The adoption of a mobile payment system: the user perspective [α]

Carlos León [β]

Abstract

Mobile wallets replicate physical wallets on a mobile device, in which users can store different payment instruments to make mobile payments. As the mobile wallet is adopted, a mobile payment system emerges. I study the mobile payment system of Movii— the first fintech firm in Colombia operating under a financial non-banking license for electronic deposits and payments. Based on a unique dataset of daily bilateral transfers between Movii's mobile wallet users, I build, visualize and analyze Movii's network. Besides the anticipated increase in the number of users and the value of transfers, the visual and quantitative complexity of the network of transfers increases over time. This increase in complexity is likely to be linked to the adoption of Movii's mobile wallet. The behavior of users in the network of transfers shows that they find new ways to use mobile payments beyond person-to-person transfers, including person-to-business and business-to-business.

JEL Classification: L14, D85, E42

Keywords: payments, mobile, networks, fintech, paytech, complexity.

[α] Opinions and statements in this article are the sole responsibility of the author, and do not represent neither those of Banco de la República nor of Movii. This article was possible thanks to the contribution of Movii; particularly, I thank Moryoiry Ávila, Alexander Benavides, Katherine Roa, Hernando Rubio, and Andrés Suárez for discussion sessions and Alexander Benavides and Andrés Suárez for data processing. I thank Pamela Cardozo, Freddy Castro, Aura Ciceri, Clara Machado, and Serafín Martínez-Jaramillo for their comments and suggestions. Any remaining errors are my own. I declare that I have no financial, commercial, legal, or professional relationship with Movii.

[β] Financial Infrastructure Oversight Department, Banco de la República; Department of Finance, Tilburg University. E-mail: cleonrin@banrep.gov.co / c.e.leonrincon@tilburguniversity.edu.

1. Introduction

Digital wallets provide a method for making payments electronically, enabling users to transfer funds between transaction accounts—either traditional banking accounts or electronic money[1] deposit accounts—and to use other payment instruments. When the digital wallet is based on mobile devices (e.g., smartphones, tablets) it is referred to as a mobile wallet (see Bezhovski, 2016, Kaur, et al., 2020, Mumtaza, et al., 2020). Therefore, mobile wallets replicate a physical wallet on a mobile device, in which users can store different payment instruments (e.g., cards, transfers) to make mobile payments.

Mobile payments can promote and encourage the provision of payment services, especially person-to-person transfers, but also government-to-person transfers, online and offline purchases of goods and services (i.e., person-to-business transfers), and the payment of bills and fees (see Bezhovski, 2016, Iman, 2018). Hence, mobile payments and mobile wallets are considered beneficial to (unbanked) upper-middle and lower-class population, and a tool amid disaster recovery and emergency responses (see Iman, 2018, Surtikanti & Mustofa, 2019).

Movii was the first fintech[2] firm in Colombia operating under a financial non-banking license for electronic deposits and payments—known as a Sedpe license. As of September 2020, Movii is the leader of the five firms that hold a Sedpe license: Movii has about 85 percent of the value of electronic deposits and about one million clients, i.e., circa 94 percent of the market by the number of clients.[3] Movii aims at mobile person-to-person payment solutions (i.e., a *paytech* firm) with a mobile wallet under the same brand. This article aims at studying the evolution of the mobile payment system, i.e., the transfers made among Movii users with the mobile wallet.

To the best of my knowledge, there are no research works that study the evolution of mobile wallets from the users' transactional perspective. Based on a unique dataset containing the bilateral transfers between Movii users from its first transfer on November 18, 2017, to November 25, 2020, this article studies the evolution of the person-to-person networks that emerge from users' mobile

[1] Directive 2009/110/EC of the European Parliament defines electronic money as "electronically […] stored monetary value as represented by a claim on the issuer which is issued on receipt of funds for the purpose of making payment transactions […] and which is accepted by a natural or legal person other than the electronic money issuer". The same Directive grants electronic money issuers the name of "electronic money institution".
[2] FSB (2017, p.7) defines fintech as "technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services". Paytech is the payment services-oriented part of fintech sector (see Polasik, et al., 2020).
[3] The Sedpe license was created in 2014 to promote access to transactional financial services; Sedpe is a Spanish acronym for electronic deposit and payments specialized societies. The Sedpe license resembles that of electronic money institutions under European regulation, where the main difference with banking institutions is that holders of the Sedpe license are not allowed to make loans directly; akin to a banking institution, a Sedpe is authorized and supervised by the Financial Superintendence of Colombia. Movii was the first Sedpe authorized by the Financial Superintendence of Colombia (December 11, 2017).

payments.[4] The methodological approach is network analysis, which is used to build, visualize, and analyze the person-to-person mobile payments networks.

I find that the evolution of Movii as a mobile payment system goes beyond the usual measures of adoption such as the increase in the number of users and the value of transfers between them. The visual and quantitative complexity[5] of the network shows a clear upward trend, meaning that the users' behavior reveal they find new ways to use the mobile payment capabilities of the mobile wallet—beyond person-to-person transfers. Examining these new ways to use the mobile wallet suggests that some users are small vendors (e.g., micro-businesses) that start accepting transfers in exchange for goods and services. Interestingly, the emergence of person-to-business mobile payments in a person-to-person system may expose the limitations faced by small vendors to accept non-cash payment instruments. In this vein, as highlighted by Maurer (2012), people do not just use mobile money services: they innovate and they subvert, they become designers and innovators in mobile money.

Also, concurrent with evidence of fintech firms as distributors of government transfers during the Covid-19 pandemic (see Cantú & Ulloa, 2020), the government's decision to disburse transfers to the low-income population through mobile wallets parallels with a remarkable increase in the number of users and the total value of transfers during 2020. Likewise, some peaks in the usage of Movii correspond to dates in which the disbursement of those government transfers occurred.

This article contributes to related literature in two ways. First, to the best of my knowledge, there are no studies of the evolution of payment systems based on mobile wallets. As mobile payments and mobile wallets are gaining traction worldwide, studying the networks that emerge from users' transactional behavior is a convenient step for financial authorities in their quest for understanding, monitoring, regulating, supervising, and overseeing retail payment systems. Governments can enhance poverty reduction programs and disaster recovery and emergency responses by studying how government-to-person transfers are dispersed and used. Governments and market participants can study the emergence of person-to-business transfers to understand the limitations faced by small vendors to accept non-cash payment instruments. Further, studying those networks can help market participants in the paytech industry to understand how a payment system evolves. Second, from a network analysis perspective, it is interesting to examine how a

[4] Concurrent with the declared aim of Movii to provide mobile person-to-person payment solutions, as of September 2020, the Financial Superintendence of Colombia reports that 99.99 percent of clients of Movii are individuals (i.e., natural persons) and 99.96 percent of outstanding electronic deposits are below COP$ 4,300,000 (about US$1,260). Yet, the usage of Movii's mobile wallet to receive payments in exchange for goods or services (i.e., person-to-business transfers) by small vendors is likely because they—usually—can't accept other non-cash payment instruments.

[5] Simon (1962) suggests that a complex system is made up of a large number of parts that interact in a non-simple manner. However, complexity is a term with many different notions and can't be measured by a single measurement scale (see Lloyd, 2001, Mitchell, 2009). Lloyd (2001) relates measures of complexity to three dimensions: *difficulty of description*, *difficulty of creation*, and *degree of organization*.

network of interacting users evolves from the start. In this article, it is remarkable to study the formation of a non-small network, from two users on its first day to an average of about 2620 users in the last 100 days of the sample.

The rest of this paper is organized as follows. Section 2 reviews mobile wallets. Section 3 describes the dataset. Section 4 details the methodological approach. Section 5 presents the main results. Section 6 discusses the results. Section 7 concludes.

2. Mobile wallets: A literature review

Evidence suggests fintech is growing where the current financial system is not meeting the demand for financial services; in the case of Latin America and Southeast Asia, unmet demand for basic banking, payments, and money transfer services is likely the key factor behind the rapid growth of paytech firms (Frost, 2020). In this vein, paytech firms take advantage of technological progress; demographic trends; regulatory changes; changes in the socio-cultural, economic, and political environment; and their simpler organizational structures to deploy new payment technologies faster than traditional banks (Polasik, et al., 2020).

Among paytech solutions, mobile wallets are digital wallets based on a mobile device (e.g., smartphone, tablet), which enable users to make mobile payments in the form of transfers between transaction accounts, and online and offline purchases (see Bezhovski, 2016, FSB, 2017, Kaur, et al., 2020, Mumtaza, et al., 2020). Some mobile wallets also allow users to make cash withdrawals (Mumtaza, et al., 2020)—Movii, for example.

