Parallel Markets: Decentralized Governance without Voting

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Abstract:

Aggregating dispersed information into high-quality collective decisions remains a central challenge in corporate governance. Traditional voting mechanisms suffer from well-documented vulnerabilities such as whale dominance, rational apathy, and strategic manipulation. This study proposes Parallel Markets, a market-based governance system that replaces voting with market equilibrium prices for collective decision-making. The proposed system replicates ownership shares into conditional shares for each decision choice, and participants trade these shares in separate markets, in which equilibrium prices serve as decision signals; the system then ratifies the choice with the highest price, voiding and refunding trades on the other choices.

We implement the system in a web application and evaluate it through controlled online experiments. Under normal conditions, the system consistently selects the value-maximizing choice; under stress test conditions with near-identical choices, selection accuracy degrades, revealing liquidity as the key constraint. To address this, we introduce Parallel Primary Markets, an improved system that uses bonding curves to supply continuous liquidity independent of counterparty availability. We formally show that conditional share prices reflect underlying expected values independently of winning probabilities, and that ratification is resistant to manipulation given sufficient market liquidity. This research contributes to the corporate governance literature by introducing and empirically evaluating a novel class of voting-free governance systems for collective choice.

Keywords:

Corporate Governance; Collective Choice; Collective Intelligence; Prediction Markets; Decentralized Autonomous Organization (DAO); Decentralized Autonomous Corporation (DAC)

1.Introduction

1.1. Motivation

Crowdsourcing outsources work to a large, often external, crowd and can support multiple phases of managerial decision-making (Chiu et al., 2014). The crowdsourcing paradigm challenges traditional hierarchical decision-making and blurs the organizational “boundaries” separating contributors inside an organization from outsiders (Thuan et al., 2017). DAOs represent an extreme category of this shift, as they crowdsource governance decisions rather than rely on centralized managerial authority.

Joyce et al. (2013) describe rules and roles as components of governance. DAOs codify precise governance rules but obviate the need for hierarchical roles such as directors, leaving collective decisions to token holders directly. This aims to produce self-governing collaboration without reliance on cooperation, trust, or external authority. But they face a core challenge: aggregating dispersed information and preferences into high-quality collective decisions. Accordingly, governance and decision-making processes remain the primary obstacle to DAO adoption in practice (Xie & Tsang, 2025).

The corporate governance paradigm separates ownership (residual claims) from control (decision-making), letting investors and managers specialize (Fama & Jensen, 1983). However, managers' interests may deviate from owners', creating a vertical agency conflict. Corporations mitigate this by splitting decision management (initiation, implementation) from decision control (ratification, monitoring): managers handle the former, and a board the latter (Fama & Jensen, 1983). However, the board mechanism is imperfect; directors' incentives can also diverge from shareholders', introducing another layer of vertical agency conflict (Bebchuk & Fried, 2003). Corporations also face a horizontal problem: conflict between dominant, controlling shareholders and distant, minority shareholders (Roe, 2004).

DAOs bypass the vertical problem by eliminating the board, enabling token holders to vote directly in proportion to their holdings (Saesen et al., 2025). But this amplifies the horizontal problem, as token-weighted voting inherits the plutocratic, one-share-one-vote logic of corporate voting (Anand & Chauhan, 2020) and carries the same vulnerabilities.

The first vulnerability is the "tyranny of the majority": a subset of shareholders who hold 51% of shares can control 100% of resources and decisions, at the expense of the rest. Supermajority requirements are meant to mitigate this but instead grant veto power to a minority, exacerbating the problem. For instance, under Hong Kong law, 10% of shares can block a buyout, and hedge funds have used this threshold to block value-accretive deals (e.g., Henderson Investment), while holding short positions on the target (Hu & Black, 2006). Value-destruction strategies such as empty voting or shorting while in control remain a significant risk for DAOs (Strnad, 2025).

