change in the time trend at the time of the incentives policy makes the new trend almost flat or even negative, a similar result as in Table 2 and Table 5 for the continuing users. The difference now with respect to continuing users is that a change in the time-trend after the policy is present for number of transactions, total value of transactions and number of partners. The infusion of many new (*Late*) actors (who are not directly in the regression data but who potentially provide partners for those who are in the regression data) increases the number of transactions because there are more people in the network but decreases the value as it is oriented more towards small transactions spending out the incentives. Since these new actors are not joining to transact with peers, but rather with the macro-agents and companies, the clustering coefficient increases marginally at the time of the policy but decreases with time. This is exactly what we saw in the temporal analysis (Figure 3-6).

7. Discussion

Despite several results that support government subsidies to early adopters of new technologies in a wide range of markets from agriculture to telecommunications (23), the Ecuadorian MM project illustrates the need to find more effective mechanisms to distribute these subsidies in MM markets. Our analysis suggests that tax refunds had marginal temporary effects that were diluted with time. In particular, tax-incentives minimally distorted the network of agents that were already using the tool and brought a massive number of new users that were only motivated to cash-out the incentives rather than adopt the innovation as a regular substitute for cash transactions. Many MM accounts were activated for the refund of taxes but did not carry out any transactions. By the end of December 2017, there were 402,515 MM accounts. However, only 41,966 accounts (10.43%) were used to acquire goods and services or to make payments, as seen in the Transaction Network. There are 76,105 accounts (18.91%) that deposited and withdrew money without making any transaction with a third party. These are users that are benefiting from the OLEPF and OLSRRAZE laws, and from time to time they withdraw what the Government refunds for payments made by credit cards or debit cards. These refunds are part of the Tax Incentives Network. Finally, 284,444 accounts (70.67%) were activated but never used in any operation. These could be accounts that were created from the beginning of the project and did not find the “connection” or the right incentive to expand its use.

The MM project in Ecuador draws important lessons on diffusion, adoption, and penetration in MM markets that are vastly different from other markets studied in the past. We distinguish them into three main components: First, we distinguish topological arguments in the network that facilitate diffusion and whether they are present in the Ecuadorian MM project. Second, we address literature on the adoption of behaviors and its connection to the Ecuadorian MM project. Finally, we distinguish specific aspects that are characteristic of Ecuador and the Ecuadorian MM project that likely contributed to low penetration in comparison to other MM projects.

Regarding the topology of the transaction network, we note that studies of the spread of diseases in contact networks and of information in communication networks show that the spread is enhanced in “scale-free” networks, or more generally those with heavy-tailed degree distributions (24). These networks are dominated by a relatively small number of high degree nodes: hubs. In contrast with this literature, the MM transaction network is a heavy-tailed network that has low clustering coefficients and is scale-free, yet we see low adoption. However, we note that those who are in the MM transaction network have already adopted the behavior. Thus, the network of transactions may not say much about whether the larger network consisting of all economic activity of agents is scale-free. We also note that we did not find the formation

of clusters in the transaction network that evidence diffusion and network effects, a relevant feature for technology adoption in automated clearinghouse (ACH) electronic payments systems (25). Furthermore, even if the right conditions in the topology of the network for information spreading were present, this is different from the adoption of behaviors: news of an MM innovation can spread to individuals who choose not to adopt it – this is not directly observed in our data—leading to the next category of distinctions.

Regarding the adoption of behaviors, information diffusion may not be the correct model. “Complex contagion” is present when adoption requires exposure to a new behavior via multiple ties (rather than a single tie). It is present, for example, when the new behavior has greater value if network partners adopt it. Under this condition, single long distance or “weak” ties such as are found in scale free networks, and that are so effective for spreading information, are not effective for spreading adoption of behavior (26). “Wide bridges” (exposure via multiple partners) are required. Indeed, clusters of users engaged in prior behaviors (e.g., conventional economic transactions) are resistant to change to new behaviors unless a threshold of adopting neighbors is overcome (27). Our data does not include these prior behaviors nor the prior network that results, so we cannot evaluate these interpretations directly, but they are plausible literature-based arguments that indicate directions for further research.

Our data evidences that only a small proportion of agent’s contacts engaged in the adoption of MM, and therefore even if an agent adopted MM as its preferred method of payment, non-MM transactions with non-adopters were dominant in their daily life. While our data do not have information about the full social and economic network of agents (outside MM), we do know that the average number of MM partners remained constant at 2.4 per 30-days; by any measure this number is too small among the number of active partners of an average individual. Furthermore, we know that in the best case, only 22,106 agents transacted regularly, that's about 0.25% of the active economic people in Ecuador. These numbers are not enough for the adoption of a new behavior in traditional models of adoption in networks (29–32).

