User migration across Web3 online social networks: behaviors and influence of hubs

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***Abstract*—The current online social network landscape is characterized by competition to get larger audiences leading to massive user migrations which will determine the shape of the future Web. However, user migration phenomena have not been fully understood and their driving mechanisms are still not well identified; in particular, the behaviors of hubs and the influence they exert on their followers are unclear. In this work, we focus on these aspects by analyzing the propensity of hubs to migrate towards a new social platform as a consequence of a shocking event; and the influence they exert on the decision of their neighbors of migrating to a new platform or staying on the native one. We conducted analysis on data made available after a user migration consequence of a hard fork involving two Web3 online social networks based on the blockchains Steem and Hive. Due to the blockchain nature of these Web3 platforms, we got detailed data about social and financial interactions among the users, along with information that allowed a precise reconstruction of the context surrounding the migration. The main findings suggest that different types of hubs apply different strategies when choosing to migrate, e.g. financial hubs diversify their strategy by staying and migrating at the same time. As for hub influence, results suggest that users directly interacting with hubs tend to migrate. In general, findings on influence indicate that understanding the activity and the influence of hubs is crucial in monitoring and controlling the user migration process.**

***Index Terms*—user migration, Web3 online social networks, hubs, influence, financial networks, social networks**

I. Introduction

The common and growing phenomenon of site user migration, i.e. the movement of large groups of users from one social platform to another one, is playing a crucial role in the social web sphere as users represent the true assets of platforms. In fact, social platforms are competing to get a larger audience by introducing novel and disruptive services that better accomplish the new requests from an ever-changing audience or by posing themselves as new social spaces overcoming the well-known issues of the current social networks, such as misinformation, fake news, censorship, harassment, and privacy violations. Despite its central role in many online dynamics, user migration phenomena have not been fully understood and are still challenging, mainly due to the impossibility of fully tracking a large volume of users moving across different online social networks administered by different companies, even by using sophisticated account matching techniques.

In this context, the emergence of the new paradigm of the Web, the blockchain-based Web 3, offers unexpected help to get around these obstacles. In fact, Web3 social platforms, being based on blockchain technologies, offer huge volumes of easily accessible and high-resolution data that can support in-depth analysis of phenomena characterizing socio-technological systems where social, financial, and political dynamics are strictly intertwined [1]. Specifically, in the case of user migration, researchers are able to completely track and match accounts across the platforms and precisely reconstruct the socio-financial context surrounding the migration. User migration across Web3 platforms generates in a very peculiar way: disagreements during data validation processes or, in more striking cases, conflicts within the community may result in turning-point events, namely hard forks, that lead to a complete duplication and bifurcation of the entire social network, along with detailed data on the process. When these hard fork events occur, a user can decide to *a*) be active on both the original and the new social networks (diversifier), *b*) stay only on the original platform (resident), *c*) definitively migrate on the new platform and abandon the old one (migrant) or *d* abandon both platforms (inactive).

In this complex scenario, different factors may influence the user's decision to choose between the aforementioned options. And, while it is hard to gain insight into the user's motivations, it would be meaningful to investigate what decisions the most important and central nodes, namely the *hubs*, make when faced with the possibility of migrating and to what extent they influence the behavior of their neighbors. In particular, our research questions are: (a) How do the hubs behave when faced with the choice to migrate to a new platform? Are they more likely to migrate or stay, so keeping their role and status? (b) Since in modern Web3 OSNs, accounts may gain importance or popularity through different types of interactions and strategies, even involving financial transactions, do different definitions/types of hubs lead to different behaviors when faced with the choice of migrating or not? (c) Does the decision made by hubs whether to migrate or not influence their neighboring nodes? Do they exert of sort of social/financial pressure on their neighborhood?

To this end, we studied a hard fork event on Steemit, one of the most widespread Web3 online social networks, whose reference blockchain is Steem. In this Web3 online social network, the fork event has led to the birth of a new blockchain, Hive, which is now supporting different social platforms, such as Hive Blog. In this specific fork event, users maintained the same username across the two blockchains and were able to be active on both social networks. These characteristics sustain the study of the decision made by users, and, in particular, by the hub accounts. The identification of the hubs and the extraction of all the characteristics and properties to support the answers to the above research questions are based on a complete data collection of all the social and financial operations before and after the hard fork event, along with a modeling of the interactions based on different temporal network representations [2]. Our study has highlighted some interesting findings on the role of hubs during a user migration process: (a) the definition of a hub, i.e. if we consider the degree or the number of management operations as a measure of centrality, impacts the distribution of the decisions. For instance, hubs with the highest number of management operations on the underlying blockchain and active on the social network have made sharper decisions w.r.t. the same kind of management hubs but active on the financial side; (b) despite the differences determined by the hub definition, we observe that the majority of central nodes have decided to migrate to the new platform; and (c) regardless of the definition of hub, hubs always exert a certain influence on their direct neighbors since the latter are more likely to migrate w.r.t. the average behavior computed on the active users in the entire social network.