Mobile wallets and mobile payments have been studied recently.[6] Iman (2018) highlights that mobile payments are particularly important for developing countries because they enable the delivery of financial services to unbanked populations, therefore promoting and encouraging a variation of service provisions, namely person-to-person transfers. Kaur, et al. (2020) document that although mobile payments have existed for some time, mobile wallets have added a new and more versatile way of processing payments through the internet. Mumtaza, et al., (2020) emphasize that mobile wallets can be the future of a cashless system because of their ease and positive impact on non-cash transactions.[7]

[6] For a review of the evolution of mobile payments, see Iman (2018) and Acker & Murthy (2020). As one of the most celebrated advantages of mobile wallets is to enable users to store and transfer electronic money, the literature about electronic money is relevant too (see Singh, 1999, Solomon, 1999, Fung, et al., 2014, de Almeida, et al., 2018, Surtikanti & Mustofa, 2019, and McAndrews, 2020).
[7] Mumtaza, et al., (2020) highlight that credit cards are the most dominant cashless payment method on an international scale, but their restrictive access renders them—and other banking products—unfit to be the future of a cashless system.

Also, the factors behind the usage of mobile payments and mobile wallets have been studied. Karsen, et al. (2019) make a systematic review of the key factors that make people use mobile payments. They identify ten key technological, personal, and environmental factors: ease of use, perceived usefulness, perceived trust, perceived risk, social influence, perceived security, effort expectancy, attitude, performance expectancy, and facilitating condition. Correspondingly, Kaur, et al. (2020) report that mobile wallets are designed to offer swiftness, ease of use, efficiency, effectiveness, transparency, and accessibility. Mumtaza, et al. (2020) highlight that the ease caused by mobile wallets should be the main reason for implementing this system on to daily basis. Iman (2018) concludes that it is the lack of alternatives to cash, lack of access to banking products, poorly developed infrastructure, and high fees for money transfer services, that make mobile payments and mobile wallets attractive in developing countries.

Although mobile wallets have gained much attention in emerging markets, their adoption is still low and uneven (see Kaur, et al., 2020, Mumtaza, et al., 2020). Differences in access to the internet, literacy, access to banking services, and infrastructure are among the determinants of disparities in mobile wallets' adoption (see Mumtaza, et al., 2020). Iman (2018) reports that where mobile payment systems have been deployed, they were mostly used for person-to-person transfers, but also to purchase goods or services, and to pay bills and fees. Furthermore, Iman (2018) reports that mobile payment systems have enabled government-to-person payments and have proved to be helpful in disaster recovery and emergency responses. As the Covid-19 pandemic demonstrated (see Cantú & Ulloa, 2020), several governments—including Colombia's—successfully used mobile wallets and other paytech solutions to transfer funds to the bottom-of-the-pyramid unbanked population in the form of subsidies.

A long-lived shortcoming in payments literature is the lack of the users' perspective. As put forward by Singh (1999), the available payments data focus on the volume and value of payment instruments rather than users' use of forms of payment—on the technology rather than the user. Concurrently, most literature on the use of mobile wallets still focuses on the volume and the value of transactions, the number of users, or the intention to use or to recommend, either from reported data, surveys, or interviews (e.g., Iman, 2018, Surtikanti & Mustofa, 2019, Mumtaza, et al., 2020, Kaur, et al., 2020). In this vein, as highlighted by Unger, et al. (2020), there is a deficiency of research work that tracks changes in behavior within payment platforms over time.

A noteworthy exception to this shortcoming is the study of Venmo, a US-based mobile wallet that incorporates social network features, i.e., a social payment system. [8] Unlike most mobile

[8] Venmo allows its users to store balances and make transfers to each other, using connected bank accounts, debit cards or credit cards. What makes Venmo unique is its resemblance to a social network: users add other users from their friends or contacts (e.g., from Facebook or mobile phone contact list) and each transaction may be commented by the users with text or emojis in a memo field (see Unger, et al., 2020). Venmo started in 2009 and it is a subsidiary of Paypal since 2013.

wallets, payments with Venmo are—by default—included in a publicly available social media feed that has allowed researchers to study how users pay; although the amount of the transaction is not disclosed, the time, the payer, the payee, and the memos (i.e. texts and emojis commenting the transactions) between these two are available. Zhang, et al. (2017) study Venmo's social and payment networks, comprising friendship and transaction linkages, respectively; they credit themselves as the first large-scale analysis of financial transactions networks on person-to-person mobile payments such as Venmo. Acker & Murthy (2020) explores the main characteristics of Venmo, focusing on the usage of emojis and texts to comment users' transactions. Unger, et al. (2020) focus on the evolution of Venmo's transactional network to study the changes in the behavior of its users.

Therefore, this article is inspired by Singh (1999), who argues that the users' perspective is needed to better understand payment systems and money. Also, this article is strongly related to Zhang, et al. (2017) and Unger, et al. (2020), who study the transactional network of Venmo. However, several differences are noteworthy. First, Movii's data is not publicly available. Second, Movii's data includes the value of the transactions—a most interesting addition for analytical purposes. Third, Movii's data starts on the day when the first transfer occurred, and it is daily from that day (November 18, 2017) to November 25, 2020; this allows a comprehensive study of the transactional network over time, including day-by-day network statistics and visualizations—absent in Zhang, et al. (2017) and Unger, et al. (2020). Fourth, this article focuses on how the visual and quantitative complexity of the transfers network evolves as a token of users' behavior and adoption of the mobile wallet.

3. The dataset

The dataset is available from Movii in edge list format. This is a common structure in which daily transfers are individually registered in rows, with columns containing the timestamp (i.e., date), the source (i.e., the payer), the target (i.e., the payee), and the amount (in Colombian Pesos). There are 461,749 rows, comprising transfers from November 18, 2017, to November 25, 2020 (i.e., 983 days), between 178,750 users.[9] Both the payer and the payee are Movii users, thus transactions correspond to transfers of funds between Movii accounts only; these transfers are free of charge.

Table 1 reports basic statistics from the dataset. The mean value of transfers is about COP$ 94,000 (circa US$ 27), with a minimal and maximal about COP$ 100 (around US$ 0.03) and COP$ 11,900,000 (around US$ 3,400), respectively.

[9] Users are identified with an anonymous key based on their national identification number, mobile phone number, and client number. Hence, the users were anonymous throughout the research process.

	COP$	US$
Mean	93,991.00	27.12
Median	40,000.00	11.54
Mode	160,000.00	46.16
Standard deviation	149,030.00	43.00
Min	100.00	0.03
Max	11,900,000.00	3,433.20
Skewness	7.66	7.66
Kurtosis	224.87	224.87

Table 1. Descriptive statistics of the dataset. Calculated on daily transfers between users. Conversion from COP$ to US$ is based on December 2020's average official exchange rate (US$/COP$ 3466.13).

Kurtosis and skewness show that the distribution of transfers by value is right-skewed with a fat right tail, as depicted in the double-log plot in Figure 1. Correspondingly, the median and the mode are below and above the mean. This suggests that the value of transfers is not evenly distributed: a few transfers greatly contribute to the total value of transfers, whereas most transfers contribute marginally.

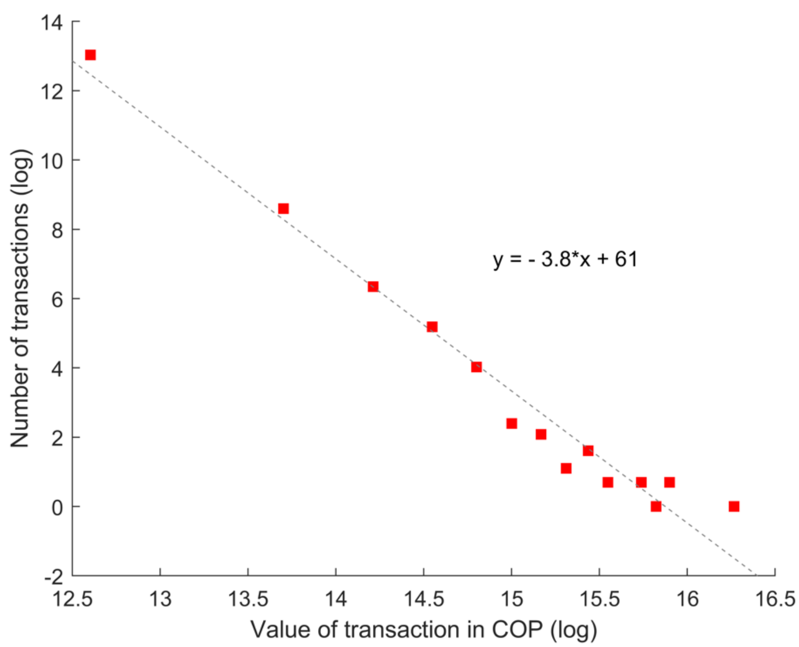

Figure 1. Distribution of transfers by value. In COP$, in double-log plot.