Several reasons likely contributed to the low penetration of MM in Ecuador. Heyer & Mas (33) highlight the importance of network effects, momentum, and trust in their explanation of the successful case of M-PESA in Kenya, none of which seem present in Ecuador. Camner et al. (34) compare the cases of MM in Kenya and Tanzania, both managed by the mobile operator, and shows how the development of their business model in conjunction with the design of the MM project plays a role in the success of the adoption. This is in contrast with Ecuador, where the implementation was left to the Central Bank of Ecuador and where the mobile operators were never part of this implementation. Balasubramanian & Drake (35) look at how the demand for MM in Kenya and Uganda is affected by macro-agent quality and competition. For the case of Ecuador, we have seen that the incentives were directed to final users and had

no significant effect on macro-agents. It is unclear what the effects on adoption would have been had the incentive strategy targeted agents with the largest centralities, such as the macro-agents or companies.

Finally, the credibility of the actor implementing a MM project plays an important role. Abdul-Hamid et al. (36) demonstrated that trust in service providers and economy-based trust are positively associated with customers' intent to use MM services. White (37) argues that an important determinant of the failure in Ecuador is that people do not trust the government, especially the Central Bank, given the history of default on sovereign bonds and its participation in the 1999 economic crisis.

8. Conclusions

Mobile Money in Ecuador was introduced by the government as a tool to help an economy with a shortage of liquid assets. The measures taken by the government to encourage its use had modest result that distorted the economic behavior of users. Transfers from the government mainly incentivized the recurring use of current connections rather than a network expansion. Using our unique data set of the entire MM network, from its conception to its ending, we tracked agents within a network and quantified the exact effects of these incentives. The expansion and diffusion conditions that the government of Ecuador expected with this policy were never generated.

The Transaction Network tells us that the total amount of dollars a user transacts per 30-day was around \$58.6, approximately \$11.3 per transaction. The structure of the network shows us that most relationships were only between macro-agents and users, not good for peer to peer information diffusion and expansion.

In this network we measured the effect of agents that we could identify as continuing users. The policy had a significant immediate effect on the behavior of continuing users, increasing the number of transactions by 4.67, increasing the average value of transactions by \$4 and increasing the total value of transactions by \$120 per 90 days. The long-term trend effect of the incentives is never positive, with a negative effect of 0.336 in the time trend of the mean transaction value. Therefore, the effect of tax-incentives is immediate but dissipates as time passes. As such, MM never occupied a large space in individuals' economic activities.

We also found that the policy changed the number of partners by an average of 1.5 and the local cluster coefficient for continuing users by 0.013, but had a marginal effect on the interconnection over time. Moreover, the incentives policy had no effects on the behavior of continuing companies and macro-agents. Hence, tax-incentives did not produce significant network effects that persisted over time and failed to incentivize the macro-agents.

The Exchange Networks for Cash-in shows that on average 2,657 people cash-in money into this network in an amount of \$273 per month and the Exchange network for Cash-out shows that on average 13,070 users withdrew money from this network for an amount of \$140 per month after the incentives laws, evidencing that many people joined the network only to cash-out their tax refunds.

Government incentives resulted in a high price tag with respect to the total amount of transactions used for the purchase of goods and services. A total of \$8 million worth of purchases of goods and services were transacted with MM after the tax refund policy was adopted yet the government refunded a total of \$16 million in taxes.

Although MM technologies have shown promising results in many developing countries and have the potential to revolutionize the way people transact, it is still unclear how to design and implement an optimal tax-incentive mechanism that would maximize adoption in such large networks and is consistent with the behaviors of different type of agents.

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10. Supplementary Information

Robustness Checks for Regression Results for 30-day and 150-day spans

Table S.I.1
Number of transactions - 30-day spans

	Users	Companies	Macro-Agents
Time	0.043*** (0.008)	2.433 (1.250)	0.810 (0.983)
After	1.614*** (0.372)	147.574 (306.746)	369.765 (330.296)
(After)(Time)	-0.059 (0.034)	86.881 (55.245)	14.609 (36.745)
Constant	0.878*** (0.090)	28.468** (13.936)	25.192 (14.425)
Observations	39,795	665	210

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.2
Mean transaction value - 30-day spans