The paper is organized as follows. Section II presents the fundamental concepts related to Web3 platforms and hard forks along with the related works on user migration. Section III describes the dataset used in our work. Section IV describes how we model the social and financial interactions gathered from the blockchains and introduces the main definitions regarding hub activities and hub influence. Section V presents our main findings concerning the decision made by the different types of hubs and the influence they exert on their neighborhood when deciding to migrate or not. Finally, Section VI summarizes the main contribution of the paper, pointing out possible future works.

II. Background and Related Works

Hard fork in Web3 online social networks. We conducted our study on a new emerging paradigm for the Web, also supporting online social networks, i.e. Web3. Web3 mainly relies on blockchain technologies to support a wide ecosystem of services. In the case of Web3 online social networks - Web3 OSNs - the underlying blockchain provides data storage and data validation for all the social operations. The validation process enables the production and exchange of cryptocurrencies, used in financial operations in the Web3 platform [3]. Among the proposed Web3 OSNs, Steemit [4], and the underlying blockchain Steem, has been the pioneer of the paradigm. Like other Web3 OSNs, it relies on a cryptocurrency, called STEEM, that can be exchanged for goods or services. Moreover, the cryptocurrency fuels a reward mechanism, which supports network growth by repaying users for their activity on the platform. Web3 social platforms may offer data about a phenomenon that is peculiar to blockchain-based systems: a hard fork, i.e. an event that occur when miners do not consider as valid the blocks validated with a newly proposed consensus protocol so that two different branches are created if validators do not reach a consensus on the protocol to use. In this situation, the members of the original branch may decide to migrate to the platform based on the new branch, leading to a user migration. Such a split has happened on Steemit as well. After a dispute inside the network, a group of users on the 20th of March 2020 copied the blockchain data into a new blockchain called Hive. In this case, users are provided with the same username on both platforms, which means that they can still be active on both platforms.

User migration in OSNs. User migration is a "universal" process spanning online social media and networks but is not fully understood yet, especially in the Web3 world. Most of the studies are based on the most spread social platforms. For instance, by matching user accounts through external data, Kumar *et al.* [5] have analyzed user migration patterns. Newell *et al.* have conducted an analysis of user activity during a cross-platform migration with the goal of understanding the motivations behind migration. Other works have focused on users migrating across groups on the same platform, showing non-random migration patterns in Facebook groups [6]. A more in-depth analysis has been conducted by Davies *et al.* [7] in the case of user migration across COVID-19 subreddits. All previous studies are based on data collected from centralized social platforms and none of them has looked at user migration across Web3 platforms, especially as a consequence of a hard fork. Only recently Ba *et al.* [8] have focused on user migration in Web3 social platforms by evaluating the effects of user migration on the graph structure of the interactions and assessing the predictability of migrating. Finally, Ba *et. al.* [9] studied the Steemit user migration from a mesoscopic point of view, observing how communities are characterized by different migration behaviors. With respect to these latter works, here we focus on the behavior and role of hub nodes in leading the user migration process, and on the evaluation of the influence hubs may exert on their closest connections.

III. Dataset

One of the main advantages when dealing with blockchain data is data availability. In our case, all users' activities of both Hive Blog and Steemit are tracked down by the actions they perform - called *operations* - and are captured with a three-second granularity. The blockchains - Steem and Hive - supporting the two platforms store user operations as *transactions*. Guidi *et al.* [10] categorized the several types of operations (more than 50) into three macro types: *social, financial, and management*. Here, we are interested in interactions between users, so we focus only on social operations, such as "follow", rating, sharing, and posting; and financial ones, whose goal concerns reward, transfer sharing, token management, and asset. Through specific API, we collected all the users' financial and social operations from June 3, 2016, up to January 21, 2021. Specifically, for the Steem blockchain, the obtained data collection consists of $993,641,075$ social operations and $72,370,926$ financial operations; while Hive registers a total number of $206,224,132$ social operations and $4,041,060$ financial actions. The cited number of operations concerns more than 1.4 million users on the social layer and around 1.3 million on the financial layer.