About the users' activity, let t_{first} and t_{last} be the first and last date a user made a transfer, respectively, t_{end} the last date in the dataset, and $\langle\cdot\rangle$ an operator that counts the number of days with transfers between two dates, the activity ratio (y) is calculated as in (1). The activity ratio is a measure of how frequent the user transfers since he first made a transfer. “One-and-done” users, also known as “instant quitters”, result in $y \sim 0$, whereas an everyday user will result in $y = 1$.[10]

$$y = \frac{\langle t_{last}, t_{first} \rangle}{t_{end} - t_{first} + 1} \tag{1}$$

Figure 2 shows the histogram of the activity ratio. About 34.22 percent of users are of the “one-and-done” type. Users whose activity ratio is in the $0.01 \geq y > 0.10$ range are about 59.47 percent, whereas those in the $0.10 \geq y \geq 1$ are about 6.31 percent. Therefore, the activity ratio suggests that most users are sporadic.

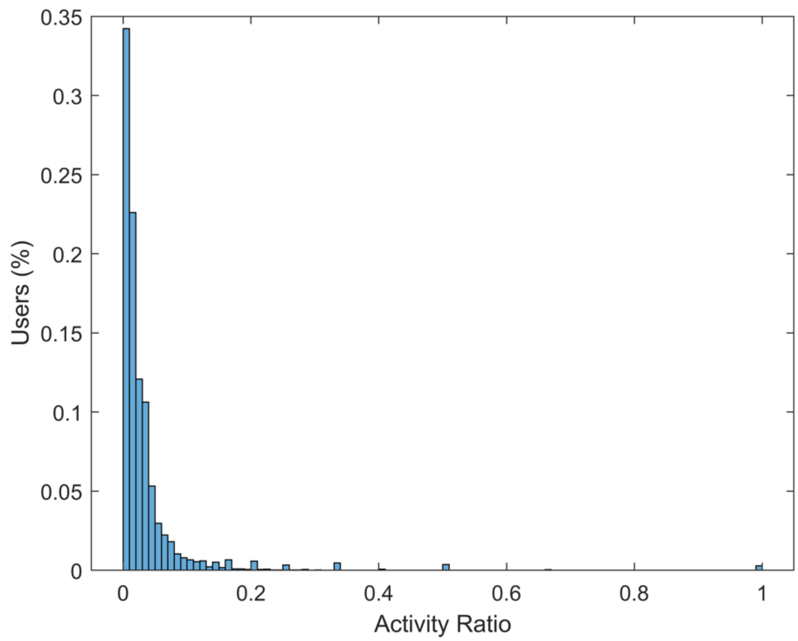

Figure 2. Histogram of the activity ratio.

4. Methodology

Networks are a natural representation of complex systems (Caldarelli, 2020). Movii users are the elements of the (complex) system, whereas their transfers are their relations. As I represent Movii’s

[10] This is a modified version of the activity ratio suggested by Unger, et al. (2020). As the numerator in their ratio is calculated as the subtraction between two dates (i.e., without the $\langle \cdot \rangle$ operator), it does not consider how frequent transfers are; for instance, if a user makes two transfers only, and the last one matches the last date of the dataset, his activity ratio will be 1—notwithstanding he only made two transfers.

system as a network, its users are represented as nodes that interconnect when they send or receive a transfer from other users.

As the direction and value of the transfer are available, I work with a directed and weighted network. Let n represent the number of users in the network at time t, W is a matrix of dimensions $n \times n \times t$, with each element $w_{i,j,t}$ containing the sum of the values (in COP$) of the transfers made by user i (the payer) to user j (the payee) during day t.

$$W = \begin{bmatrix} 0 & w_{1,2,t} & \cdots & w_{1,n,t} \\ w_{2,1,t} & 0 & & w_{2,n,t} \\ \vdots & & \ddots & \vdots \\ w_{n,1,t} & w_{n,2,t} & \cdots & 0 \end{bmatrix} \tag{2}$$

From the matrix of transfers in (2), the size of the matrix may change over time; that is, n, the number of users, may not be the same throughout the sample. Also, as the transfers from i to j and from j to i may be different, the matrix may be asymmetric. Transfers sent and received by the same user do not exist.

Network analysis is the methodological approach to study Movii's network of transfers. Network analysis is dedicated to describing and understanding an underlying system, focused on capturing its structure (Börner, et al., 2007). From W and the Boolean or binary version of W, A, I calculate a selected set of network statistics for each day, namely i) the size of the network; ii) the total value of transfers; iii) the density; iv) the average number of connections per node; v) the reciprocity; vi) the transitivity; vii) the number of connected components; viii) the number of components with two and more than two nodes; ix) the size of the largest component; and x) the degree structure entropy of the network.[11]

The size of the network (n) measures the number of users. In the first days of operation, n should be rather low, with just a few users transferring funds between them. As adoption increases, n should increase; that is, the larger n, the higher the adoption of Movii. The total value of transfers has a similar interpretation: As adoption increases, the value of transfers between users should increase. The number of users and the value of transfers are customary measures of adoption.

Density (d) measures the cohesion of the network. It is calculated as the ratio of the number of actual connections (m) to the possible number of connections, bounded to the $0 < d \leq 1$ range.

[11] A, the Boolean version of W, is obtained by transforming all non-zero values in W into 1. A is commonly referred to as the adjacency matrix, whereas W is referred to as the weighted adjacency matrix. For detailed explanations of the selected network statistics, see Börner, et al. (2007) and Newman (2010).

Networks approximating the upper limit are labeled as *dense*, whereas those with a much smaller density ($d \ll 1$) are labeled as *sparse*. Taking into account that the possible number of linkages is of the order $n^2 - 1$ and that the number of connections of each user should be rather low, the density of the network should decrease as adoption increases. Low-density—order of magnitude $1/n$ or less—is usual in financial networks, thus I expect the network to be sparse.

$$d = \frac{m}{n^2 - 1} \tag{3}$$

Likewise, the average number of connections per node measures the cohesion of the network. Nevertheless, unlike the density, it is an absolute measure of the number of counterparties the typical node has—irrespective of the size of the network. As before, I expect that the number of connections of each user remains rather low, even as the adoption increases.

Reciprocity (r) measures the frequency with which a transfer from i to j is complemented by the reciprocal transfer, i.e. from j to i. Reciprocity is calculated as the fraction of transfers for which there is a transfer in the opposite direction in the network; it is bounded to the $0 < d \leq 1$ range, where $r = 1$ when the network is purely bidirectional and $r = 0$ when the network is purely unidirectional. I don't expect reciprocal relations in the network at a daily frequency because it should be uncommon to find that user i transfers to user j and j transfers to i on the same day. Yet, first-time users of Movii may attempt to send funds back and forth to an acquaintance as an experiment; making or amending a mistake are reasonable explanations too.

$$r = \left(\sum_{ij} A_{ij} A_{ji} \right) \Big/ m \tag{4}$$

Transitivity (c), commonly referred to as clustering coefficient, measures the frequency with which loops of length three appear in the network. It is the ratio of the number of triangles (i.e., three nodes interlinked by three connections) to the number of connected triples (i.e., three nodes linked by two or three connections). In this case, it measures how often two users, i and j, that make transfers with a third user, h, also make transfers between them. I expect transitivity to be low but with an increasing trend. In the early stages, low levels of adoption make triangular loops among users unlikely. However, as adoption increases, it is likely that three users exchange funds among them.

The number of connected components is the number of groups of nodes that are interconnected but remain unconnected to nodes from other groups.[12] Among the connected components, I focus on groups with two nodes and with more than two nodes. Groups with two nodes are the most basic type of relation in the network, corresponding to two users knowingly exchanging funds in isolation from all other users. Groups with more than two nodes correspond to users converging—knowingly or unknowingly—into more complex transfer structures. These more complex structures include, for example, stars (i.e., a central node connected to many other nodes), chains (i.e., a sequence of connected nodes), circles (i.e., a loop of connected nodes), etc., which may reveal the concurrence of users in the Movii system. As the adoption of Movii increases, I expect the number of groups with two nodes and more than two nodes to increase. However, I expect groups with more than two nodes to rise as a distinctive feature of higher stages of adoption.