The second vulnerability is free-riding: small holders have little incentive to monitor management or vote (Cvijanovic et al., 2019). Strnad (2025) notes that voting in DAOs presumes away the "rational apathy" of small token-holders, and Lo Monaco et al. (2025) show that value creation in DAOs depends significantly on voter participation. This dependency is the “tragedy of the digital commons”: low participation and free-riding invite manipulation (Li & Chen, 2024), and this compounds the first vulnerability, since free-riding lets a dominant holder control a DAO with far less than 50% of voting power. Practitioners call this “whale dominance”: large token-holders exert disproportionate influence and alienate smaller stakeholders (Han et al., 2025). Some DAOs try to incentivize participation with tokens or NFTs, but such rewards attract uninformed, low-quality participation, which adversely affects performance and sends negative signals to investors (Saesen et al., 2025), confirming that non-market mechanisms generally fail to incentivize accurate revelation of alternatives' value (Ba et al., 2001).

Third, with more than two choices, any voting scheme falls under Arrow’s impossibility theorem; the plurality rule violates Independence of Irrelevant Alternatives, leaving collective decisions sensitive to strategic voting (Arrow, 2012). With exactly two choices, efficiency depends on the vote threshold required: Buchanan and Tullock (1962) showed that low thresholds let a few individuals impose costs on others, while high thresholds raise the cost of reaching any agreement. When a "right" choice exists and is broadly detectable, majority vote performs well (Ertekin et al., 2013), but disagreement grows when evaluating choices requires effort and expertise (Gillick & Liu, 2010), and in the absence of strict financial alignment, voting tends to redistribute surplus rather than generate efficiency gains (Abadi & Brunnermeier, 2024).

In short, voting schemes aggregate dispersed information poorly and are prone to manipulation. Existing safeguards, such as boards and regulation, are themselves products of voting arrangements and inherit similar limitations (Khaledi, 2018). Platform and DAO governance therefore face an unresolved design problem: how to ratify collective decisions without relying on voting and its associated failure modes.

This study introduces Parallel Markets, a governance system that replaces voting with market equilibrium prices to ratify collective decisions. The next subsection reviews the relevant literature, and Section 2 presents the system in detail.

1.2. Related Work

Two literatures bear on this problem. The first proposes alternative governance mechanisms for DAOs.

As Wang et al. (2019) describe, DAOs rely on generalized blockchains like Ethereum as the technology layer and tokens as the incentive layer. Their governance rules are encoded directly into smart contracts on blockchains (Morrison et al., 2020). Unlike contractual governance, which depends on external judiciaries, or relational governance, which relies on interpersonal trust, blockchains autonomously enforce and execute smart contracts (Lumineau et al., 2021). Although DAOs operate on chain, they can control physical assets through an external verification layer (Blum et al., 2025).

Saesen et al. (2025) show that DAO governance design choices are critical signals of organizational quality and token performance. Ellinger et al. (2024) describe a tension between the "House of Commons" (democratic off-chain forums) and the "House of Lords" (plutocratic on-chain voting), arguing that voting mechanisms are structurally unable to equitably capture collective intent. They note that some DAOs (e.g., MakerDAO) manage this tension through "polycentric governance," a synthesis of off-chain discussion and delegation politics that incurs high coordination costs.

Han et al. (2025) provide a systematic comparison, noting that DAOs aim to democratize governance through smart contracts but introduce structural trade-offs distinct from traditional corporate hierarchies. For example, on-chain voting incurs high operational costs, while off-chain voting is associated with valuation discounts due to transparency and trust deficits (Bellavitis & Momtaz, 2025). Consistent with this, Chen et al. (2021) find full decentralization is not uniformly optimal for platform performance and a hybrid governance structure may outperform pure centralization or decentralization.

Strnad (2025) proposes Sequential Auctions, where temporary control is sold to the bidder posting the highest deposit; bidders must also post substantial surety deposits to deter manipulation such as empty voting. This approach auctions off centralized control, producing periodic recentralization, and assumes the winning bidder has sufficient resources to acquire a controlling stake temporarily, after which control reverts to voting. None of these proposals removes voting from the final ratification step.

The second literature links decisions to market prices. Price aggregates dispersed information more efficiently than voting or polling (Hayek, 1945; Hanson, 2002): it is a sufficient statistic that summarizes individual valuations into a single collective valuation, free of the free-riding, majority tyranny, and strategic manipulation that affect voting. Such a collective valuation yields a group utility function that escapes the impossibility theorems constraining voting-based aggregation (Scott & Antonsson, 1999). Blockchain-based markets extend this aggregation further, increasing transparency and liquidity and speeding convergence to equilibrium prices (Yermack, 2017).