IV. Methodology

Despite the variety of operation types, the operation schema is unique, so we can model each transaction collected by APIs as a tuple $I = (u, v, t, r)$, which describes an interaction between users u and v of type r at time t. As mentioned before, we leveraged the transactions' classification introduced in [10] and focus only on operations between users such that $r \in \{social, financial\}$.

A. Graph modeling

Based on the set of tuple interactions Is, we built different network-based representations of the interactions among users, according to the time period we dealt with. Specifically, we adopt an incremental graph-based representation for data up to the hard fork moment, denoted by T_{fork}, and a snapshot-based graph representation for interactions that happened after the hard fork:

- **Incremental graph:** Concerning operations that happened before T_{fork}, we build two different graphs - layers - that isolate the different types of operations. So, we obtain two directed weighted graphs G_s and G_f, that include edges with r equal to social s or financial f, respectively. Both G_s and G_f adopt the incremental model, this implies that once an interactions are added to the graph, their elements and the resulting interactions cannot be removed but only updated in their edge weight. Specifically, an edge $e = (u, v, w) \in G_r$ indicates that nodes u and v had w interactions of type r with $t \leq T_{fork}$, so once e is added, its weight w can only increase over time.
- **Sequence of graphs** The transactions occurring after the hard fork can happen on two different layers (social or financial), but they also involve one of the two blockchains (Hive or Steem). For these reasons, after the hard fork, we adopt the snapshot-based model to get four different graphs that isolate the different kinds of operations and blockchains. Formally, we deal with four directed weighted temporal graph sequences $G_s^H[1\ldots9], G_f^H[1\ldots9]$ and $G_s^S[1\ldots9], G_f^S[1\ldots9]$, where s and f stand for social or financial, respectively; while H and S indicate on which blockchain the operations have been recorded, so Hive or Steem, respectively. Each graph G_r^P, representing transactions of type r happened on platform P, is defined as the sequence $< G_{r1}^P, .., G_{r9}^P >$, where each $G_{ri}^P, i = 1, \ldots 9$ represents a 1-month window aligned to the day of the hard fork. Specifically, each graph (snapshot) G_{ri}^P covers transactions with a timestamp from the 21st of the $i-1$-th month to the 20th of the i-th month, starting from March 2020. This snapshot-based model allows us to observe the activity of nodes in each period, and consequently to study the migration choices with a monthly granularity.

B. Hub definition

We decided to investigate the role of two very different kinds of hubs based on *(a)* the degree and *(b)* their involvement in platform management. Concerning the degree, we select two sets of hubs: *(i)* **social in-degree hubs** are the 21 nodes with the highest in-degree on the social layer, and *(ii)* **financial degree hubs** are the 21 nodes with the highest degree on the financial layer. We choose to use the undirected version of degree in the financial layer in order to get the nodes that economically interact the most with other nodes, considering the in-degree or out-degree too restrictive in this case. The set of financial and social degree hubs only includes nodes that performed at least an operation in the last month before the fork, thus being active. This filter is needed to be sure to select hubs that could actually influence other nodes with their action at the hard fork time.

The other kind of hubs concerns a type of user that plays an essential role on Steem, called witness [11]. Basically, they are the set of people that can actually create and validate blocks on the blockchain, and they are voted by users of the platform according to a consensus mechanism called Delegated Proof of Stake (DPoS). The witness role is assigned at every election round to the 21 most-voted users. In this work, we select as central witness nodes, the 21 accounts that performed the highest number of *feed publish* operations. This operation can only be performed by the top 21 witness nodes at each round. So, the ranking based on the number of feed publish operations performed is a good estimator for selecting the nodes that played more times the witness role. Based on this ranking, we obtain two sets of witness hubs: *(i)* **social witness hubs** are the top 21 nodes active in the last month before the fork on the social layer; *(ii)* **financial witness hubs** are the top 21 nodes active in the last month before the fork on the financial layer. Note that we filter on the active nodes in the last month before the fork and not those active in a longer period (3 months or one year before) because rumors about the hard fork began only one month before it happened. Therefore, we are only interested in hubs that are active in the actual period when they could have influenced their neighborhoods. After obtaining the four sets of hubs, we were able to study their role in the user migration process. The methodology is divided into two parts: in the first one we study the level of activity of hubs on the two platforms and their final decisions; then, we observe how the 1-hop neighbors of each hub behave with respect to the rest of the network.

