Does Vote Trading Improve Voting Outcome?

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Decentralized autonomous organization design implies that stakeholders vote to express their individual opinions. Nonetheless, this design is disrupted by vote trading. We take advantage of the blockchain data transparency and explore how vote trading affects voting outcome. Our findings indicate that vote trading facilitates the decision-making by better informed stakeholders. Specifically, informed stakeholders use purchased votes to signal the quality of their contributions to the platform and thereby attract the non-purchased votes of uninformed stakeholders. Vote buying typically attracts 51% more non-purchased votes, and the reputation of vote buying stakeholders improves over time. Therefore, it is unlikely that vote trading leads to overselling the platform contributions. We conduct an experiment to confirm the robustness of our findings. Finally, an event study reveals that a demand shock in the market for votes encourages voting by those stakeholders who used to abstain from voting before the shock. Our findings lend support to theoretical and experimental research showing the benefits of vote trading in the absence of the majority rule.

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1. Introduction

Decentralized autonomous organizations (DAOs) allow observing a transparent and unrestricted market for votes. And while vote trading exists in both corporate and political environments, such trading is either hidden or takes forms other than outright monetary transactions. Casella and Macé (2021) emphasize that researchers tend to be particularly creative in drawing insights from the little data that can be observed. In contrast, our study takes advantage of the transparency of the blockchain environment. In our setup, all participants can observe every detail of the market for votes.

A typical concern in a market for votes is that vote buyers will reallocate the wealth of other stakeholders towards themselves. Alternatively, vote trading can facilitate the decision-making by better informed stakeholders.[1] We rely on data from the DAO platform Steemit to explore how vote trading affects voting outcome. Overall, our findings indicate that vote trading facilitates the decision-making by better informed stakeholders.

The core assumption in our study is that the vote trading in a particular Steemit DAO environment is representative of vote trading in general. Makarov and Schoar (2022) and Appel and Grennan (2023) suggest that a typical DAO faces similar governance issues as a conventional business. If the concerns of DAO and corporate stakeholders are the same, then we believe that the vote trading incentives and outcomes should be comparable. Also, our study sheds light on the behavior of vote market participants under a specific voting mechanism explored in the political economics literature. Consistent with the literature[2] we show that vote trading can be

[1] See Christoffersen, Geczy, Musto, and Reed (2007), Brav and Mathews (2011), Dekel and Wolinsky (2012), and Han, Lee, and Li (2023).
[2] Casella, Llorente-Saguer and Palfrey (2012), Xefteris and Ziros (2017), and Tsakas, Xefteris and Ziros (2021).

beneficial when there is no majority rule. Section 8 further discusses the extent to which our findings can be generalized.

Blockchain platforms offer decentralized, unregulated, and transparent mechanism of profit-sharing. For instance, token owners (stakeholders) may vote on the written and visual contributions to the platform made by their fellow stakeholders. When the voting is complete, the platform distributes newly-minted tokens to the contributors in proportion to the amount of votes their contributions have received. Several blockchain platforms, including Steemit, Minds, Sola, Kin, and Karma adopt this approach.

Our findings indicate that buying votes serves as a tool to convince stakeholders to vote in favor of certain contributions to a blockchain platform. Specifically, vote buyers typically cast purchased votes at the commencement of voting. The remaining stakeholders observe the purchase of votes and become inclined to cast their own votes in line with the purchased votes. As a result, the contributions that receive purchased votes gain popularity and attain 51% more non-purchased votes than the contributions of a similar quality, which do not benefit from vote trading.

This increase in votes translates into a higher number of newly-minted tokens distributed to the authors whose contributions receive traded votes. Specifically, the payout attributable to non-purchased votes increases by 0.021% per one percent increase in votes purchased. To put this into perspective, our estimates show that an author can attain a 50% greater reward by buying 1% extra votes than by improving skill as contributors over the course of a week. As such, vote buying helps authors to increase their reward significantly.

Despite the concerns over the ethics of vote trading, we find that the reputation of vote-trading contributors improves over time. We attribute this result to the relatively high market price of votes. This makes purchased votes an expensive signal. Moreover, the price of votes can be observed by a vote-buyer at the commencement of the voting while the voting outcome cannot be observed. In fact, the outcome of voting is rather uncertain. As a result, there is a substantial risk that the price per vote exceeds the payout per vote. Thus, the short-term strategy of overselling the contribution with purchased votes proves to be infeasible.

We conduct an experiment to confirm our main findings. First, we rely on three paid experts to assess the quality of a subsample of contributions. Next, we find which of the articles in the subsample have received purchased votes and match them by the expert ranking to the articles without purchased votes. Consistent with the main results, we find that vote buying attracts other users to cast their own non-purchased votes in favor of a contribution. For a given quality contribution, the payout from non-purchased votes in contributions that received purchased votes is four times greater than the payout in the contributions that did not receive purchased votes.

Going further, we explore the consequences of an exogenous shock to demand for purchased votes on the platform. The focus of the event study is the official approval and technical facilitation by Steemit designers of the practice of promoting articles using purchased votes. This event incentivized many users to buy votes. The influx of demand to buy votes affected the price of votes and attracted new vote sellers. In fact, the ratio of purchased votes in the total number of votes more than doubled after the event date. Consistent with our main findings, the number of non-purchased votes has increased after the event. The underlying mechanism for this outcome is that those stakeholders who used to abstain from voting become more informed because of higher vote-trading intensity. Overall, the shock to vote trading leads to greater voter participation.

Harvey and Rabetti (2024) identify the question "Should there be markets for vote buying?" as an important avenue for research on DAOs. We take this challenge and present evidence that a transparent market for votes has merit. Makarov and Schoar (2022) point out that blockchain platforms may face issues arising from the misaligned incentives of different stakeholders. Similar to the corporate environment, one of the major issues is the concentration of voting power. According to Goldberg and Schär (2023), centralization and concentrated voting power may lead to rent extraction behavior. In line with this, Han, Lee and Li (2023) show that DAO platforms grow faster when voting power is more decentralized. Our paper contributes to the literature on DAO governance by showing that vote trading can contribute to decision making and promote the inclusiveness of the voting process.

Christoffersen, Geczy, Musto and Reed (2007) explore empty voting in the corporate environment and find that the price of votes approaches zero. In contrast, we find that DAO votes are rather expensive. We believe that the main factors behind the differences in our results are as follows. First, in our setup, passive vote sellers do not benefit directly from the activism of informed vote buyers. Second, Zingales (1995) emphasizes that the price of a vote depends on whether a vote has a pivotal role for the voting result. Since there is no majority rule, no vote has a pivotal role in our setting. In our setup, the contributor with the most voted contribution does not receive all of the payout. Instead, the payout is a continuous variable proportional to the number of votes. Section 2 provides further explanation of the voting mechanism.

Casella, Llorente-Saguer and Palfrey (2012) show that vote trading under the majority rule leads to a suboptimal outcome. However, Xefteris and Ziros (2017) theoretically argue that vote trading unambiguously improves voters' welfare when there is no majority rule. This argument receives support in an experimental study by Tsakas, Xefteris and Ziros (2021). We lend further support to this argument by providing direct evidence of the benefit of the market for votes in absence of the majority rule.

The remainder of the paper is as follows. Section 2 discusses the mechanics of vote trading in DAO. Section 3 describes the data and sample. Section 4 reports the main results. Section 5 presents the results of an experiment that shows the robustness of our findings. Section 6 introduces an event study. Section 7 explores the role of vote trading in cryptocurrency performance. Section 8 discusses whether our findings can be generalized. Section 9 concludes.

2. Vote trading in a blockchain environment

Our study relies on Steemit – a DAO built on a proof of stake blockchain. Steem became the third-largest cryptocurrency with a market value exceeding $1.8B shortly after its launch in 2016.[3] We chose Steemit because it allows us to observe a market for votes that is fully transparent, unrestricted, and separated from the market for ownership. Conventional empirical studies of corporate governance in the presence of vote trading (often referred to as empty voting) examine a dark market, where the intention to acquire votes is undisclosed and often inseparable from the intention to acquire ownership rights. In fact, SEC (2010) sees a lack of transparency in the market for votes as the main issue preventing an educated regulatory response to vote trading. In contrast, as Yermack (2017) points out, blockchain data allows us to examine a lit market with the unambiguous intentions of counterparties to offer and acquire votes. Moreover, the data let

[3] https://www.marketwatch.com/story/new-digital-currency-sees-2000-price-rise-in-a-week-2016-07-15

us observe how vote owners choose to cast votes. As such, the proof-of-stake blockchain environment of Steemit gives us a unique opportunity to shed some light on whether vote trading improves the voting outcome and benefits stakeholders.

Steemit enacts decentralized governance through a voting-based system.[4] Specifically, individual users make contributions to the platform as authors by writing articles while other users assess the quality of these contributions and vote on them. According to Appel and Grennan (2023), Web3 platforms, such as Steemit are prevalent and account for 32% of all DAOs. The platform distributes newly created tokens to contributors according to the proportion of votes in favor of a contribution within the first seven days of its publication.[5] Figure 1 illustrates the voting timeline.

[Figure 1]

The possession of Steemit tokens empowers stakeholders with voting rights. Similar to the corporate environment, the size of ownership defines the governing power of an individual stakeholder. The Steemit DAO environment, however, is different in one important aspect. In particular, Steemit features an open market where stakeholders may offer to cast votes for a specific contribution in exchange for a fee. Table A.1 provides an example of typical offers to sell votes. This environment allows us to explore the role of vote market in the allocation of rewards for contributions to the platform. The following section describes the data sources and the choice of variables.

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[4] Steem whitepaper provides a detailed description of the platform: https://steem.com/SteemWhitePaper.pdf.

[5] The value received by a contributing author is determined as follows. First, the proportion of the newly created tokens allocated towards reward for a contribution is calculated with the following formula: (New coins allocated for articles on day *t*) × r_i/R_t, where r_i is the votes for the article *i* and R_t is the total votes for all articles on day *t*. Then, usually 75% of this amount goes to the contributing author and 25% is distributed among the voters.