Akin to the number of groups with more than three nodes, the number of users in the largest group in the network is indicative of how users converge—knowingly or unknowingly—into complex structures. Therefore, I expect the size of the largest component to increase as adoption increases.

The degree structure entropy (E) is used to measure the topological complexity of the network. Calculating the entropy allows to better understand the structural complexity of the network; it is a numerical expression of network structure (Cai, et al., 2017). The degree structure entropy is based on Shannon entropy and the distribution of nodes' connections. Let k_i be the number of—undirected—connections of node i (i.e., the degree of i), the entropy of a probability scheme constructed by assigning the probability $p_i = k_i / \sum_i^n k_i$ to each node i can be viewed as a probabilistic measure of the complexity of the network (see Mowshowitz, 1968, Bonchev & Buck, 2005, Mowshowitz & Dehmer, 2012).[13]

$$E = -\sum_{i=1}^{n} p_i \, log(p_i) \tag{5}$$

[12] A connected component is a subset of nodes of a network such that there is at least one undirected path (i.e., a sequence of connections disregarding their direction) between each member of the group, and such that there are no paths with nodes in other groups.

[13] Other probability schemes are available besides the distribution of degree (see Bonchev & Buck, 2005, Cai, et al., 2017, Wen & Jiang, 2019). In Figure A3 (in the Appendix), I compare the degree entropy with other probability schemes and with *cycle rank*, a measure of organizational complexity (see Concha, et al., 2018, Flood, et al., 2020); cycle rank measures complexity as the number of linkages that must be removed to get a *minimal spanning tree*, i.e., the simplest graph covering all nodes but containing no cycles. Table A1 (in the Appendix) shows that entropy-based and cycle rank are highly correlated and—thus—overlap in their informational content. Therefore, for brevity, we focus on degree structure entropy.

The degree structure entropy of the network is widely used for measuring networks' structure complexity (Wen & Jiang, 2019). It represents the amount of information required to provide a statistical description of the network (Morzy, et al. 2017). It satisfies the criteria for a complexity measure because it increases with connectivity and other complexity factors, such as the number of branches, cycles, etc. (see Bonchev & Buck, 2005).

Although the degree structure entropy is purposely designed to measure the complexity of a network, the other network statistics previously described may be regarded as measures of network complexity too. For instance, the size of the network is a simple measure of its complexity (see Mitchell, 2009, Morzy, et al. 2017). Also, networks are considered complex if they exhibit features such as the presence of patterns of interconnections involving a small set of nodes in the form of reciprocal and transitive relations (see Morzy, et al. 2017). In this vein, the number of components and components of a certain type have been used as measures of network complexity (see Bonchev & Buck, 2005). Further, as components are subsystems, their existence is indicative of hierarchy, a common attribute of complex systems (Simon, 1962, Mitchell, 2009). Accordingly, in this article there is an implicit idea: the complexity of the transfers network is indicative of the adoption of the mobile wallet from the users' perspective.[14]

Additionally, network visualization is used to examine the complexity of the system over time. As put forward by Lima (2011), network visualization is a potential visual decoder of complexity—a remarkable discovery tool, able to translate structural complexity into visual insights. In this vein, network visualization will help to track the evolution of the system of transfers among Movii users, focusing on the increase in size and the emergence of intricate transactional patterns in the network, such as stars, chains, loops, etc.

5. Main results

I present the main results in two subsections, corresponding to visual and quantitative results. I start with network visualization to exploit the immediacy of visualization power of complex networks (see Caldarelli, 2020). Afterward, I present and interpret the network statistics.

5.1. Network visualization

Graphs are the most suitable method for the depiction of networks due to their intrinsic organization based on nodes and connections (Lima, 2011). Nodes represent Movii's mobile wallet

[14] Under the three dimensions of complexity measures (see Lloyd, 2001), the selected network statistics could be classified into categories *difficulty of description* and *degree of organization*.

users, whereas the directed connections represent transfers between them, pointing from the payer to the payee. For visualization purposes, all nodes in a graph have the same size, whereas the connections differ in their width according to the value of the transfer. I employ a force layout to arrange the nodes, which attracts adjacent nodes and repulse distant nodes. To enhance the visualization as the network becomes large, I impose a gravity layout that spreads components radially around the origin and uniformly reduce the size of the nodes for graphs with $n > 100$.

There are 983 networks, corresponding to 983 days from November 18, 2017, to November 25, 2020. Time is one of the hardest variables to map in any complex system, yet it is also one of the richest (Lima, 2011). Displaying all 983 networks is unfeasible. Therefore, in Figure 3, eight graphs are representative of the evolution of the network.[15]

The evolution of the network is manifest in the sequence of graphs in Figure 3. It starts with a rather simple network with a few users displaying simple connective patterns among them (graphs a. to c.). It evolves to several tens (graphs d. and e.), several hundred (graphs f. and g.), and about two thousand users (graph h.), displaying both simple and intricate connective patterns. Regarding the intricacy of connections, as expected, new transactional patterns emerge in the form of stars, chains, and loops. Nevertheless, the vast majority of transactions are transfers between two otherwise isolated users.

Also, it is apparent the emergence of components with a non-small number of users. The largest components from 2019 onward display a common feature: they are star networks or a collection of interconnected star networks. Most of those star networks consist of surrounding nodes that transfer funds to the central node only; there are no transfers between peripheral nodes or from the central node to peripheral nodes. This is likely the footprint of a vendor of goods and services that receives payments from his customers. Further, connections between centers of stars (see graphs d. and e.) may reveal payments between users that act as individuals or businesses.

[15] The eight graphs were selected to display how the network has evolved, avoiding seasonality. The complete set of 983 graphs is available upon request.