C. Hubs activity

We first cope with the hubs and the dynamic of their activity. Specifically, we leverage the snapshot-based representation to collect the number of operations on each platform for each hub. Formally, for each hub h, we compute the activity level separately on both platforms $P = \{S, H\}$, for each month i. The activity level of each hub is defined as follows:

$$p_i(h, P, r) = c_i(h, P, r)/c_i(h, r)$$

where:

$$c_i(h,P,r) = \sum_{\{(u,v) \in E_{G^P_{ri}} | u=h\}} w(u,v)$$

and:

$$c_i(h,r) = \sum_{\{(u,v) \in E_{G^S_{ri}} \bigcup E_{G^H_{ri}} | u=h\}} w(u,v)$$

In short, the activity level p_i for a hub h indicates the fraction of social or financial operations done on a specific blockchain.

Activity visualization. In order to get a direct view of the preferred platform for each hub, we process its activity on both platforms, for each period and operation type. We define $max\_p_i(h,r)$ as follows:

$$max\_p_i(h,r) = \begin{cases} +p_i(h,H,r) & \text{if } p_i(h,H,r) > p_i(h,S,r) \\ -p_i(h,S,r) & \text{otherwise} \end{cases}$$

Through this indicator, we are able to summarise through a heatmap the preferred platform for each hub, monthly, and by type of operation. The more each cell of the heatmap is red, the more $max\_p_i(h,r)$ is close to 1, meaning that the hub performed almost every operation on Hive. On the contrary, the more the cell is blue (-1), the more the hub remained on Steem. Softer colors correspond to a more balanced activity level on both platforms.

Migration decision. After observing the preferred platform for each hub, we assign a migration decision to each hub. Note that $max\_p_i(h,r)$ admits values in the interval $[-1,-0.5]$ or $[0.5,1]$, so we define *inactive* the periods where $max\_p_i(h,r) = 0$. Moreover, the migration decision depends on the value of $max\_p_i(h,r)$ in the most recent active month, (noted as $max\_lastive(h,r)$) and it is defined as follows:

$$\textbf{decision} = \begin{cases} \textit{migrant} & \text{if } max\_lastive(h,r) \geq 0.75 \\ \textit{resident} & \text{if } max\_lastive(h,r) \leq -0.75 \\ \textit{inactive} & \text{if } max\_lastive(h,r) = 0 \\ \textit{diversifier} & \text{otherwise} \end{cases}$$

D. Hubs' influence

Our main goal is to discover whether and to what extent hubs influence migration choices. Specifically, we investigate whether direct neighbors of hubs tend to make different decisions with respect to the other nodes in the network. To this aim, first, we compute the migration decision of all nodes in the neighborhoods of hubs through the same criteria described in the previous section. Then, we compare the distribution of decisions of all the nodes in the graph against the nodes that belong to the neighborhood of at least one hub. Note that, we consider as neighbors of a hub all nodes with an outgoing edge towards the hub from the beginning of the data collection (June 3, 2016) up to the fork date (March 20, 2020). Moreover, when we mention all nodes, we actually mean all the nodes in the layer we are considering (social or financial) that were active in the last month before the fork, i.e. all nodes that could make a migration choice. Finally, for each hub h we define the tuple $(m(h), r(h), d(h), i(h))$ that reports the percentage of its neighbors, computed in the incremental graph $G^{layer}_{T_{fork}}$, that are classified as migrant (m), resident (r), diversifier (d) or inactive (i), respectively.

V. Results

In this section, we introduce the main insights following the methodology described in Section IV. Indeed, we first analyze the activity of hubs, then we investigate the influence they exert on their neighborhood as for the decision of migrating or remaining.

A. Hubs activity and migration choice

As previously mentioned, we identify hubs based on centrality criteria and the network layer. First, we focus on social and financial witness hubs. The two sets share the majority of nodes (16 common hubs over 21). However, their activity is significantly different in the two layers, so it is worth analyzing them separately. In the same way, we can distinguish two sets of degree hubs: the in-degree hubs in the social layer and the undirected-degree hubs in the financial layer. Due to the different definitions of central nodes, the sets of the two different layers share fewer nodes with respect to the witness case (12 over 21 hubs).