3. Data and variables

We collect comprehensive data on the activities of all users on the Steemit platform.[6] These data include the characteristics of stakeholders and their contributions, voting records, transfers of tokens, and most uniquely, the detailed information on the market for votes. The market price of Steemit tokens comes from www.CoinMarketCap.com. The sample spans 28 week from April 5 to October 19, 2017. Overall, our sample contains 2,240,820 contributions made by 82,902 users who collectively received 2.456×10^9 votes and were rewarded with the total of 1.389×10^7 tokens (2.282 million USD) for their contributions. We further identify 71,167 contributions which received purchased votes with the aggregate value of 0.205 million tokens (0.275 million USD).

Table 1 describes the characteristics of contributions that received purchased votes (Panel A) and did not receive purchased votes (Panel B). In what follows we refer to the contributions that received purchased votes as “vote-traded contributions” and the contributions that did not receive purchased votes as “non-traded contributions”. Both groups of contributions exhibit considerable variation in characteristics. Nonetheless, the vote-traded contributions tend to be longer, more illustrated, and are typically written by more experienced authors. Our regression models control for the potential differences in the contributions between these two groups.

[Table 1]

Steemit contributions generate reward for the creators of the contributions in the form of native cryptocurrency. This reward is proportional to the number of the votes the contribution has received. We focus on two sources of such rewards. The first source is the payout from non-

[6] Source: https://github.com/SteemData/steemdata-mongo.

purchased votes and the second source is the payout from purchased votes. Table 2 shows that as much as 25.5% of the total payout is generated through purchased votes in the group of vote-traded contributions. While this number appears to be economically significant, it is crucial to recognize that the contributors have to pay for the votes they purchase. The data reveal that the payout from purchased votes only marginally exceeds the cost. When we account for the cost, only 4.3% of the net profit comes from purchased votes. Moreover, the contributors also face a considerable risk that the cost of votes exceeds the value of these votes. In fact, in 40.1% of the sample, the contributors pay more for the votes than the payout that they end up receiving from these votes. In the following sections, we uncover the rationale behind buying votes and investigate how vote trading affects voting outcome.

[Table 2]

4. Results

Vote trading can be detrimental if the platform contributors extract profits through buying cheap votes and voting for their contributions of poor quality. This strategy, however, can be infeasible if the vote selling stakeholders charge too high of a price per vote. Summary statistics reveal that indeed the votes are rather expensive, and the price of a vote often exceeds the payout per vote. We, therefore, proceed with exploring the motivation of vote buyers and the impact of vote trading on the buyers' reputation.

4.1 Does vote trading improve the voting outcome?

The observation that the payout per purchased vote is roughly equal to the price of a vote defines the course of our further steps. Specifically, we explore whether there are indirect benefits to vote buying. One such a benefit may be that the vote-buying contributors signal the quality of their work through buying votes and casting them in favor of their contribution. Since vote buying is transparent, the stakeholder community observes this signal and casts their own votes in favor of the vote-traded contribution.

We, therefore, hypothesize that a vote-traded contribution will receive more non-purchased votes than a comparable non-traded contribution. We test this hypothesis by looking into the accumulation of votes by vote-traded and non-traded contributions. Recall that the contributors receive a payout proportional to the total amount of votes that their contribution receives in the first seven days after publication. Figure 2 illustrates vote accumulation by vote-traded and non-traded contributions in these seven days. We observe that vote-traded contributions accumulate twice as many total votes as non-traded ones. Moreover, if we disregard purchased votes, the number of votes in the vote-traded group of contributions still exceeds the number of votes in the non-traded group.

[Figure 2]

Figure 3 further illustrates this finding. A typical contribution in the vote-traded group receives 370 non-purchased votes more than a contribution in the non-traded group on the first day after publication. This gap continues to grow, and by the end of the seventh day, the vote-traded contribution typically receives 540 more votes from independent voters than a contribution in a non-traded group. This constitutes a 51% gap. Overall, these results suggest that vote-traded contributions enjoy greater attention from the platform stakeholders than non-traded ones. Does this imply that the authors who buy votes use these votes to signal the quality of their contributions?

[Figure 3]

A signal is valuable because it conveys information beyond what can publicly observed by an unsophisticated platform stakeholder. In other words, the author of a contribution can buy expensive votes and thereby vouch that the quality of the contribution exceeds the expectations given the immediately observed characteristics. Alternatively, vote buying may not convey material information on top of the observed characteristics. If this is the case, then purchased votes are just a confounding attribute of the contributions with above average observed quality. To distinguish between these two possibilities, we run the following regression controlling for the observed characteristics of contribution quality.

$$Ln(Non\ Purchased\ Votes_{i,t}) = \alpha_i + \beta Ln(Purchased\ Votes_{i,t-1}) + Controls_i + \varepsilon_i,$$

where $Non\ Purchased\ Votes_{i,t}$ is the total non-purchased votes received for a contribution i on day t, which takes value from 2 to 7; $Purchased\ Votes_{i,t-1}$ is the amount of total purchased votes that the contribution i receives on day $t-1$; and $Controls_i$ include a set of variables indicating the publicly observed characteristics of a specific article contributed to the platform. These variables include the number of words in an article, the number of images in the article, the number of times the article is shared in the platform, the article author's reputation as evaluated by the platform, and the author's experience measured as the time between the author's registration date and the article's publication date. The raw measure of vote and reputation are scaled by 10^9 and 10^{12}. Both measures of purchased and non-purchased votes are skewed with the mean exceeding the median. We, therefore, perform log transformation on these variables in the regression.[7]

The results in Table 3 indicate that vote buying by the author of a contribution motivates other users to cast their own non-purchased votes in favor of such contribution. Importantly, the effect is significant after we control for the contribution's characteristics observable to unsophisticated platform participants. This suggests that purchased votes convey a signal beyond these observable characteristics. Specifically, a 1% increase in purchased votes leads to a 0.21% increase in non-purchased votes. Thus, vote-buying is more likely to be a signal of the contribution's unobserved quality rather than a confounding attribute of observed characteristics. We recognize that our regression setup may not account for a complete set of relevant observed characteristics. To account for this possibility, Section 5 further extends our analysis in an experimental setup.

[Table 3]

A strategy that involves buying votes to attract more votes from the other participants is effective if it allows to generate profit. In the next step, we confirm that buying votes leads to a significant increase in payout from the non-purchased votes. Specifically, we run the following model.

[7] Occasionally, the amount of non-purchased votes is negative. This happens when some of the stakeholders downvote an article. Downvoting is rather rare because in this case the voter spends the vote that does not generate the payout. Only 0.3% of observations yield negative non-purchased votes. When this happens, we replace the log-transformed value with zero. Our results are also consistent if we add the value of the most negative quantity of non-purchased votes to all observations and then perform the log-transformation.

$$Ln(Payout\ Non\ Purchased\ Votes_i) = \alpha_i + \beta Ln(Purchased\ Votes_i) + Controls_i + \varepsilon_i,$$

where $Payout\ Non\ Purchased\ Votes_i$ is the proceeds attributed to total non-purchased votes of the contribution i from day t to $t+6$; $Purchased\ Votes_i$ is the amount of total purchased votes that the contribution i receives from day t to $t+6$; and $Controls_i$ includes a set of control variables defined previously.

The results in Table 4 show that vote-traded contributions enjoy greater payout. Moreover, the payout from non-purchased votes increases with the number of votes purchased. The payout attributable to non-purchased votes increases by 0.021% per one percent increase in votes purchased. While the effect may appear to be economically small, it carries a large impact in comparison to other ways in which the quantity of votes typically improves. For instance, the payout increases by only 0.014% when a contributor attains one extra week of experience in the platform. Therefore, a contributor can attain a 50% greater reward by buying 1% extra votes than by improving the skill over the course of a week. As such, vote buying helps contributors to significantly increase their reward.

[Table 4]

4.2 How does vote buying affect the reputation?

Vote trading can be detrimental if it results in overselling of the contributions. Recall that the payout is calculated only with the votes acquired in the first week after the publication of a contribution. It may well be that the vote-buying contributors attract extra non-purchased votes in the first week that are in excess of the true quality of the contribution. Unfortunately, the voting activity predominantly takes effect in the first week after publication. Therefore, we cannot observe whether there is a long-term reversal in voting for the vote-traded contributions. However, the platform allows us to observe change in the vote-buyer's reputation.

We hypothesize that if purchased votes serve the purpose of signaling the contribution's quality, then the reputation of the vote buyers should improve when the first week after publication has passed. Alternatively, if a vote-buyer tends to oversell their contributions, then their reputation should drop over time.

The data contains the contributor-specific reputation score. This score constitutes a complex measure of the contributor's quality and reflects the Steemit stakeholders' opinion as well as the characteristics of the contributor's articles. We combine these scores across all contributors and calculate the percentile rank for every contributor each week. This allows us to observe the relative dynamics of the contributors' reputations.

Panel A of Table 5 shows that the vote-buying contributors experience an increase in reputation in the week after they purchase votes. The relative reputation of the contributors who do not buy votes declines slightly. To formally assess the impact of vote buying on reputation, we run the following regression.

$$Change\ in\ Reputation\ Rank\ _{i,t} = \alpha_i + \beta Vote\ Buyer_{i,t-1} + Controls_i + \varepsilon_i,$$

where $Change\ in\ Reputation\ Rank_{i,t}$ is the difference between the reputation rank of contributor i between week t and week $t-1$; $Vote\ Buyer_{i,t-1}$ takes 1 when a contributor i purchases at least one vote for contributions created at week $t-1$ or 0 otherwise; $Controls_i$

include a set of control variables including the $Vote\ Buyer_{i,t}$ dummy; Average Words, which is an average number of words in all articles by i created on week t; Average Images is the average number of images in all articles by i created on week t; Experience measures the time contributor i spends in platform before creating articles on week t; and Average Shared is the average number of times all articles created by i on week t are shared in the platform.