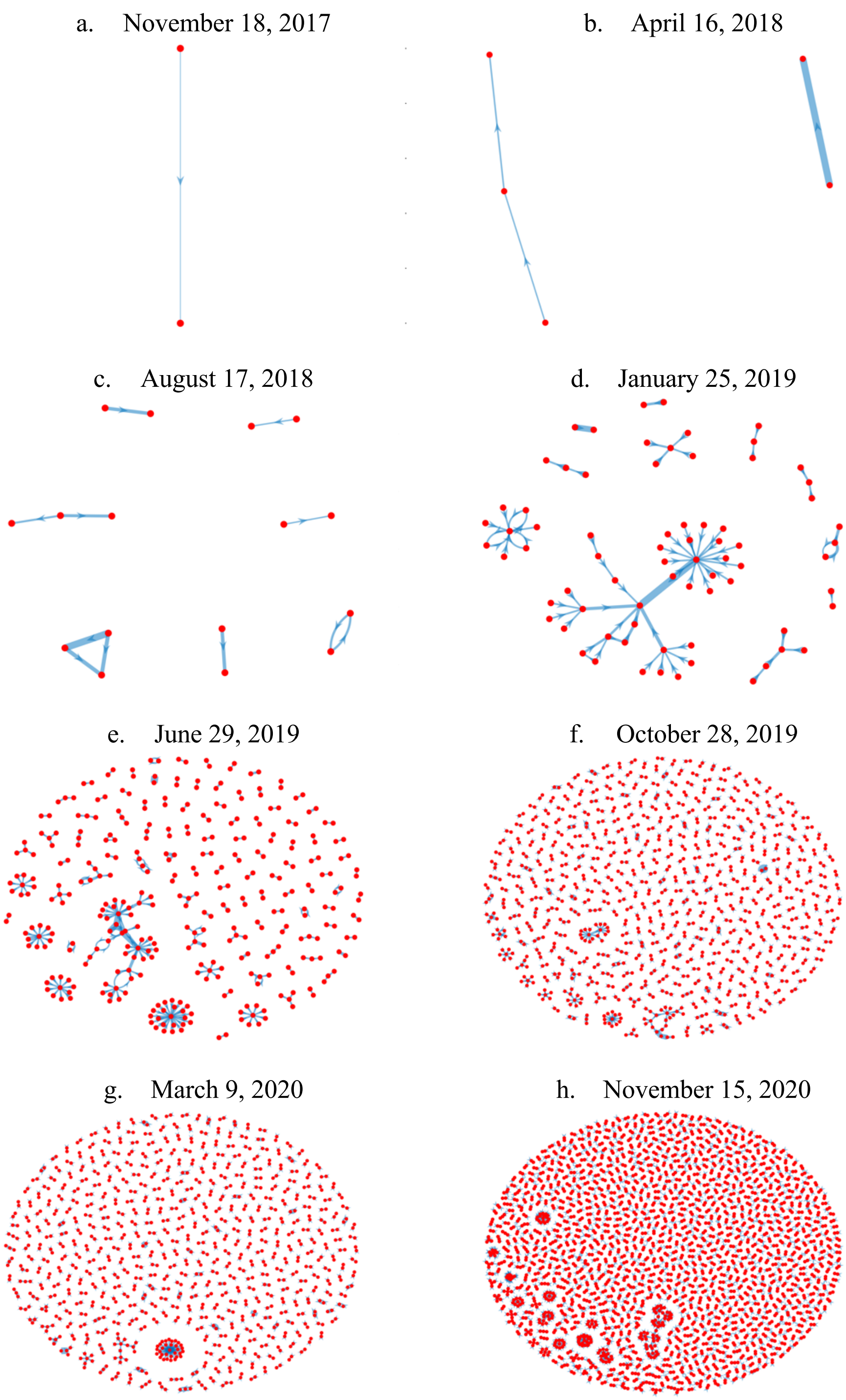

Figure 3. Selected graphs from Movii's dataset. Nodes represent Movii users, whereas the directed connections represent transfers between them, pointing from the payer to the payee. For visualization purposes, all nodes in a graph have the same size, whereas the connections differ in their width according to the value of the transfer.

Finally, to attain a complete and illustrative visualization of the evolution of the network, Figure 4 contains a video that presents the daily evolution of the graphs, from November 18, 2017, to November 25, 2020. Akin to the selected graphs in Figure 3, the video shows how a small and simple network of transfers evolves to a larger and more intricate network. Moreover, the video shows other particularities. First, the size and visual complexity of the network increased remarkably during 2020—parallel to the Covid-19 pandemic. Second, there are several abrupt increases in the size of the network during 2020, which concur with the availability of funds transferred by the government amid the Covid-19 pandemic. Third, there is a marked seasonality in January, when the size and visual complexity of the networks decreases.

[video here]

Figure 4. Video of networks from November 18, 2017, to November 25, 2020. The video is available in the PDF file when using Adobe Acrobat Reader. If using other reader or if the video does not display properly, please click or copy-paste the following link: https://youtu.be/D_BTDplRxA4.

5.2. Network statistics

The set of ten statistics described in section 4 (Methodology) is displayed in Figure 5.[16] The first two (from top to bottom, in the first row), corresponding to the size of the network and the total value of transfers, have a similar dynamic, with rather low values at the beginning of the series and an evident increase at the end. This upward trend suggests the usage and adoption of Movii's mobile wallet increased. The government's decision to disburse Covid-19 pandemic transfers to the low-income population through mobile wallets only, explains the remarkable increase in the size of the network and the total value of transfers during 2020; the spikes at the end of the series correspond to (or are close to) the days in which those government transfers peaked.[17]

[16] Figure A1 (in the Appendix) displays the same set of statistics with a logarithmic transformation. Table A2 (in the Appendix), shows descriptive statistics. For robustness, Figure A2 (in the Appendix) displays the set of statistics calculated on weekly frequency; it is manifest that weekly series correspond to smoothened versions of daily frequency series, which suggests that results and analysis are robust to changes in the frequency of the dataset.

[17] In descending order, the top-5 days by value of government transfers via Movii are September 22, November 20, August 1, July 31, and November 19, 2020. The highest peak in the size and the value of transfers corresponds to September 22 and 23.

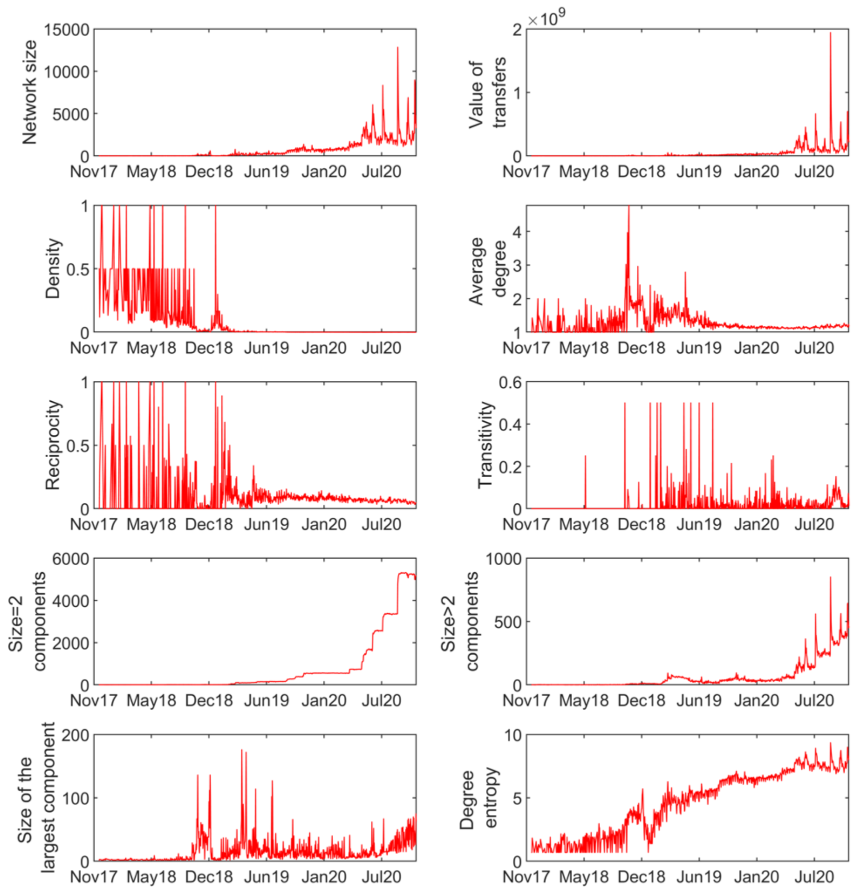

Figure 5. Network statistics (November 17, 2017, to November 25, 2020).

The second two statistics displayed in Figure 5 show two measures of network cohesiveness, namely the density and the average degree. As expected, the density decreased over time until reaching levels close to zero (i.e., a sparse network); the mean density in the first 100 days of the series is about 36 percent, whereas in the last 100 days it is about 0.03 percent.

Likewise, as expected, the average degree shows that users have a few counterparties throughout the period. In most of the series, the average degree is below two counterparties, except for a brief period in the last quarter of 2018.[18] In the first 100 days of the series, the mean average degree is about 1.17, whereas in the last 100 days it is 1.18. Figure 6 displays the distribution of degree in a double-log plot. It shows that the distribution of degree is particularly right-skewed,

[18] Compared to Venmo's average degree (5.7), the Movii's network displays a less cohesive structure. This may be related to the social network features of Venmo and the temporal aggregation in Unger, et al. (2020).

i.e., most nodes have few connections, whereas a few nodes have many connections.[19] As in Unger, et al. (2020), the skewed degree distribution may reveal the existence of businesses among the heavily connected nodes.

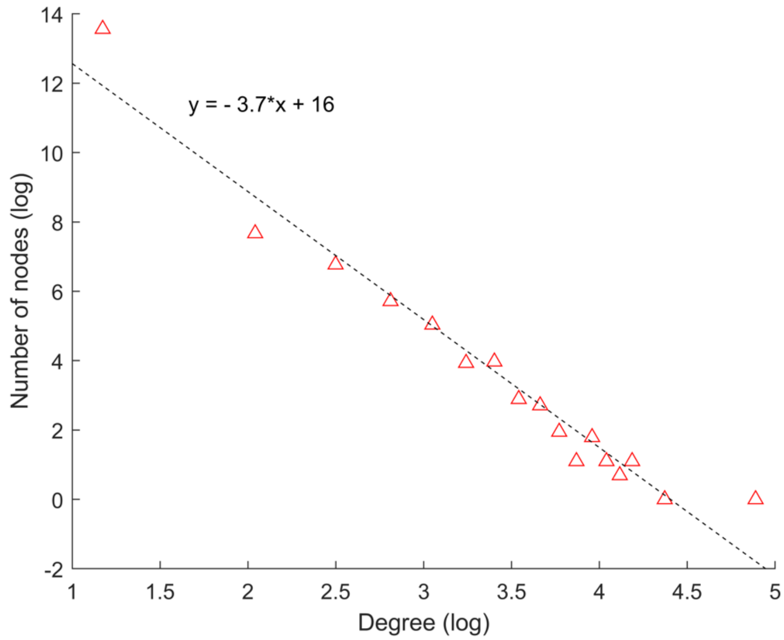

Figure 6. Distribution of degree (i.e., connections per node). In double-log plot.