Social witness hubs. Fig. 1a describes the social witness hubs' activity from three different points of view: Fig. 1a-A shows the activity level $max\_p_i(h,r)$ for each hub h and period i for $r = social$; Fig. 1a-B concerns the migration choice level of hubs ($max\_lastive(h, social)$); and Fig. 1a-C reports the distribution of the migration decision. In this case, it highlights that hubs tend to migrate, but the decision is not immediate, as indicated by the heatmap. In fact, we can observe that the typical behavior of migrant hubs (7 over 11 migrants) is to be active on both platforms for some months and then prefer the new platform Hive. On the other hand, the resident hubs do not manifest a period of dual activeness. In general, both resident and migrant decisions are strong, meaning that one dedicates the entire activity to one platform only. In fact, as displayed in Fig. 1a-B, most of the resident and migrant hubs are on the +1 or -1 lines, i.e. a full-time activity on a single platform.

Financial witness hubs. Fig. 1b reports the three viewpoints about witness hubs' financial activity, as in the previous case. It is clear that, even if the set of financial witness hubs shares the 76% of users with the social witness one, the activity is really different. The more evident difference concerns the increase of inactivity (grey cells). Another difference concerns the lapse of time between the hard fork and the hubs' decision: there is a group of hubs that decide in the very first period (2 months); on the other hand another group is more hesitant in making a strong decision but tends to have a preferred platform instead of staying active on both ones. In fact, two hubs only stay active on both platforms at the end. Concerning the strength of the migrant or resident decision, in the financial case, we observe that when the decision is *migrant* the totality