[Table 5]

The results in Panel B of Table 5 reveal that the reputation of vote-buying contributors improves relative to the reputations of the other contributors. The reputation begins to improve in the same week, when the contributor purchases votes and continues to improve in the following week. Moreover, the magnitude of the reputational gains grows with time after the vote-buying event. On average, the contributors enjoy a one-point gain in the relative reputational ranking after they buy votes. This indicates that the market for votes allows some platform contributors to signal the quality of their contributions, which leads to reputational gains over time. The fact that reputation improves in the week after the voting is over alleviates the concern that vote buying is a tool to oversell the contributions in the short term.

5. Experiment

In this section, we conduct an experiment to confirm that vote-buying is a signal of the contribution's quality rather than a confounding attribute of observed characteristics. In our main analysis, we run regressions controlling for the observed characteristics of contributed articles and their authors. This allows us to conclude that the vote-traded contributions typically generate greater payout and improve the authors' reputation *given the observed quality of such* *contributions*. While the control variables in the regressions yield economically and statistically significant coefficients, they may not represent the exhaustive set of characteristics describing the contributions' observed quality. Such characteristics may include the article's style and grammar as well as the overall cohesion of the narrative and the relevance of illustrations. Omitting these peculiarities may result in biased findings.

The following experimental setup allows us to measure the observed characteristics of the Steemit contributions and therefore alleviate the concern about a bias in the findings. Specifically, we entrust three paid experts to assess the quality of 5,000 contributions that are randomly selected from our main sample. Each expert ranks every contribution on a scale of one to five, where the contributions assigned the rank of one have the poorest quality and the contributions assigned the rank of five have the highest quality.

Next, we find which of the contributions in the subsample of 5,000 have received purchased votes and match them by the expert ranking to the contributions without purchased votes. The total of 84 contributions out of 5,000 received purchased votes.[8] Table 6 Panel A reports the ranking of these contributions provided by the three experts. The average ranking provided by Expert 1 and Expert 2 are 1.92 and 2.01. The average ranking provided by Expert 3 is 2.81. While Expert 3 is more lenient in ranking, this leniency is consistent across the board. A detailed examination of the rankings shows that all experts tend to assign rankings consistently, with Expert 3 assigning a slightly higher ranking to the best and the worst contributions. The consistency of scores across experts indicates that the experts efficiently capture the variation in

[8] The number of vote-traded contributions is small because the subsample of 5,000 articles was chosen at random. This design intends to avoid potential selection bias.

contribution quality.

[Table 6]

We proceed with matching the 84 vote-traded contributions with the 4,916 contributions from the non-traded group (5,000 received purchased votes minus 84 contributions). In particular, for every vote-traded contribution we select a contribution from a non-traded group with the same sum of the rankings by the three experts. When multiple contributions from the non-traded group have the same sum of expert rankings as the contribution from the vote-traded group, we select the contribution with the most similar individual expert scores as a match.

Table 6 Panel B reports the summary statistics for the resulting sample of matched non-traded contributions. The average ranking of the matched non-traded sample equals that of the traded sample at 2.246. Moreover, the individual average rankings provided by the three experts are consistent. As in the traded group, Expert 3 appears to be slightly more lenient than the other two experts, and this leniency applies across the board.

Next, we replicate the analysis in Table 2 with the experiment sample and report the numbers in Table 7. Consistent with the findings in Table 2, we observe that when we account for the cost of purchased votes, only a small part of the net profit comes from purchased votes. Instead, the majority of the profit in vote-traded contributions comes from non-purchased votes. In fact, the payout from non-purchased votes in vote-traded articles is four times greater than in the non-traded articles. Therefore, it is unlikely that our main result is driven by comparing the groups of contributed articles with different observed characteristics. Indeed, it appears that purchased votes serve the purpose of disclosing information beyond of what could be captured by unsophisticated platform participants.

[Table 7]

Tables 8 and 9 replicate our analysis in Section 4.1 with the experiment sample. Consistent with the main results, we find that vote buying by the contributor attracts other stakeholders to cast their own non-purchased votes in favor of the contribution. The economic significance is a 1.65% increase in non-purchased votes on a particular voting day when there is at least one purchased vote in favor of a contribution in the previous day.[9] Going further, we also confirm that the payout from non-purchased votes increases with the number of votes purchased. Appendix Figures A.1 and A.2 replicate Figures 1 and 2 and reveal patterns that are consistent with the main analysis. Overall, the results of the experiment alleviate the concern that our findings are biased because the articles in traded and non-traded samples are incomparable in terms of such characteristics as style, grammar, cohesion, the relevance of illustrations, and other observed characteristics that are challenging to include as controls in a regression.

[Table 8]

[Table 9]

6. Event study

We confirm our main finding in an event study. Furthermore, we show that an exogenous shock to demand for votes leads to greater voting participation by stakeholders who typically abstain from voting. Specifically, we rely on the announcement of the Minnow Support community by Steemit. This event caused a shock to the demand for purchased votes in the

[9] This effect is more pronounced than the 0.21% increase in non-purchased votes per 1% increase in purchased votes observed in the main sample regression. We attribute this difference to the fact that the quality of the contributions in the matched experiment subsample is slightly higher than in the main sample.

platform.[10] Minnow Support has established a reputation for providing upvoting services. On September 12, 2017, Minnow Support was officially recognized by Steemit and appeared on the Welcome page for users.[11]

The official recognition of this community by Steemit encourages post promotion through purchased votes. This has incentivized many users to buy votes, as promoting the contributions using purchased votes is now approved by Steemit designers. Moreover, the influx of demand to buy votes has affected the price of votes and attracted new vote sellers. Indeed, we observe that votes became more expensive after this event. In response to this, we observe that more users came out to sell votes with explicit advertisements following the event date. This indicates that the announcement of the Minnow Support community by Steemit is an exogenous shock to demand in the market for votes.

Figure 4 confirms that the announcement had a major impact on the number of purchased votes. In fact, the ratio of purchased votes in the total number of votes more than doubled after the announcement date.

[Figure 4]

In the main analysis, we find that the market for votes helps vote buyers to signal the quality of their contributions and thereby attract non-purchased votes. Therefore, the shock to demand for votes should lead to greater voter participation. In particular, we hypothesize that number of non-purchased votes will increase after the event. The underlying mechanism for this outcome is

[10] The Minnow Support community has been an active influential community since the inception of Steemit in 2016. See: https://steemit.com/@minnowsupport

[11] See: https://steemit.com/minnowsupportproject/@minnowsupport/msp-2-0-we-re-steemit-official

that those stakeholders who used to abstain from voting will become more informed post-event. We test this hypothesis with the following regression model.

$$Ln(Non\ Purchased\ Votes_{i,t}) = \alpha_i + \beta Event_t + Controls_i + \varepsilon_i,$$

where $Non\ Purchased\ Votes_{i,t}$ is the total non-purchased votes received for contribution i on day t; $Event_t$ is a dummy variable equal to one if the contribution is created on or after September 12, 2017, and zero otherwise; and $Controls_i$ includes a set of control variables defined previously. The event window spans August 12, 2017 to October 11, 2017. Table A.2 reports the event window summary statistics.

Table 10 shows that the shock to demand for buying votes caused a substantial increase in voter participation. This lends support to the hypothesis that vote buying can attract non-purchased votes. On average, the number of non-purchased votes increases by 2.5% in the contributions created in the month after September 12, 2017. Therefore, a shock to demand in an open and transparent market for votes can incentivize participation by stakeholders who typically abstain from voting.

[Table 10]

7. Steemit failed. Is this an outcome of vote trading?

At its popularity peak, Steem ranked as the third largest cryptocurrency by market capitalization. In fact, only Bitcoin and Ethereum exceeded the market capitalization of Steem cryptocurrency in early 2018. However, the market capitalization of Steemit has declined from its peak value of $1.8B to only $80M as of July 2022.[12] This loss of value may raise the concern that vote trading on Steemit contributed to its failure to remain one of the top cryptocurrencies.

We begin addressing this concern by comparing the performance of Steemit to other social media and digital services DAO platforms that rely on a blockchain to reward their contributors. The platforms we select for this analysis are similar to Steemit in terms of their purpose and longevity. Moreover, we select platforms that do not rely on voting to allocate rewards or are otherwise not known for vote trading. Specifically, we choose Kin, Karma coin (Karma), and Minds for comparison. Out of these three blockchain platforms, only Kin relies on upvoting for reward distribution. Karma relies on pre-determined rewards for digital services, while Minds rewards social medial platform participants in proportion to their activity on the platform.

Figure 5 shows that the price of Steem cryptocurrency performed comparably to its competitors. We observe that all four cryptocurrencies experienced common price cycles. This suggests that common market forces influence these blockchain platforms over time. Therefore, the cryptocurrencies are indeed comparable. Importantly, Steem does not appear to perform differently from its three competitors. As such, it is unlikely that an open and transparent market for votes present on Steemit caused the decline in the platform value. On the contrary, we observe that the Steem price is less volatile than the three competing cryptocurrencies.

[Figure 5]

Next, we formally assess whether changes in vote trading can predict the price of Steem cryptocurrency. Specifically, we estimate the following system of equations.

[12] https://coinmarketcap.com/currencies/steem/

$$Ret_t = \alpha_{1,t} + \beta_1 \Delta PV_{t-1} + \cdots + \beta_3 \Delta PV_{t-3} + \gamma_1 Ret_{t-1} + \cdots + \gamma_3 Ret_{t-3} + \varepsilon_{1,t}$$

$$\Delta PV_t = \alpha_{2,t} + \sigma_1 \Delta PV_{t-1} + \cdots + \sigma_3 \Delta PV_{t-3} + \theta_1 Ret_{t-1} + \cdots + \theta_3 Ret_{t-3} + \varepsilon_{1,t}$$

where Ret_t represents the daily return of Steem cryptocurrency and ΔPV is the first difference of the total purchased votes received by all articles on day t and $t-1$.

Table 11 contains the summary estimates of the equation coefficients. None of the coefficients exhibit independent or joint significance. For example, the p-value on the sum of the β_1, β_2, and β_3 coefficient exceeds 0.8. Therefore, we cannot reject the null hypothesis that purchased votes have no impact on Steemit returns.[13] As such, it is unlikely that the decline of the market capitalization of the Steemit platform was exacerbated by the vote trading practice. This is consistent with the earlier observation that Steemit experienced the same growth and decline cycle as the social media blockchain platforms that do not offer vote trading.