The third two statistics in Figure 5 are reciprocity and transitivity. As expected, reciprocity shows a clear decreasing trend. At the start of the series, some days show that most of the relations are reciprocated, but at the end of the series, reciprocal relations are scarce. In the first 100 days of the series, the mean reciprocity is about 15.87 percent, whereas in the last 100 days it is 5.83 percent. Transitivity shows a different trend. In the beginning, when the size of the network is low, transitive relations are rare. From 2019 onwards, transitive relations become noticeable but still infrequent. In the first 100 days of the series, the mean transitivity is about 0.25 percent, whereas in the last 100 days it is 3.65 percent. Thus, as expected, transitive relations increased over time—but remain occasional.

Regarding the components in the network, components with two nodes are prevalent in the series and they show a clear increasing trend until reaching more than 4000. Components with more than two nodes show an increasing trend too, but—as expected—their level is below that of components with two nodes. In the first 100 days of the series, the mean number of components

[19] In network analysis, testing whether the distribution of degree approximates a power-law distribution is common. In that case, the network belongs to what is known as a scale-free network (see Newman, 2010). In this article, it suffices to visualize that the distribution is particularly right skewed.

with more than two nodes is about 0.7, whereas in the last 100 days it is 344.65. Likewise, the size of the largest component is low at the beginning of the series but with an increasing trend. In the first 100 days, the mean size of the largest component is 2.5 nodes, and in the last 100 days, it is 34.25.

Finally, the degree structure entropy shows a clear increasing trend, with a brief hiatus during December 2018 and January 2019. This means that complexity factors, such as connectedness, cycles, etc. increase over time—as reported in Figure 5 and with the other network statistics. In turn, this suggests that the adoption of Movii to make mobile payments increased over time.

6. Discussion

Together, the visualization of the networks and the selected set of network statistics suggest that the adoption of Movii increases throughout the period under study. Not only the number of users and the value of transfers increase manifestly as a customary token of adoption, but also the emerging intricate and multifaceted patterns of connections correspond to users—advertently or inadvertently—discovering new uses beyond person-to-person transfers. Following Maurer (2012), these emerging connective patterns are a footprint of mobile money users acting as everyday designers and innovators in mobile money.

Based on the connective patterns, I have suggested that some nodes conform to what is expected from small vendors (i.e., micro-businesses). Components in the form of star networks, with a central node exclusively receiving transfers from peripheral users that are not connected among them, is an obvious hallmark of person-to-business transfers. These person-to-business transfers materialize because small vendors are unable to accept other non-cash payment instruments (e.g., credit and debit cards, checks); that is, Movii enables small vendors to accept mobile payments in exchange for their goods and services. Also, stars tend to be interconnected through their central nodes, which may correspond to small vendors making person-to-person, person-to-business, or business-to-business payments. These particular connective patterns are regularly found throughout the series, as shown in Figure 3 and the video in Figure 4.[20]

[20] Other connective patterns that emerge as the network evolves are interesting as well, namely the lengthy loops and chains. However, these connective patterns are sporadic. These connective patterns require further study to provide a plausible explanation.

Unfortunately, the anonymity of users impedes the rigorous verification of this suggestion.[21] Therefore, I discuss how the reported connective patterns and network statistics could further support this conjecture. First, the marked increase in the number of components with more than two nodes without a parallel increase in transitivity (see Figure 3 and Table A2 in the Appendix) entails that these components tend to be interconnected around a few central nodes (vendors) without peripheral nodes transferring among them (customers). Second, related to the previous finding, there is an inverse relation between nodes' degree and transitivity (see Figure 7), typical of hierarchical modularity (see Barabási, 2003). This confirms that heavily interconnected nodes tend to transact with other nodes that do not transact between them, which yields star connective patterns that match what is expected from vendor and customer relations.

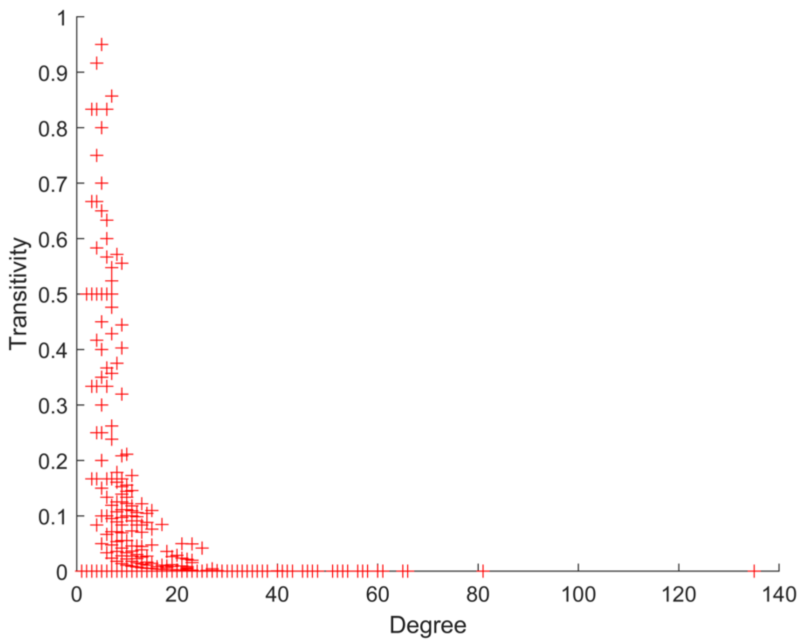

Figure 7. Distribution of in- and out-degree, i.e., incoming and outgoing connections per node.

Third, breaking down the degree distribution into in- and out-degree (see Figure 8), corresponding to the distribution of incoming and outgoing transfers, respectively, shows that the distribution is more skewed and fat-tailed in the case of in-degree. For instance, the highest in-degree is 135, corresponding to one node receiving payments from 135 nodes, whereas the highest out-degree is 37, corresponding to one node sending payments to 37 nodes.[22] That is, the highest

[21] However, when discussing results with Movii staff, there was an unofficial verification of this suggestion.

[22] Albeit the mean in- and out-degree is the same (by construction), the standard deviation, skewness, and kurtosis of the in-degree is 1.65, 4.92, and 7.42 times that of out-degree. That is, the distribution is more skewed and fat-tailed in the case of in-degree.

heterogeneity in connectedness is on the side of those who receive transfers, with a few payees concentrating a lot of payments—presumably, the vendors.

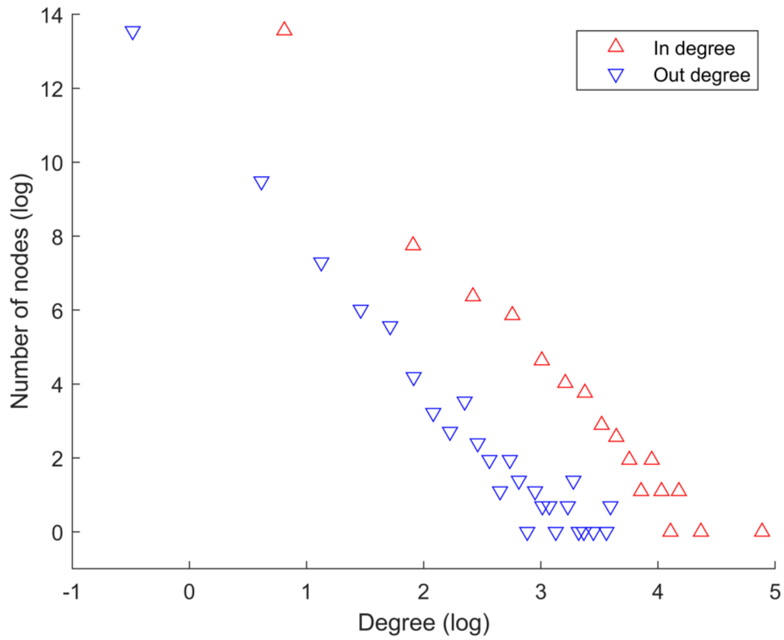

Figure 8. Distribution of in- and out-degree (i.e., incoming and outgoing connections per node). In double-log plot.

7. Final remarks

Mobile wallets and mobile payments have become a recurrent topic worldwide, with particular traction in developing countries—where the demand for basic banking, payments, and money transfer services is unmet. However, research works about how the users behave and adopt mobile wallets and mobile payments are scarce. Existing research focuses on the volume and value of mobile payments but neglects the users' behavior as they adopt mobile payments. In turn, this neglects the ability of users to become designers and innovators in mobile money (see Maurer, 2012).