	Users	Companies	Macro-Agents
Time	0.143*** (0.024)	0.394 (0.202)	0.346 (0.783)
After	3.781*** (0.854)	0.144 (3.491)	-0.137 (8.081)
(After)(Time)	-0.189*** (0.067)	-0.306 (0.261)	-0.337 (0.972)
Constant	2.179*** (0.260)	5.467 (2.898)	11.443 (8.035)
Observations	39,795	665	210

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.3
Total transaction value - 30-day spans

	Users	Companies	Macro-Agents
Time	0.551*** (0.103)	19.688 (11.023)	28.173 (51.732)
After	42.554** (19.323)	1,498.012 (2,989.690)	8,178.101 (5,859.829)
(After)(Time)	-1.687 (0.873)	609.140 (492.566)	41.523 (603.898)
Constant	7.552*** (1.106)	220.475 (120.880)	680.537 (635.181)
Observations	39,795	665	210

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.4
Number of partners per agent - 30-day spans

	Users	Companies	Macro-Agents
Time	0.011*** (0.003)	0.814 (0.380)**	0.289 (0.519)
After	0.741*** (0.133)	52.214 (106.981)	211.185 (211.090)
(After)(Time)	-0.019 (0.012)	28.039 (18.648)	14.805 (26.365)
Constant	0.382*** (0.031)	9.576 (4.247)**	12.732 (7.477)
Observations	39,795	665	210

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.5
Local clustering coefficient - 30-day spans

	Users	Companies	Macro-Agents
Time	0.000401*** (0.000132)	-0.001862 (0.001410)	-0.000761 (0.000863)
After	0.009786*** (0.002384)	0.015237 (0.009721)	0.001134 (0.011485)
(After)(Time)	-0.000346 (0.000236)	0.001377 (0.001471)	0.000964 (0.000944)
Constant	0.009257*** (0.001371)	-0.006551 (0.007123)	0.003930 (0.009028)
Observations	39,795	665	210

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.6
Number of transactions - 150-day spans

	Users	Companies	Macro-Agents
Time	0.256*** (0.051)	16.379** (7.560)	7.318 (8.329)
After	7.079*** (1.758)	567.890 (1,458.016)	1,705.888 (1,590.752)
(After)(Time)	-0.249 (0.192)	460.540 (293.528)	88.904 (210.619)
Constant	4.740*** (0.486)	170.451** (75.912)	158.263 (98.106)
Observations	35,247	589	186

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.7
Mean transaction value - 150-day spans

	Users	Companies	Macro-Agents
Time	0.429*** (0.091)	0.492 (0.295)	0.650 (0.705)
After	4.168*** (1.255)	-0.301 (4.640)	0.772 (7.827)
(After)(Time)	-0.489*** (0.166)	-0.524 (0.353)	-0.853 (0.971)
Constant	6.200*** (0.830)	8.003** (4.056)	13.798 (7.229)
Observations	35,247	589	186

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.8
Total transaction value - 150-day spans

	Users	Companies	Macro-Agents
Time	4.680*** (1.351)	127.686 (70.237)	281.227 (290.451)
After	175.594** (86.873)	6,351.110 (14,059.987)	38,566.983 (28,768.918)
(After)(Time)	-7.899 (4.554)	3,228.145 (2,624.742)	340.105 (3,451.224)
Constant	54.692*** (12.844)	1,286.036 (690.660)	4,243.024 (3,422.490)
Observations	35,247	589	186

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.9
Number of partners per agent - 150-day spans

	Users	Companies	Macro-Agents
Time	0.034 (0.017)	3.926** (1.636)	2.562 (4.069)
After	2.039*** (0.333)	179.408 (272.601)	625.673 (642.663)
(After)(Time)	-0.075 (0.040)	66.011 (47.580)	49.072 (92.630)
Constant	1.559*** (0.141)	41.563** (16.553)	67.615 (45.312)
Observations	35,247	589	186

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.

Table S.I.10
Local clustering coefficient - 150-day spans

	Users	Companies	Macro- Agents
Time	0.003143*** (0.000546)	-0.008072 (0.005851)	-0.000997 (0.000802)
After	0.009152 (0.006151)	0.091741 (0.048634)	0.00822 (0.010773)
(After)(Time)	-0.003300*** (0.000791)	0.002977 (0.006569)	0.000715 (0.001021)
Constant	0.054885*** (0.005287)	-0.010067 (0.027701)	0.000789 (0.004959)
Observations	35,247	589	186

Note: Standard errors in parentheses. **p < 0.05, ***p < 0.01.
Each column reports a separated regression, conducted for each agent's type: Users, Companies and Macro-Agents.