[Table 11]

8. Can our findings be generalized?

It is challenging to observe whether vote trading could improve voting outcome in the corporate environment, because to the best of our knowledge, there are no precedents of an open and transparent market for votes. Therefore, our paper resorts to studying an environment that has the characteristics of shareholder voting, yet is free from the restrictions imposed on such

[13] We report the parsimonious model with three lags. We have also estimated the models with different number of lags based on the Akaike information criterion. The coefficients (available on request) are consistent with the main findings.

voting. Although we acknowledge that some limitations remain, such as the absence of the majority rule in Steemit, the transparency of vote trading in blockchain allows us to make the unique contribution and shed light on the outcome of vote trading. A similar approach has been adopted by several studies, including Jensen (2007), Ahern (2017), and Rantala (2019). Below, we discuss the challenges that these studies have faced and the empirical setup used to address these challenges.

Jensen (2007) relies on the adoption of mobile phone technology throughout Kerala, a state in India with a large fishing industry, to investigate the effect of improvement in information access on the market performance and welfare. Testing this effect in alternative settings is challenging, as the industry nature and characteristics (the perishability of fish and related items and locations, etc.) define the great importance of information access and collectively make it a unique set up for natural experiment. He finds that the access to information through the adoption of the mobile phones by fishermen and wholesalers was associated with a dramatic reduction in price dispersion, the complete elimination of waste, and near-perfect adherence to the Law of One Price. This result leads to a generalized conclusion that information access improves overall market efficiency and welfare across all industries, as even industries without perishable goods can benefit from access to information regarding the methods of distribution and transportation.

Ahern (2017) uses an illegal insider trading network to underscore the importance of social network in diffusing private information among investors. He relies on this settings as it is virtually impossible to observe the direct communication of valuable investment information by investors. He finds that inside information flows through social connections. Moreover, insiders at the center of the network earn a higher return compared to the other insiders. The information passing through network improves price efficiency. This suggests that in general investors share material information across close social connections and the spread of information across social network affects market efficiency.

Rantala (2019) relies on a Ponzi scheme to study the word-of-mouth diffusion of investment information. Studying the diffusion of investment information constitutes a challenge because it is virtually impossible to directly observe the dissemination of word-of-mouth information and its effect at an individual level. He finds a social network structure in the Ponzi scheme that allows the diffusion of the investment idea and contributes to the growth and survival of the socially spreading scheme. The study concludes that investment ideas spread via social networks.

Similar to Jensen (2007), Ahern (2017), and Rantala (2019), we believe our results can shed light on whether vote trading can improve voting outcome. Below we address a few concerns that are specific to our empirical setup.

8.1 Selection bias

Our data comes from the Steemit platform. Therefore, the results are conditioned on the characteristics pertaining to the Steemit environment. If these characteristics drastically differ from corporate voting, this may create a biased sample and biased results. We, however, emphasize that the key characteristics of Steemit are comparable to the corporate voting environment.

First, there is a similarity in voting between Steemit and corporate entities. In line with the purpose of corporate voting (which is the agenda affecting the firms' value), the purpose of voting in Steemit is to ensure the efficient allocation of rewards to encourage quality content creation and involvement resulting in an ultimate increase in Steemit market value. Second, there is similarity in voting protocol. In particular, Steemit offers decentralized voting rights, an extended voting period, and accessibility to agendas.

Unlike corporations, Steemit is a DAO built on a blockchain platform. While this makes it different from the subject of the studies exploring corporate shareholder voting, it also provides a unique opportunity to track transparent vote trading among stakeholders, where voting rights are clearly separated from ownership rights. This allows us to test vote trading outcome without measurement error, which can otherwise result in biased estimates. Furthermore, our empirical tests are based on a large sample, ensuring a greater power of statistical analysis. We observe a large number (over 2.2 million) of voting agendas (articles) where voters can cast votes on 2,240,820 × 7 = 15,685,740 voting days.

8.2 The incentives of vote traders

Stakeholders in Steemit have monetary incentives to trade votes.[14] Vote sellers enjoy immediate gain in the form of the payment that a vote buyer makes. Vote buyers can gain from purchased votes in a number of ways. First, they can have a net cash inflow from a purchased vote. Second, they can use it as a signal to attract others to vote voluntarily in favor of their articles resulting in additional rewards. Finally, they can improve their reputation in this process

[14] The following Steemit discussions underscore this incentive:
https://steemit.com/steemit/@hodlorbust/buying-votes-infinite-profit
https://steemit.com/curation/@liberosist/a-review-of-vote-buying
https://steemit.com/steem/@smartsteem/we-want-you-as-vote-sellers
https://steemit.com/smartsteem/@ilyastarar/understanding-smartsteem-how-to-use-smartsteem-a-vote-selling-buying-service-you-can-benefit-from-and-other-investment

as purchased votes can signal the general quality of their creativity to others. Section 4 suggests that all these incentives exist in Steemit.

We believe that the incentives of Steemit users are similar to the incentives of voters in other settings. For example, corporate shareholders have monetary incentives to vote for agendas that would make them better off. In this way, they have incentives to gather as many votes as needed to improve their financial welfare.[15]

9. Conclusion

The literature conjectures that vote trading occurs frequently. However the empirical evidence of vote trading outcome is often limited as there is virtually no observable transparent market for votes where voting right is clearly separable from ownership right. We overcome these challenges by using a transparent market for votes in a decentralized autonomous organization environment, where votes are traded against monetary payments and separated from ownership rights. In our setting, stakeholders cast votes to express their opinion of the quality of contributions to the DAO platform. Then the newly-minted tokens are distributed to the stakeholders proportional to the accumulated votes received in favor of a contribution. Given that similar concerns for governance prevail in both DAOs and conventional corporate entities, we believe that voting incentives and outcomes are also comparable between them.

We find that buying votes serves as a tool to convince others to vote voluntarily in favor of vote buyers' contributions. Vote buyers cast purchased votes for their articles at the commencement of voting and others become attracted to vote for those contents. Their votes then

[15] For instance, See- Stulz (1988), Christoffersen, Geczy, Musto, and Reed (2007), Klein and Zur (2009)

translate into a net increase in the amount of non-purchased votes. This results in higher newly-minted token rewards for the vote buying contributors.

Our result also shows that purchased votes can serve as a signal of the general quality of vote buyers' contributions to others, as we observe that reputation of vote-trading contributors improves over time. To confirm the validity of this result, we conduct an experiment with the help of hired experts. Consistent with our main results, we find that purchased votes can increase non-purchased votes and rewards for vote buyers.

Further, we explore an exogeneous shock to the demand for purchased votes preceded by official approval and technical facilitation by the platform designers that encourages the promotion of contents using purchasing votes. This results in an influx of demand for purchased votes, which makes the votes expensive. We consistently find that non-purchased votes increase after the event, which suggest that higher vote-trading intensity causes more informed voting and results in greater voter participation.

Overall, our results contribute to the literature in several ways. First, our paper is the first to test vote trading outcome empirically based on explicit vote trading data distinguishing voting right from ownership right. Second, we show that vote trading in DAOs may not be taken for granted as welfare reducing. Rather, it can be used as a supplementary medium to increase efficiency in wealth distribution. Finally, we provide evidence that vote trading can serve as a signal to reduce information asymmetry.

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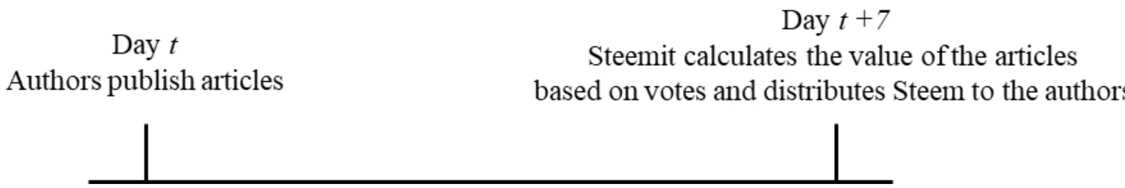

Figure 1. Timeline of distribution of rewards to an author in Steemit

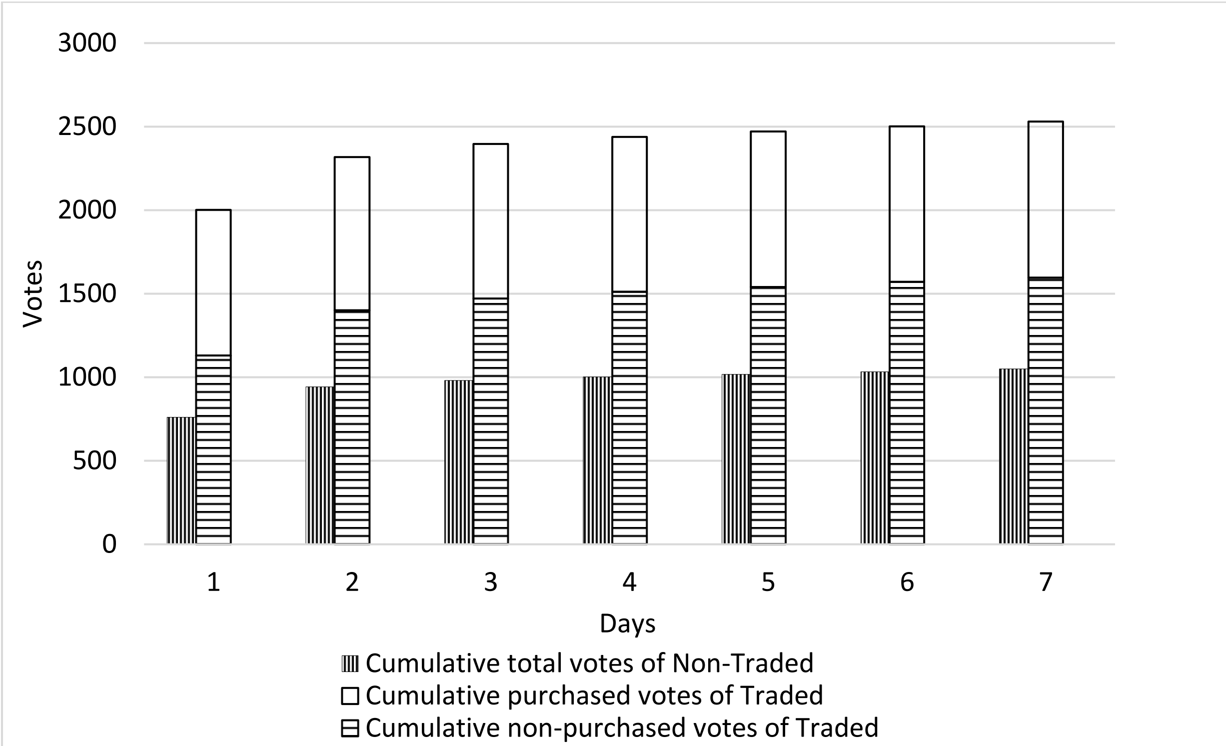

Figure 2. Accumulation of votes by Traded group and Non-traded contributions.
This figure illustrates the average cumulative amount of votes received by Traded and Non-traded contributions over the first seven days after publication. The number of votes is scaled by 10^9.