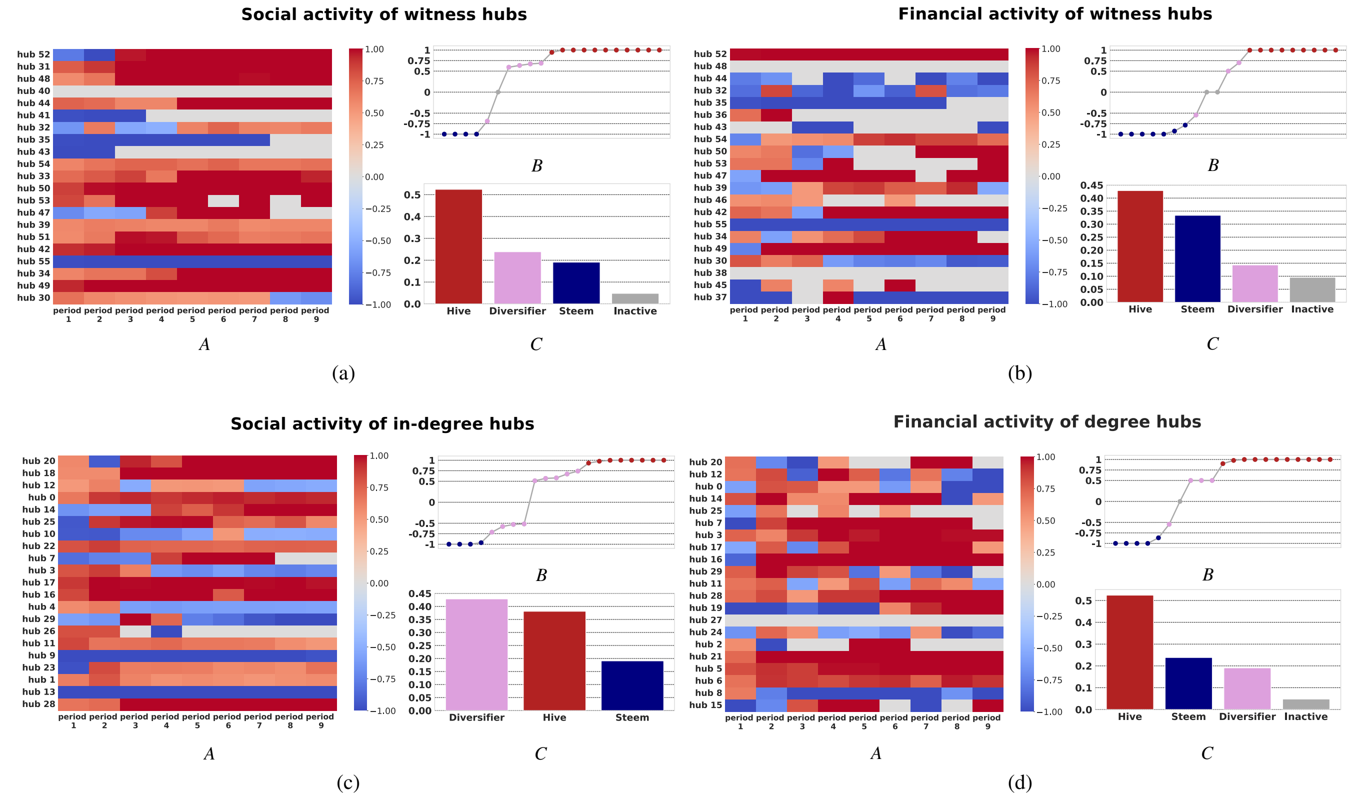

Fig. 1. From a) to d), properties of the activity level of social witness hubs (a), financial witness hubs (b), social in-degree hubs (c), and financial degree hubs (d). For each type of hub, we report the heatmap - A - displaying the monthly trend of $max\_p_i(h, r)$ for the 21 hubs; B) the hubs increasingly ordered by $max\_lastive(h, r)$ and colored according to their final decision; and C) the distribution of the decision (migrant, resident, diversifier and inactive) of the hubs.

of operations are done on the new platform Hive, while a few *resident* hubs still perform some operations on Hive, resulting into a not completely symmetric scenario.

Social in-degree hubs. Fig. 1c reports the study on the activity levels and migration choices of in-degree hubs in the social layer. The main feature that distinguishes this set of hubs from the other ones is the absence of inactivity. Note that only hubs with no activity for the entire post-fork period are considered as *inactive*, otherwise we consider the most recent activity for assigning a label/choice. Looking at the distribution of decisions in Fig. 1c-C, it is clear that the prevalent decision is to stay active on both platforms. The indecision is still in the behavior of some hubs that decided to migrate since the migration choice is often preceded by an indecision period. Finally, as in the previous cases, once the hubs make a decision, they are fully committed to the preferred platform, as shown in Fig. 1c-B.

Financial degree hubs. Fig. 1d depicts the activity data about the financial degree hubs. It confirms the lower tendency for degree hubs to become inactive after the fork - only 1 over 21. In general, the financial degree hubs seem to be undecided about their choice because, even if in the last active period they perform operation only in one platform, it took them some months to decide. For instance, "hub 2" started by exploring Hive more, after two months he moved back to Steem, then it returned to Hive, and so on. An interesting feature of the final decisions can be observed in Fig. 1d-B: when the decision is *diversifier*, it corresponds to an activity that is almost perfectly balanced on the two platforms. The *diversifier* decision that is more imbalanced is related to a percentage of 0.54 in favor of Steem. In general, financial degree hubs have played an expected diversification strategy where initially they started to explore the economical value of the new platform, then they diversified their actions between the two blockchains.

B. *Influence of hubs*

A further important element that may drive a user migration process is the influence hubs may exert on their direct neighborhood. Here we report the findings on this aspect from two viewpoints: *(a)* a comparison among the distribution of hubs' choices, that of all nodes in the graph and that of nodes that are neighbors of at least one hub; and *(b)* a comparison between the distribution of choices within each hub neighborhood and the distribution of nodes' decisions in the graph. Specifically, we only report the trends that are worthy of analyzing from a single-hub perspective.

Social in-degree hubs influence. Fig. 2a reports the outcomes of our analysis on the influence of social in-degree hubs. The first row (from A to C in Fig. 2a) visualizes the distributions of the decisions grouped by the three different cohorts detailed above. Here, we can observe that the choices of hubs follow a different distribution with respect to all the nodes active at T_{fork}: while the majority of hubs stay active on both platforms or migrate, in the entire network it is more common to be *resident*. Further, the key element to discovering whether hubs influence their neighbors is to compare the distributions of every node decision w.r.t neighbors' decisions (B and C in Fig. 2a). Even if the ranking of labels is the same, the percentage of nodes in each class is different: in fact, in the neighborhood's distribution the *migrant* label gains 7.3%. This difference is confirmed by the distribution of $m(h)$ for the 21 social in-degree hubs shown in Fig. 2a-D: for every hub, their neighborhood is characterized by a higher percentage of migrants with respect to the expected fraction of migrants. Moreover, the neighbors of hubs tend to be less inactive (shown in Fig. 2a-E), maybe as a consequence of the absence of inactive in-degree social hubs. So, social in-degree hubs are never completely inactive and tend to prefer Hive, either in an exclusive way or in addiction to Steem. This tendency is reflected in their neighbors, where the percentage of users moving to Hive always increases together with a decrease in the inactive decision.