This article contributes to achieving a user perspective of the adoption of mobile wallets and mobile payments. I study the networks that emerge from the transfers between users of Movii—the mobile wallet of the first fintech firm in Colombia operating under a financial non-banking license for electronic deposits and payments. A unique dataset of bilateral transfers between users is used to build, visualize, and analyze Movii's network in great detail over its lifetime. I find that the anticipated rise in the number of users and the value of transfers is accompanied by an increase in the visual and quantitative complexity of the network. I suggest that this increase in complexity is likely to be linked to the adoption of Movii, which results in users finding new ways to use mobile payments beyond person-to-person transfers, including person-to-business and business-to-business. Also, as the anonymity of users impedes the rigorous verification of this suggestion, I discuss how the reported connective patterns and network statistics could further support it.

Achieving the user perspective of the adoption of mobile payments is valuable for financial authorities, governments, and market participants. Studying the networks that emerge from users' transactional behavior is a convenient step for financial authorities in their quest for understanding, monitoring, regulating, supervising, and overseeing retail payment systems. For instance, governments can enhance poverty reduction programs and disaster recovery and emergency responses by studying how government-to-person transfers are dispersed and used. Also, governments and market participants can study the emergence of person-to-business mobile payments in a person-to-person system to understand the limitations faced by small vendors to accept non-cash payment instruments. For market participants in the paytech and fintech industry, understanding how a payment system evolves is crucial to design and implement new products and services.

There are several pending issues and challenges. First, as this article studies the transfers between Movii users, it is about an isolated system. Yet, Movii interacts with other systems (e.g., banking accounts and other electronic deposits) and services (e.g., cash in and cash out, debit card purchases); those should be integrated into the network to attain a better understanding of Movii's evolution. Second, I acknowledge that the link between the adoption and the complexity of the transfer network is an intuitive and judicious yet undeveloped concept. It is advisable to develop a proper theoretical framework that establishes this relation. Third, studying other mobile wallets—in Colombia and abroad—will contribute to determining whether the findings in this article are stylized facts of their evolution. Fourth, results suggest that the connective patterns in the transfer networks may reveal the type of nodes and relations in the system. For example, the network importance (i.e., the centrality) of nodes may reveal which nodes correspond to users selling goods and services, and which relations correspond to person-to-business transfers. Also, the connective patterns may help to identify unusual transfers worth scrutinizing. Fifth, adding users' features to the dataset (e.g., gender, age, geolocation, income, economic activity, mobile device) may open new dimensions to the analysis of the networks.

8. References

Acker, A. & Murthy, D. (2020). What is Venmo? A descriptive analysis of social features in the mobile payment platform. *Telematics and Informatics, 52*, doi: 10.1016/j.tele.2020.101429

Barabási, A.-L. (2003). *Linked*. Plume, New York.

Bezhovski, Z. (2016). The Future of the Mobile Payment as Electronic Payment System. *European Journal of Business and Management, 8(8)*.

Bonchev, D. & Buck, G.A. (2005). Quantitative measures of network complexity. In: Bonchev D., Rouvray D.H. (eds) *Complexity in Chemistry, Biology, and Ecology*. Springer, Boston.

Börner, K., Sanyal, S., & Vespignani, A. (2007). Network science. *Annual Review of Information Science and Technology, 41(1)*, 537–607.

Cai, M, Cui, Y., & Stanley, E. (2017). Analysis and evaluation of the entropy indices of a static network structure. *Scientific Reports, 7*:9340.

Caldarelli, G. (2020). A perspective on complexity and networks science. *Journal of Physics: Complexity, 1(2)*.

Cantú, C. & Ulloa, B. (2020). The dawn of fintech in Latin America: landscape, prospects and challenges. *BIS Papers, 112*, Bank for International Settlements.

de Almeida, P., Fazendeiro, P., & Inácio, P.R.M. (2018). Societal risks of the end of physical cash. *Futures, 104*, 47-60.

de la Concha, A., Martínez-Jaramillo, S., Carmona, C. (2018). Multiplex financial networks: revealing the level of interconnectedness in the banking system. In: Cherifi C., Cherifi H., Karsai M., & Musolesi M. (eds) *Complex Networks & Their Applications*. Springer, Cham.

Financial Stability Board – FSB (2017). *Financial stability implications from fintech*. Financial Stability Board.

Flood, M.D., Kennet, D.Y., Lumsdaine, R.L., & Simon, J.K. (2020). The complexity of bank holding companies: a topological approach. *Journal of Banking and Finance, 118*.

Frost, J. (2020). The economic forces driving fintech adoption across countries. *BIS Working Papers, 838*. Bank for International Settlements.

Fung, B., Molico, M., & Stuber, G. (2014). Electronic money and payments: recent developments and issues. *Bank of Canada Discussion Paper, 2014-2*, Bank of Canada, April.

Iman, N. (2018). Is mobile payment still relevant in the fintech era? *Electronic Commerce Research and Applications, 30*, 72-82.

Karsen, M., Chandra, Y.U, & Juwitasary, H. (2019). Technological factors of mobile payment: a systematic literature review. *Procedia Computer Science, 157*, 489–498.

Kaur, P., Dhir, A., Bodhi, R., Singh, T., & Almotairi, M. (2020). Why do people use and recommend m-wallets? *Journal of Retailing and Consumer Services, 56*.

Lima, M. (2011). *Visual complexity: Mapping patterns of information*. Princeton Architectural Press, New York.

Lloyd, S. (2001). Measures of complexity: a nonexhaustive list. *IEEE Control Systems Magazine, 21(4)*, 7-8.

Maurer, B. (2012). Mobile money: communication, consumption and change in the payments space. *Journal of Development Studies, 48(5)*, 589-604.

McAndrews, J.J. (2020). The case for cash. *Latin American Journal of Central Banking, 1*.

Mitchell, M. (2009). *Complexity*. Oxford University Press, New York.

Morzy, M., Kajdanowicz, T., & Kazienko, P. (2017). On measuring the complexity of networks: Kolmogorov complexity versus entropy. *Complexity*. doi:10.1155/2017/3250301

Mowshowitz, A. (1968). Entropy and the complexity of graphs: An index of the relative complexity of a graph. *Bulletin of Mathematical Biophysics, 30*, 175-204.

Mowshowitz, A. & Dehmer, M. (2012). Entropy and the complexity of graphs revisited. *Entropy, 14*, 559-570.

Mumtaza, Q.M.H.M., Intishar, S., Amaliya, S., Rosabella, Y., & Hammad, J.A.H. (2020). Worldwide mobile wallet: a futuristic cashless system. *Bulletin of Social Informatics Theory and Application*, 4(2), 70-75.

Newman, M.E.J. (2010), *Networks*. Oxford University Press, New York.

Polasik, M., Huterska, A., Iftikhar, R., & Mikula, S. (2020). The impact of Payment Services Directive 2 on the paytech sector development in Europe. *Journal of Economic Behavior and Organization, 178*, 385-401.

Simon, H.A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society, 106(6)*, 467-482.

Singh, S. (1999). Electronic money: Understanding its use to increase the effectiveness of policy. *Telecommunications Policy, 23*, 753-773.

Solomon, E. (1999). What should regulators do about consolidation and electronic money? *Journal of Banking & Finance, 23*, 645-653.

Surtikanti & Mustofa, R.H. (2019). Utilization of electronic money. *IOP Conference Series: Materials Science and Engineering, 622(2)*.

Unger, C.J., Murthy, D., Acker, A., Arora, I., & Chang, A.Y. (2020). Examining the evolution of mobile social payments in Venmo. *International Conference on Social Media and Society*, 101-110, doi: 10.1145/3400806.3400819

Wen, T. & Jiang, W. (2019). Measuring the complexity of complex networks by Tsallis entropy. *Physica A, 526*.

Zhang, X., Tang, S., Zhao, Y., Wang, G., Zheng, H., & Zhao, B.Y. (2017). Cold hard e-cash: Friends and vendors in the Venmo digital payments system. *Proceedings of The International Conference on Web and Social Media (ICWSM)*, 387-396.