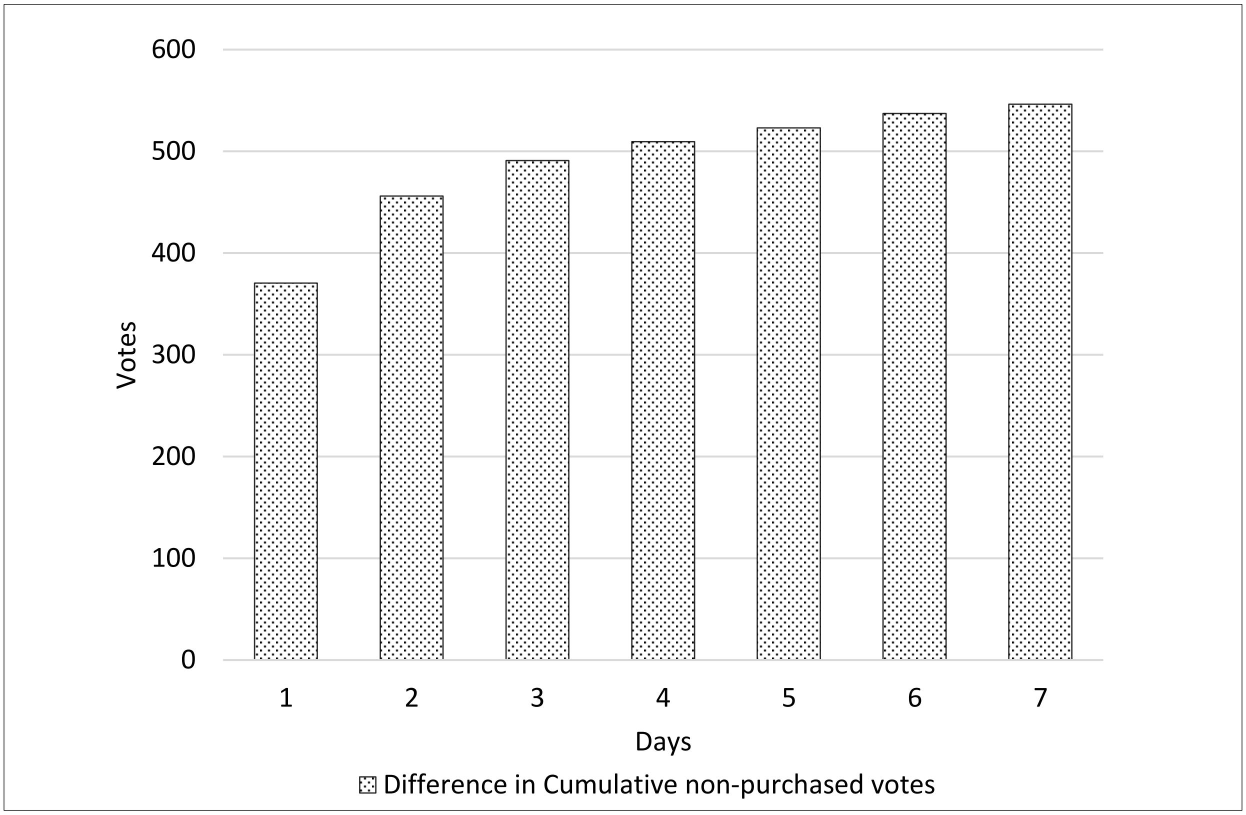

Figure 3. Difference in cumulative non-purchased votes between Traded and Non-traded contributions.
This figure illustrates the difference in average cumulative amount of non-purchased votes received by Traded and Non-traded contributions over the first seven days after publication. The number of votes is scaled by 10^9.

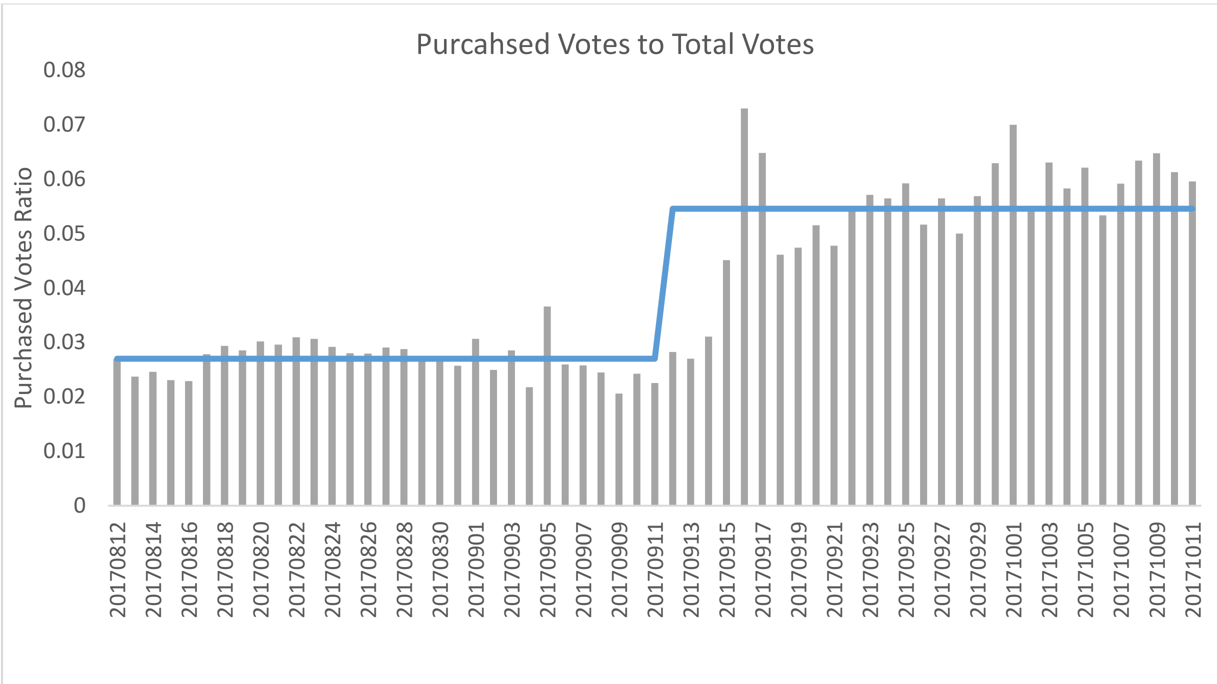

Figure 4. Purchased votes ratio around the event.

This figure plots daily purchased votes ratio measured as the total purchased votes scaled by the total votes in all contributions to the platform around the event date. The announcement triggering changes in purchased votes is on September 12, 2017. The blue line represents average purchased votes ratio. We consider the interval between August 12, 2017 and September 11, 2017 as the pre-event window and the interval between September 12, 2017 and October 11, 2017 as the post-event window.

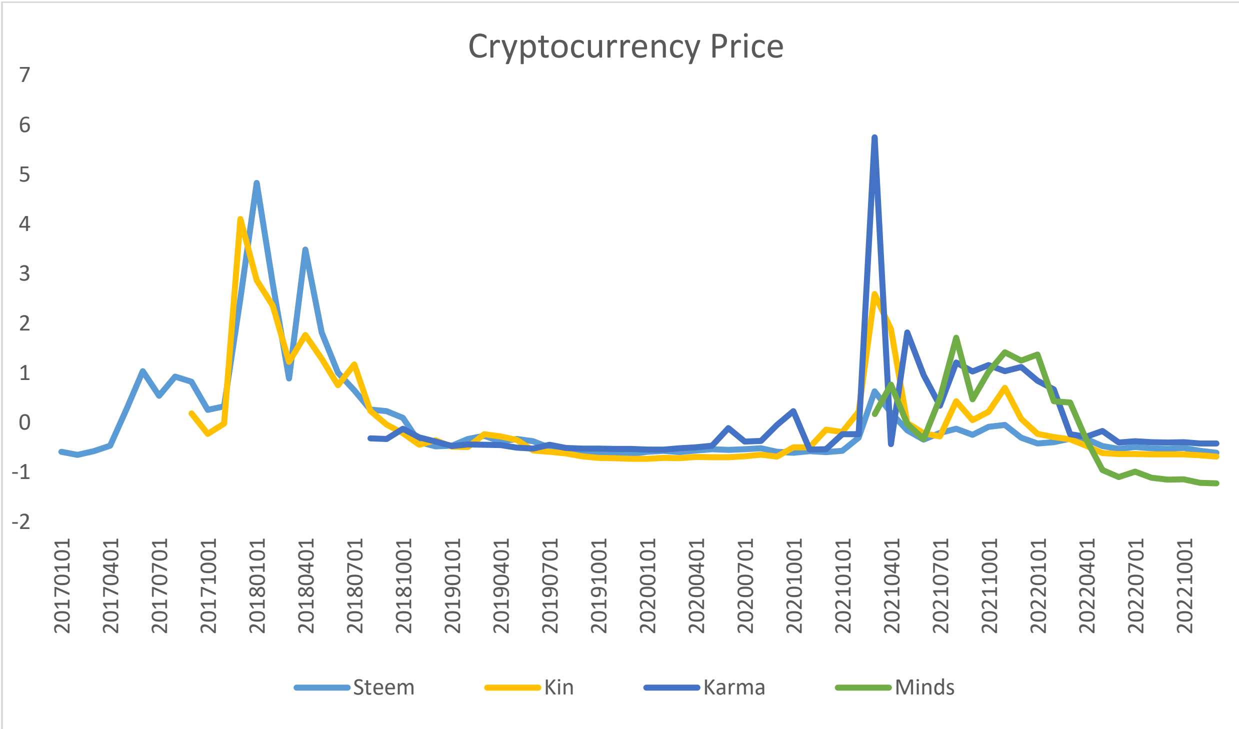

Figure 5. Prices of cryptocurrencies in platforms similar to Steemit.
This figure illustrates the time-series of standardized prices of Steem, Kin, Karma, and Minds cryptocurrencies which are used as reward for contribution in Steemit, Kik, Karma and Minds platforms, respectively. The price data is collected from www.coinmarketcap.com.