Social witness hubs influence. Fig. 2b is structured in the same way as for the social in-degree hubs. From a global point of view, the distribution of hubs' migration choices differs completely from the one concerning all active nodes that could be influenced: the trend is the opposite because 52.4% of hubs are migrants, while 54.8% of active nodes are residents. In this case, the gain of the migrant decision in the hubs neighborhoods is 11.7%. In Fig. 2b-D it is more evident because in some hub's neighborhoods the migrant fraction (red) is even higher than the resident one (blue). Moreover, the percentage of inactive is always lower than the one relative to *diversifier* decision, as shown in Fig. 2b-E. So, the key feature of social witness hubs is their strong preference for migrating to Hive. This is reflected in the neighbor nodes, and it is particularly evident when looking at the neighborhood of every hub separately.

Financial witness hubs influence. Fig. 2c reports findings on the financial witness hubs' influence. The first observation about this result concerns the distribution of migration choices of active nodes: in contrast with the previous ones, the distribution of labels here is almost homogeneous. As for the distribution of labels among hubs' neighborhoods (see Fig. 2c-C), it is more similar to the distribution of hubs' choice (see Fig. 2c-A) w.r.t. the active nodes one (see Fig. 2c-B). As detailed in Fig. 2c-D, hubs neighbors tend to migrate more and become inactive less, since the labels with the highest variations are migrant and inactive. In short, financial witness hubs play an influential role on their neighbors because the decision distribution differs a lot from the expected one. The difference is mainly driven by the strong increase in the decision of migrating towards Hive, in contrast with the decision of being inactive.

Financial degree hubs influence. Finally, Fig. 2d shows how financial degree hubs influence their neighbors. In contrast with the previously described case of financial witness hubs, here the distribution of migration choice of hubs neighbors, shown in Fig. 2d-C, is more similar to the general one, reported in Fig. 2d-B. However, when observing the single $m(h)$ values plotted in Fig. 2d-D, we can see an actual difference, similar to the one shown in the financial degree hubs case: the migrant choice fraction always (except 1) exceeds the percentage of expected migrants provided by the overall fraction of active nodes, while the percentage of inactive nodes always decreases. So, financial degree hubs present a dominant tendency to choose to migrate to Hive. Concerning the hubs' neighbors, despite the similar homogeneous distribution, the gain in the percentage of migrant decisions is evident.

After observing the influence of every type of hub, we can now highlight the main characteristics regarding the influence hubs have exerted on their neighbors when it came to deciding to migrate or remain. First, it is clear that hubs' neighborhood tends to migrate more frequently than "average" active users. Moreover, being a neighbor of a hub correlates with a lower probability of being inactive after the fork, i.e. neighbors of hubs are more likely to keep their activities in one of the two blockchains. In general, the influence that hubs exert on their neighborhood does not reflect in a complete change in the ranking of most frequent decisions. In fact, the most frequent decision in the overall graph is the same as the one of the hubs' neighbors, but the distribution change. Moreover, on the financial layer, in each hub's neighborhood, the fraction of migrant nodes particularly increases in contrast to the fraction of nodes that become inactive. This suggests that being close to financial hubs makes a node more motivated to be active even after a strong event like the hard fork. The same observation holds for the social layer, where there is also a tendency for hub neighbors to be active on both platforms - diversifiers - with a higher probability with respect to the "average" decision.

VI. Conclusions

In conclusion, this works aims to observe the decisions of central nodes and the influence on their neighbors, in the context of a blockchain-based social network's split event. We focused on the fork event involving Steemit, leading to the birth of a new social network, Hive. Since the latter has maintained the same usernames as Steemit, we were able to track the user migration. We modeled the transactions [12] before the hard fork using an incremental weighted graph. On the other hand, we adopt a snapshot-based approach to model operations after the fork on both platforms, building a sequence of edge-labeled multigraphs, divided into two layers: social and financial ones. On this data source, we observe the variety of decisions of four types of hubs defined by degree and involvement in management operations, on both social and financial layers, highlighting that the most common decision for hubs is to migrate. Then, we focus on the decisions of hubs' neighbors, studying if they are influenced by the choice of their hub. Results suggest that when a node is