9. Appendix

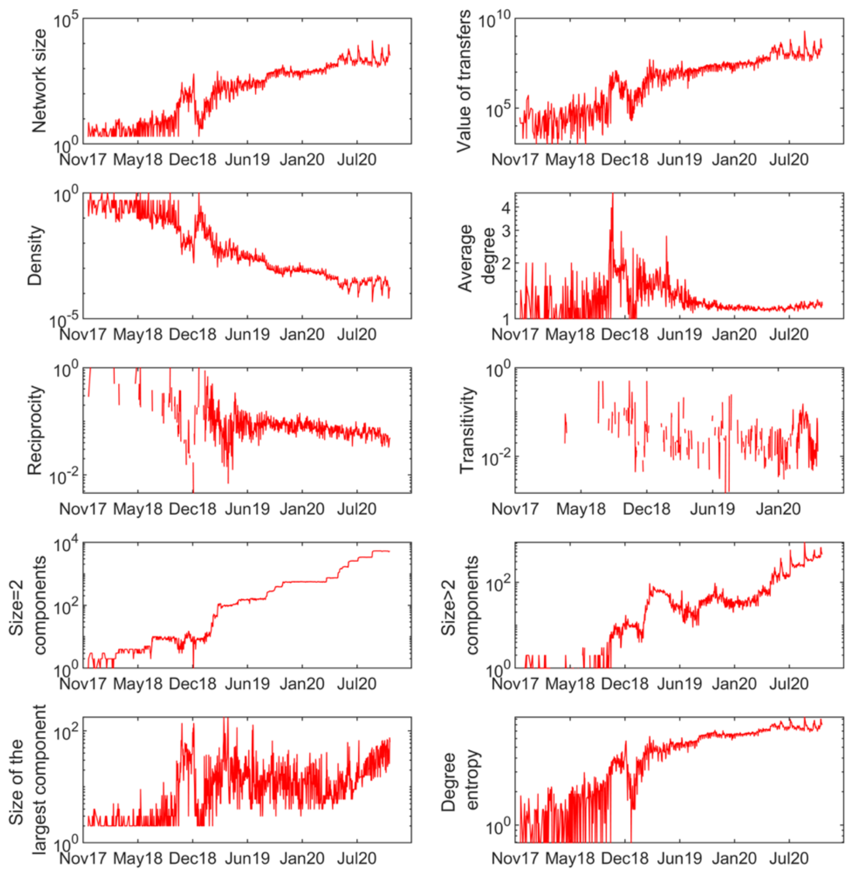

Figure A1. Network statistics, in logarithmic scale (November 17, 2017, to November 25, 2020).

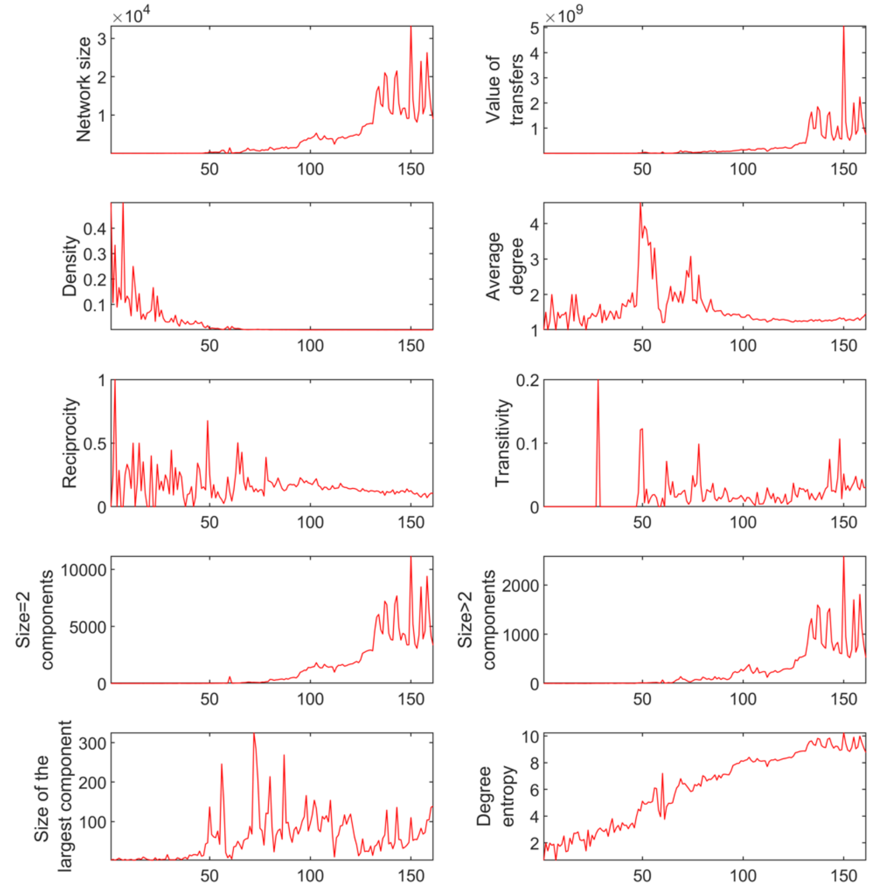

Figure A2. Network statistics, weekly, in linear scale (November 17, 2017, to November 21, 2020).

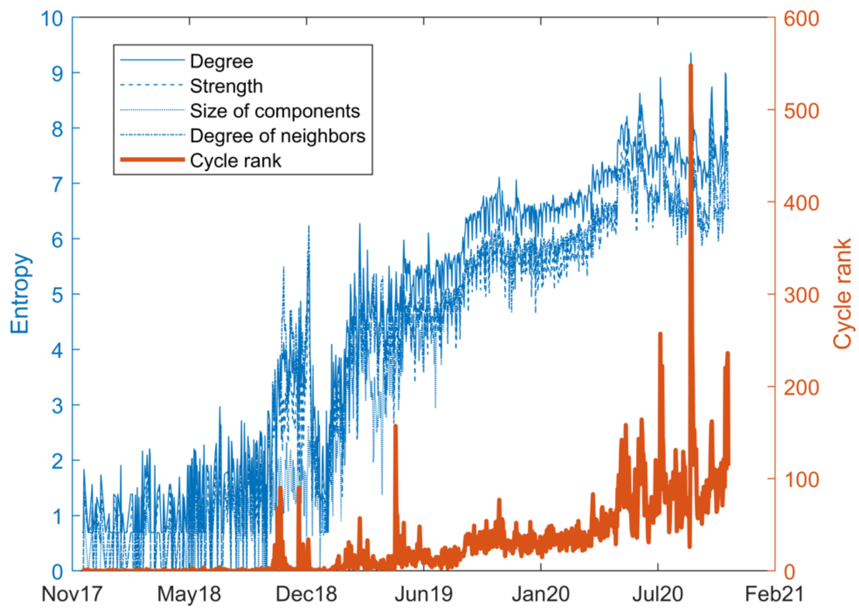

Figure A3. Comparison of entropy on selected probability schemes and cycle rank (November 17, 2017, to November 25, 2020). Degree corresponds to the probability scheme based on nodes' degree (see Figure 5). Strength corresponds to the probability scheme based on the contribution of each node to the total value of transfers. The size of components corresponds to the probability scheme based on the number of nodes in each component. The degree of neighbors corresponds to the probability scheme based on the average number of connections of each node's neighbors. Cycle rank corresponds to the number of linkages that must be removed to get a minimal spanning tree, i.e., the simplest graph covering all nodes but containing no cycles or loops.

	I	II	III	IV	V
I. Degree					
II. Strength	.99				
III. Size of components	.99	.98			
IV. Degree of neighbors	.99	.98	.95		
V. Cycle rank	.69	.73	.70	.66	

Table A1. Correlation matrix of entropy on selected probability schemes and cycle rank.

Statistic	Mean	Standard Deviation	Maximum	Minimum	First 100 days (mean)	Last 100 days (mean)
Network size	794.69	1196.00	12841.00	2.00	3.81	2620.30
Total value of transfers [a]	44.15	107.63	1942.60	0.00	0.05	183.83
Density	0.07	0.16	1.00	4.7×10^{-5}	0.36	2.8×10^{-4}
Average degree	1.29	0.34	4.78	1.00	1.17	1.18
Reciprocity	0.09	0.14	1.00	0.00	0.16	0.06
Transitivity	0.02	0.06	0.50	0.00	0.00	0.04
Size=2 components	838.54	1447.70	5313.00	1.00	2.81	4570.10
Size>2 components	71.44	112.29	851.00	0.00	0.70	345.88
Size of largest component	16.48	19.33	176.00	2.00	2.50	34.25
Degree entropy	4.99	2.34	9.36	0.69	1.16	7.62

Table A2. Network statistics. [a] In $COP million, rounded to the second decimal place.