Table 1. **Summary statistics of contribution characteristics.**

This table reports summary statistics of the quality and characteristics for Steemit contributions created between April 5, 2017 and October 19, 2017. *Words* represent the number of words in a contribution, *Images* show the number of images in the contribution, *Reputation* is the contribution author's reputation as evaluated by the platform, *Experience* represents the authors's experience measured as the time between the author's registration date and the contributions's publication date, *Shared* shows the number of times the contributions is shared in the platform. The contributions are divided into two groups: i) Traded group includes the contributions receiving both purchased and non-purchased votes, ii) Non-traded group contributions do not receive any purchased votes. All of these are contribution-level measures. The number of votes is scaled by 10^9.

Variables	Mean	Std	p25	median	p75
Panel A: Traded group					
Words (hundreds)	2.7032	4.0951	0.39	1.35	3.51
Images	3.6691	4.6727	1	2	5
Reputation	9.3057	23.7145	0.8056	2.3759	6.5137
Experience (weeks)	15.3642	16.7489	5	9	16
Shared	1.9447	6.4089	0	1	2
Total contributions 71,167					
Panel B: Non-traded group					
Words (hundreds)	2.041	3.8217	0.16	0.76	2.45
Images	2.5418	4.1479	1	1	3
Reputation	8.0007	34.9916	0.0277	0.3168	2.1505
Experience (weeks)	10.7488	15.3742	1	4	12
Shared	0.8658	7.3461	0	0	0
Total contributions 2,169,653					

Table 2. **Summary statistics of voting.**

This table reports descriptive statistics for Steemit contributions created between April 5, 2017 and October 19, 2017. *Total payout* is the total Steem reward received by an author from a contribution. *Payout from purchased votes* is measured as *Total payout* divided by *Total votes*, times *purchased votes* received for the contribution, *Payout from non-purchased votes* is measured as *Total payout* divided by *Total votes*, times *Non-purchased votes* received for the contribution, *Cost of purchased votes* is the total Steem paid to buy votes for the contribution and *Net profit* is measured as *Total payout* minus *Cost of purchased votes*. *Total votes* are the total amount of votes accumulated over first 7 voting days, which is the sum of *Purchased votes* and *Non-purchased votes*. Contributions are divided into two groups: i) Traded group and ii) Non-traded group. Please, refer to Table 1 for the definition of each group. All of these are contribution-level measures. The number of votes is scaled by 10^9.

Variables	Mean	Std	p25	median	p75
Panel A: Traded group					
Payout from non-purchased votes	9.6906	59.0401	0.201	1.3092	4.88
Payout from purchased votes	3.3178	5.2899	0.6754	1.6986	3.7246
Total payout	13.0084	60.7162	1.5718	3.9182	9.6068
Cost of purchased votes	2.8753	5.5081	0.704	1.425	3.562
Net profit	10.1331	60.4685	0.3954	1.8048	5.5611
Non-purchased votes	1595.306	4730.643	65.6005	363.8875	1284.738
Purchased votes	935.077	1634.81	250.0142	403.3786	917.4831
Total votes	2530.383	5089.652	448.9118	1013.527	2717.312
Total contributions 71,167					
Panel B: Non-traded group					
Net profit	5.9764	49.2347	0	0.0889	1.0825
Total votes	1049.018	4669.785	2.4309	23.2956	269.5664
Total contributions 2,169,653					

Table 3. The effect of vote buying on non-purchased votes.

This table tests whether buying votes attracts non-purchased votes. Panel A compares the number non-purchased votes received for contributions in Traded and Non-traded groups. Panel B summarizes the result of following regression model:

$$Ln(Non\ Purchased\ Votes_{i,t}) = \alpha_i + \beta Ln(Purchased\ Votes_{i,t-1}) + Controls_i + \varepsilon_i,$$

where $Non\ Purchased\ Votes_{i,t}$ is the total non-purchased votes received for a contribution i on day t, which takes value from 2 to 7; $Purchased\ Votes_{i,t-1}$ is the amount of total purchased votes that the contribution i receives on day $t-1$; and $Controls_i$ include a set of control variables indicating the publicly observed characteristics of the specific article i contributed to the platform, including *Words*, which represent the number of words in the contribution; *Images* show the number of images in the contribution; *Reputation* is the article author's reputation as evaluated by the platform; *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date; *Shared* shows the number of times the contribution is shared in the platform. The raw measures of votes and reputation are scaled by 10^9 and 10^{12}, respectively. For log transformation of a variable, negative values are replaced by 0 and then 1 is added. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Non-purchased votes at day t
Traded	77.5132
Non-traded	48.2232
Traded minus Non-traded	29.29***
	(0.000)

Panel B: Regression analysis

	Dependent variable: Ln non-purchased votes at day t	
	(1)	(2)
Ln purchased votes at day t-1	0.2667***	0.2143***
	(0.000)	(0.000)
Words (hundreds)		0.0102***
		(0.000)
Images		0.01***
		(0.000)
Reputation		0.004***
		(0.000)
Experience (weeks)		0.0104***
		(0.000)
Shared		0.0067***
		(0.000)
Intercept	0.3943***	0.1974***
	(0.000)	(0.000)
N	13,444,920	13,444,920
Adjusted R^2	0.0083	0.1639
Author fixed effect	No	Yes
Creation date fixed effect	No	Yes

Table 4. The effect of vote buying on payout from non-purchased votes.

This table tests whether buying votes leads to greater payout from non-purchased votes. Panel A compares the payout from non-purchased votes for contributions in Traded and Non-traded groups. Panel B summarizes the result of following regression model:

$$Ln(Payout\ Non\ Purchased\ Votes_i) = \alpha_i + \beta Ln(Purchased\ Votes_i) + Controls_i + \varepsilon_i,$$

where $Payout\ Non\ Purchased\ Votes_i$ is the proceeds attributed to total non-purchased votes of the contribution i from day t to $t+6$; $Purchased\ Votes_i$ is the amount of total purchased votes that the contribution i receives from day t to $t+6$; $Controls_i$ include a set of control variables indicating the publicly observed characteristics of the specific article i contributed to the platform including *Words*, which represent the number of words in the contribution; *Images* show the number of images in the contribution; *Reputation* is the contribution author's reputation as evaluated by the platform; *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date; *Shared* shows the number of times the contribution is shared in the platform. The raw measures of votes and reputation are scaled by 10^9 and 10^{12}, respectively. For log transformation of a variable, negative values are replaced by 0 and then 1 is added. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Payout from non-purchased votes
Traded	9.6906
Non-traded	5.9764
Traded minus Non-traded	3.7142***
	(0.000)

Panel B: Regression analysis

	Dependent variable: Ln payout from non-purchased votes	
	(1)	(2)
Ln purchased votes	0.0937***	0.0212***
	(0.000)	(0.000)
Words (hundreds)		0.0159***
		(0.000)
Images		0.0176***
		(0.000)
Reputation		0.0166***
		(0.000)
Experience (weeks)		0.0135***
		(0.000)
Shared		0.0078***
		(0.000)
Intercept	0.6184***	0.2661***
	(0.000)	(0.000)
N	2,240,820	2,240,820
Adjusted R^2	0.0086	0.6609
Author fixed effect	No	Yes
Creation date fixed effect	No	Yes

Table 5. The effect of vote buying on author's reputation.

This table shows how buying votes affects the vote-buyer's reputation. Panel A compares the change in reputation rank between contributors who purchase votes and contributors who do not purchase votes. Panel B summarizes the result of following regression model:

$$Change\ in\ Reputation\ Rank_{\ i,t} = \alpha_i + \beta Vote\ Buyer_{i,t-1} + Controls_i + \varepsilon_i,$$

where $Change\ in\ Reputation\ Rank_{i,t}$ is the difference between the reputation rank (0 to 99) of contributor i between week t and week $t-1$; $Vote\ Buyer_{i,t-1}$ takes 1 when a contributor i purchases at least one vote for contributions created at week $t-1$ and 0 otherwise; $Controls_i$ include a set of control variables including the $Vote\ Buyer_{i,t}$ dummy; Average Words, which is an average number of words in all articles by contributor i created on week t; Average Images is the average number of images in all articles by contributor i created on week t; Experience measures the time contributor i spends in platform before creating contributionss on week t; and Average Shared is the average number of times all articles created by contributor i on week t are shared in the platform. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Change in reputation rank
Authors with purchased votes	0.0696***
Authors without purchased votes	-0.0049**
Purchased minus non-purchased	0.0745***
	(0.000)

Panel B: Regression analysis

	Dependent variable: Change in reputation rank	
	(1)	(2)
Vote buyer dummy at week t-1	0.0745***	0.0595***
	(0.003)	(0.007)
Vote buyer dummy at week t		0.0380**
		(0.012)
Average words (hundreds)		-0.0019
		(0.124)
Average images		0.0005
		(0.624)
Experience (weeks)		0.3104**
		(0.037)
Average shared		-0.0002
		(0.709)
Intercept	-0.0049	-5.3103**
	(0.849)	(0.037)
N	309,989	309,989
Adjusted R^2	0.0003	0.1492
Author fixed effect	No	Yes
Creation date fixed effect	No	Yes

Table 6. Summary statistics of contribution characteristics in an experiment.