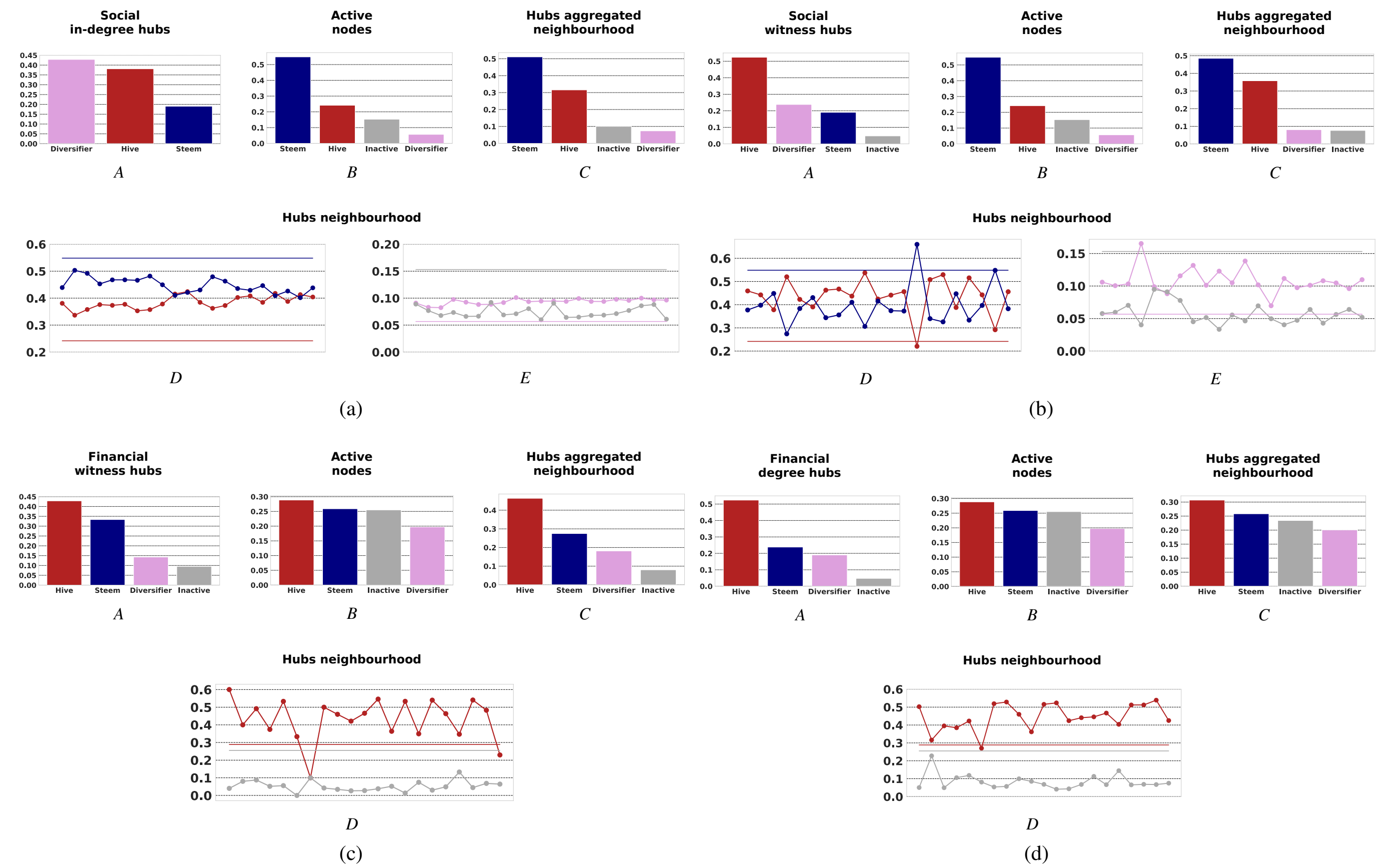

Fig. 2. From a) to d), properties of the influence exerted by social in-degree hubs (a), social witness hubs (b), financial witness hubs (c), and financial degree hubs (d). For each type of hub, we report A) the distribution of the decisions (migrant, resident, diversifier and inactive) of the hubs, B) the distribution of the decisions of all the active users, and C) the distribution of the decisions of the hubs' neighbors. Plots displayed in D) and E) report $m(h)$, $r(h)$, $d(h)$, and $i(h)$ values for the hubs. In these plots, horizontal lines represent the "expected" decision taking the distribution in B as "average" behavior.

a direct neighbor of a hub, it tends to migrate and not be inactive. Moreover, the influence behavior is more similar when observing hubs on the same layer instead of the same type of hubs. Future works in this context may concern the centrality transferability, i.e. the analysis of how the centrality of nodes is correlated across different layers. Another direction could be related to the influence of central nodes within a mesoscopic level.

VII. Acknowledgements

This work was partially supported by project SERICS (PE00000014) under the NRRP MUR program funded by the EU - NGEU.

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