This table reports descriptive statistics for the Steemit contributions used in the experiment. The contributions are created between April 5, 2017 and October 19, 2017. *Words* represent the number of words in the contribution, *Images* show the number of images in the contribution, *Reputation* is the contribution author's reputation as evaluated by the platform, *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date, *Shared* shows the number of times the contribution is shared in the platform. *Expert 1 ranking*, *Expert 2 ranking* and *Expert 3 ranking* are human ratings of an contribution's quality between 1 (low) to 5 (high) by three experts. *Average ranking* is the sum of the rankings of all experts, divided by 3. Contributions are divided into two groups: i) Traded group includes contributions receiving both purchased and non-purchased votes, ii) Non-traded group contributions do not receive any purchased votes. All of these are contribution-level measures. The measure of reputation is scaled by 10^{12}.

Variables	Mean	Std	p25	median	p75
Panel A: Traded group					
Expert 1 ranking	1.9167	1.0778	1	2	3
Expert 2 ranking	2.0119	1.1872	1	2	3
Expert 3 ranking	2.8095	1.4928	1	3	4
Average ranking	2.246	1.0168	1.3333	2	3
Words (hundreds)	4.0044	5.8264	0.89	2.43	5.645
Images	4.0357	3.6683	1	3	5.5
Reputation	11.2393	19.4150	1.3261	4.7635	11.088
Experience (weeks)	13.3691	15.9667	3	6	13
Shared	6.2262	44.0006	0	0	2
Total contributions 84					
Panel B: Non-traded group					
Expert 1 ranking	1.8452	1.047	1	1.5	2
Expert 2 ranking	2.2143	1.2131	1	2	3
Expert 3 ranking	2.6786	1.5843	1	3	4
Average ranking	2.246	1.0168	1.3333	2	3
Words (hundreds)	2.6377	4.3239	0.25	1.485	3.42
Images	3.0238	4.3436	1	1	3.5
Reputation	2.42	6.3483	0.0157	0.3743	1.7704
Experience (weeks)	8.3571	13.9220	1	3	7
Shared	0.2976	0.7882	0	0	0
Total contributions 84					

Table 7. Summary statistics of voting in an experiment.

This table reports descriptive statistics for the Steemit contributions used in the experiment. The contributions are created between April 5, 2017 and October 19, 2017. *Total payout* is the total Steem reward received by an author from a contribution. *Payout from purchased votes* is measured as *Total payout* divided by *Total votes*, times *purchased votes* received for the contribution, *Payout from non-purchased votes* is measured as *Total payout* divided by *Total votes*, times *Non-purchased votes* received for the contribution, *Cost of purchased votes* is the total Steem paid to buy votes for the contribution and *Net profit* is measured as *Total payout* minus *Cost of purchased votes*. *Total votes* are the total amount of votes accumulated over first 7 voting days, which is the sum of *Purchased votes* and *Non-purchased votes*. Contribution are divided into two groups: i) Traded group and ii) Non-traded group. All of these are contribution-level measures. The number of votes is scaled by 10^9.

Variables	Mean	Std	p25	median	p75
Panel A: Traded group					
Payout from non-purchased votes	17.1689	42.9753	1.0869	2.8165	9.6521
Payout from purchased votes	5.7588	10.0587	1.0716	2.2594	4.1097
Total payout	22.9277	46.2076	2.9928	6.0008	19.9014
Cost of purchased votes	3.4146	6.9176	1.22	2.428	3.67
Net profit	19.5131	45.8025	1.0664	3.1944	13.6455
Non-purchased votes	1714.901	3466.315	163.6641	439.588	1563.076
Purchased votes	539.7054	869.9039	201.1469	266.4221	566.5143
Total votes	2254.6064	3600.777	450.789	846.2713	2336.044
Panel B: Non-traded group					
Net profit	4.4222	17.5502	0	0.1085	1.0673
Total votes	559.0202	1812.408	2.8747	14.6763	117.5135

Table 8. The effect of vote buying on non-purchased votes in an experiment.

This table tests whether buying votes attracts non-purchased votes in the experiment. These contributions are created between April 5, 2017 and October 19, 2017. Panel A compares the non-purchased votes received for contributions from day 2 to day 7 between Traded and Non-traded groups. Please, refer to Table 1 for the definition of each group. Panel B summarizes the result of following regression model:

$$Ln(Non\ Purchased\ Votes_{i,t}) = \alpha_i + \beta Purchased\ Votes_{i,t-1} + Controls_i + \varepsilon_i,$$

where $Non\ Purchased\ Votes_{i,t}$ is the total non-purchased votes received for a contribution i on day t, which takes value from 2 to 7; $Purchased\ Votes_{i,t-1}$ if article i receives at least one purchased vote on day $t-1$ or 0 otherwise; and $Controls_i$ include a set of control variables indicating the publicly observed characteristics of the specific article i contributed to platform, including *Words*, which represent the number of words in the contribution; *Images* show the number of images in the contribution; *Reputation* is the contribution author's reputation as evaluated by the platform; *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date; *Shared* shows the number of times the contribution is shared in the platform. The raw measures of votes and reputation are scaled by 10^9 and 10^{12}, respectively. For log transformation of a variable, negative values are replaced by 0 and then 1 is added. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Non-purchased votes at day t
Traded	66.6782
Non-traded	19.6075
Traded minus Non-traded	47.0707**
	(0.015)

Panel B: Regression analysis

	Dependent variable: Ln non-purchased votes at day t	
	(1)	(2)
Purchased votes dummy at day t-1	1.7509***	1.6462***
	(0.000)	(0.000)
Words (hundreds)		0.0127**
		(0.047)
Images		0.0561***
		(0.010)
Reputation		0.0115***
		(0.000)
Experience (weeks)		-0.0029
		(0.265)
Shared		0.0115***
		(0.000)
Intercept	0.4173***	0.1023
	(0.000)	(0.261)
N	1,008	1,008
Adjusted R^2	0.1024	0.2270
Author fixed effect	No	N/A
Creation date fixed effect	No	Yes

Table 9. The effect of vote buying on payout from non-purchased votes in an experiment.

This table tests whether buying votes leads to greater payout from non-purchased votes in the experiment. These contributions are created between April 5, 2017 and October 19, 2017. Panel A compares the payout from non-purchased votes of contributions between Traded and Non-traded groups. Panel B summarizes the result of following regression model::

$$Ln(Payout\ Non\ Purchased\ votes_i) = \alpha_i + \beta Traded_i + Controls_i + \varepsilon_i,$$

where $Payout\ Non\ Purchased\ Votes_i$ is the proceeds attributed to total non-purchased votes of the contribution i from day t to $t+6$; $Traded_i$ takes 1 if contribution i receives at least one purchased vote or 0 otherwise from day t to $t+6$. $Controls_i$ include a set of control variables indicating the publicly observed characteristics of the specific article i contributed to the platform including *Words*, which represent the number of words in the contribution; *Images* show the number of images in the contribution; *Reputation* is the contribution author's reputation as evaluated by the platform; *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date; *Shared* shows the number of times the contribution is shared in the platform. The raw measures of votes and reputation are scaled by 10^9 and 10^{12}, respectively. For log transformation of a variable, negative values are replaced by 0 and then 1 is added. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Payout from non-purchased votes
Traded	17.169
Non-traded	4.4221
Traded minus Non-traded	12.7469**
	(0.0128)

Panel B: Regression analysis

	Dependent variable: Ln payout from non-purchased votes	
	(1)	(2)
Traded dummy	1.1222***	0.6937***
	(0.000)	(0.001)
Words (hundreds)		0.0142
		(0.389)
Images		0.1058***
		(0.000)
Reputation		0.0176***
		(0.004)
Experience (weeks)		0.0175**
		(0.028)
Shared		0.0065***
		(0.000)
Intercept	0.5899***	0.0472
	(0.000)	(0.772)
N	168	168
Adjusted R^2	0.1756	0.5219
Author fixed effect	No	N/A
Creation date fixed effect	No	Yes

Table 10. The effect of vote buying on non-purchased votes in an event study.

This table tests whether buying votes attracts non-purchased votes in the event study subsample. This subsample includes contributions created between August 12, 2017 and October 11, 2017. Panel A compares the number non-purchased votes before and after the event. Panel B summarizes the result of following regression model:

$$Ln(Non\ Purchased\ Votes_{i,t}) = \alpha_i + \beta Event_t + Controls_i + \varepsilon_i,$$

where $Non\ Purchased\ Votes_{i,t}$ is the total non-purchased votes received for a contribution i on day t, which takes value from 2 to 7; $Event_t$ is a dummy which takes 1 if the contribution is created on or after September 12, 2017 and 0 otherwise; and $Controls_i$ include a set of control variables indicating the publicly observed characteristics of the specific article i contributed to the platform including *Words*, which represent the number of words in the contribution; *Images* show the number of images in the contribution; *Reputation* is the contribution author's reputation as evaluated by the platform; *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date; *Shared* shows the number of times the contribution is shared in the platform. The raw measures of votes and reputation are scaled by 10^9 and 10^{12}, respectively. For log transformation of a variable, negative values are replaced by 0 and then 1 is added. Standard errors are clustered by contribution id and creation date. P-values corresponding to double clustered standard errors are reported in parentheses.

Panel A: Univariate analysis

	Non-purchased votes at day t
Event	59.6249
Pre-event	49.5489
Event minus pre-event	10.076***
	(0.000)
Total unique contributors	Event: 33,494 and Pre-event: 31,317

Panel B: Regression analysis

	Dependent variable: Ln non-purchased votes at day t	
	(1)	(2)
Event dummy	0.0282***	0.0253***
	(0.000)	(0.003)
Words (hundreds)		0.0088***
		(0.000)
Images		0.0079***
		(0.000)
Reputation		0.0363***
		(0.001)
Experience (weeks)		0.0032
		(0.106)
Shared		0.0065***
		(0.000)
Intercept	0.4066***	0.1027
	(0.000)	(0.113)
N	5,576,790	5,576,790
Adjusted R^2	0.0001	0.1718
Contributor fixed effect	No	Yes

Table 11. Vote trading and Steem return.

This table reports the test of whether purchased votes affect Steem return (Panel A) and whether Steem return affects purchased votes (Panel B). Steem return (Ret) at day t is defined as the natural logarithm of Steem price at day t divided by Steem price at day $t-1$. ΔPV is the first difference of total purchased votes (PV) received by all articles at day t. The number of purchased votes is sclaed by 10^{15}. The sample spans from April 5, 2017, to October 19, 2017. Each panel reports the sum of the lag-coefficients, the corresponding Wald χ2-statistic, and p-value for the null hypothesis that the sum of the coefficients is equal to zero.

Panel A: Test of purchased votes predicting Steem return	
	Dependent variable: Ret
Sum of lag coefficients of ΔPV	0.0494
χ^2 (Sum = 0)	0.0526
p-value	0.8186
Panel B: Test of Steem return predicting purchased votes	
	Dependent variable: ΔPV
Sum of coefficients of lags of Steem return	-0.077
χ^2 (Sum=0)	0.8000
p-value	0.3711

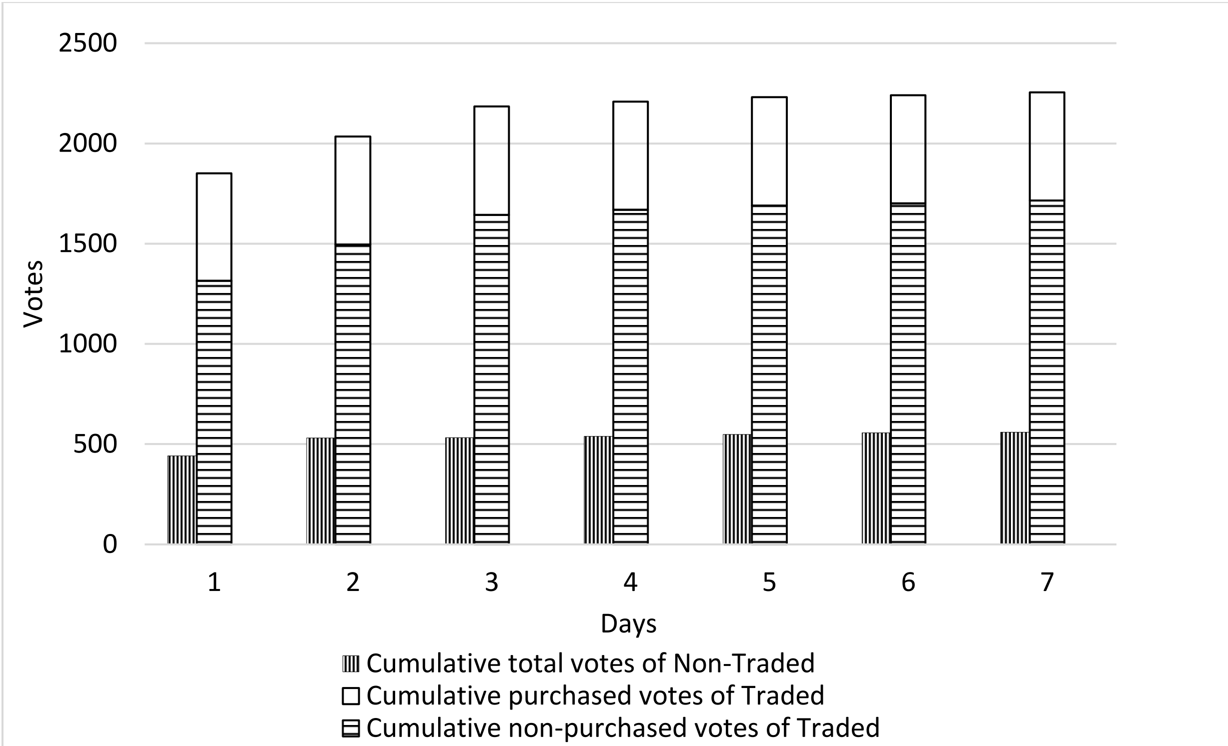

Figure A.1 Accumulation of votes by Traded group and Non-traded contributions in an experiment. This figure illustrates the average cumulative amount of votes received by Traded and Non-traded contributions over the first seven days after publication. The number of votes is scaled by 10^9.

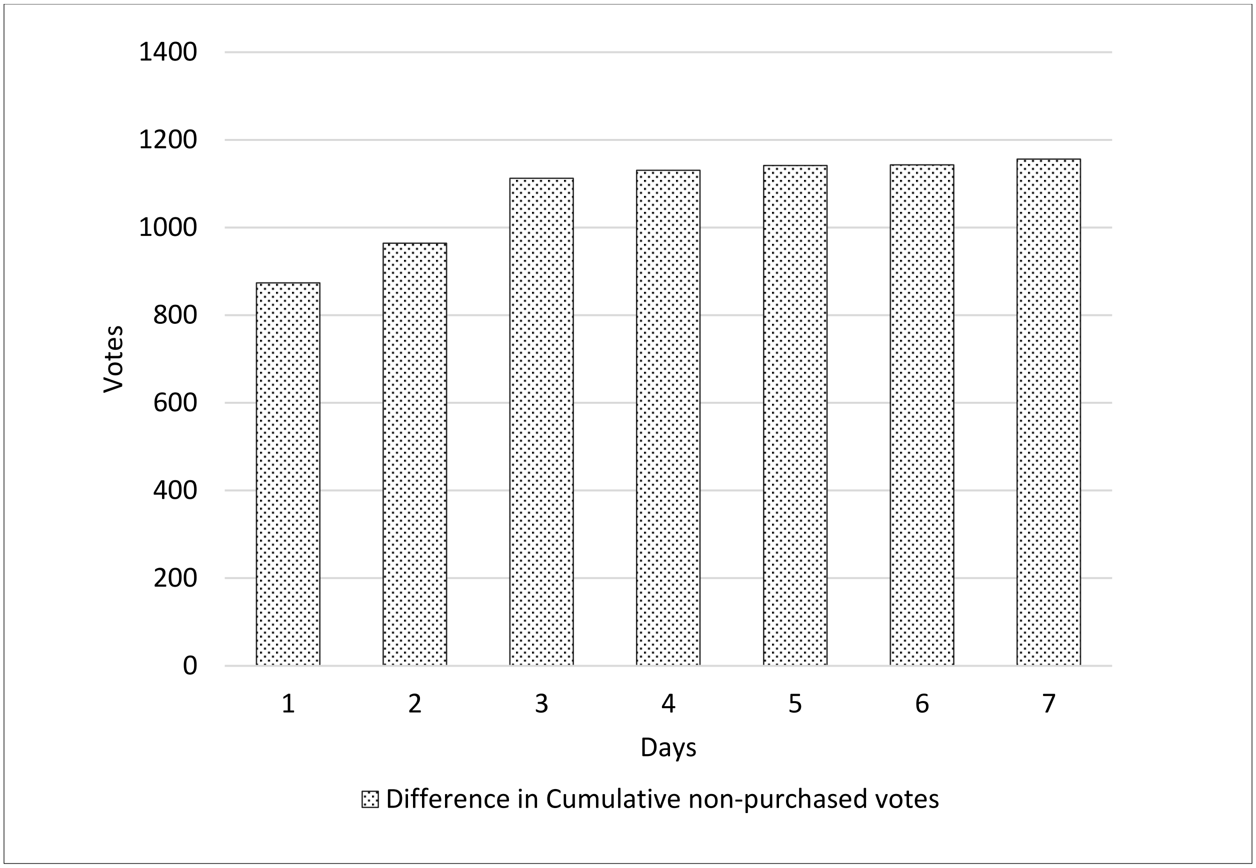

Figure A.2 Difference in cumulative non-purchased votes between Traded and Non-traded contributions in an experiment.
This figure illustrates the difference in average cumulative amount of non-purchased votes received by Traded and Non-traded contributions over the first seven days after publication. The number of votes is scaled by 10^9.

Table A.1 Vote selling offer examples

Vote seller	Offer
drotto	Bid 0.001 sbd or more every 270 seconds and get a vote of 0% - 3.13%.
tipu	Voting: active | minimum payment: 0.1 sbd/steem max upvote available: $34.
mercurybot	A voting bot. send minimum 0.25 sbd or 0.25 steem to bid for votes.
rocky1	Send at least 3 sbd or 3 steem to get an upvote on your posts.

Table A.2. Summary statistics of contribution characteristics in an event study.
This table reports summary statistics for the Steemit contributions in the August 12, 2017 and October 11, 2017 event window. *Words* represent the number of words in the contribution, *Images* show the number of images in the contribution, *Reputation* is the contribution's author's reputation as evaluated by the platform, *Experience* represents the author's experience measured as the time between the author's registration date and the contribution's publication date, *Shared* shows the number of times the contribution is shared in the platform. Contributions are divided into two groups: i) Event group includes contributions created between August 12, 2017 and September 11, 2017, ii) Pre-event group articles include contributions created between September 12, 2017 and October 11, 2017. All of these are contribution-level measures. The number of votes is scaled by 10^9.

Variables	Mean	Std	p25	median	p75
Panel A: Event group					
Words (hundreds)	2.1024	3.951	0.15	0.75	2.56
Images	2.6796	4.4621	1	1	3
Reputation	6.0222	29.4841	0.0195	0.2476	1.7688
Experience (weeks)	12.1465	15.7552	2	7	14
Shared	0.8404	6.2306	0	0	0
Total contributions 455,345					
Panel B: Pre-event group					
Words (hundreds)	1.985	3.8245	0.15	0.73	2.38
Images	2.4873	4.1631	1	1	3
Reputation	6.3849	31.321	0.0279	0.3466	2.0663
Experience (weeks)	10.6997	15.0505	1	6	11
Shared	0.8181	6.478	0	0	0
Total contributions 474,120					