Prediction markets use equilibrium prices to forecast future events (Coles & McAfee, 2007; Dong et al., 2022). Participants trade contracts whose payoffs are tied to a future outcome, and over time prices come to reflect the market's collective judgment of that outcome's probability. This proves remarkably accurate for outcomes determinable in the near term such as political elections and sporting events (Coles & McAfee, 2007), and sales forecasting (Dong et al., 2022). Holographic Consensus applies prediction markets to sort and filter DAO proposals, but not as the decisive ratification criterion; final ratification still relies on voting, as in the governance of No1s1, the self-owning house project (Blum et al., 2025).

Decision markets (Hanson, 2002), preference markets (Coles & McAfee, 2007), imagination markets (LaComb et al., 2007), and idea markets (Soukhoroukova et al., 2011) apply this logic to evaluate ideas, decisions, and early-stage technologies, but require tying payoffs to an observable, exogenous outcome (Blohm et al., 2011), typically verified by an external oracle. When no such outcome is observable in the near term, payoffs are instead tied to the market's own emerging price, turning the market into a Keynesian "beauty contest": prices chase expectations of prices rather than reflecting true value (Keynes, 1936).

Soukhoroukova et al. (2011) review proposed fixes. Waiting for real-world outcomes to materialize, as Foresight Exchange does, provides weak trading incentives when payoffs lie decades away. Proxy measures avoid this delay but are difficult to define for novel ideas and invite manipulation. Expert panels raise their own problems: defining expertise, incentivizing honest assessment, and the frequent overlap between "experts" and traders, which creates conflicts of interest, and leaves traders forecasting the panel's judgment rather than assessing true value.

1.3. Research Questions and Contributions

The literature leaves a gap: no existing proposal ratifies DAO decisions purely through market equilibrium prices, without an external oracle and without a residual voting step, while also formally characterizing the conditions under which that ratification is reliable. This paper targets that gap with four research questions.

RQ1 (Architecture): How can a decentralized governance system be structured to ratify DAO decisions through market equilibrium prices instead of voting? We answer RQ1 by introducing Parallel Markets, a voting-free governance system resistant to agency conflicts and the tyranny of the majority.

RQ2 (Empirical Boundaries): How robust is the system's selection accuracy under normal conditions versus narrow value gap stress test? We answer RQ2 with a controlled online experiment instantiating the system's selection logic as a portfolio-investment choice task. Under normal value separation, the system selects the value-maximizing choice exactly. Under a deliberate stress test with top choices engineered to have near-identical values, selection accuracy degrades, with the largest deviations coinciding with the thinnest trading volume, indicating that liquidity, not system logic, is the source of the residual error.

RQ3 (Improvement): What design change restores operational reliability under liquidity constraints, and can automated bonding curves improve resilience to low liquidity? We answer RQ3 by introducing the Parallel Primary Markets system, which uses bonding curves to guarantee continuous, unlimited liquidity independent of counterparty availability, removing the liquidity limitation observed in the experiments.

RQ4 (Formal Analysis): Under what conditions does the system guarantee selection of the value-maximizing choice, and how robust is that selection to manipulation? We answer RQ4 by formally characterizing the market mechanism's incentive properties: conditional share prices track underlying value independent of winning probabilities, ratification is value-maximizing, and manipulation resistance is bounded by market liquidity.

The answers to RQ1–RQ4 constitute the four contributions of this study.

The Parallel Markets system differs fundamentally from existing market-based collective decision-making systems. Decision Markets typically forecast a specific success metric and require expert judgment or an external oracle to verify the outcome. The Parallel Markets system avoids this dependency by pricing the market's own valuation of conditional shares: the conditional expected value of future cash flows, a continuous quantity tied to an exogenous payoff stream. No oracle is needed, because the payoff is the firm's own value rather than an externally verified outcome. It also avoids a self-referential "beauty contest," because that value is tied to actual future cash flows rather than to traders' expectations of the price itself. As in public corporations, the prospect of cash flows drives prices: "Stock prices are visible signals that summarize the implications of internal decisions for current and future net cash flows" (Fama & Jensen, 1983). Financial market prices have grown more informative about future cash flows as data-processing and information costs have declined (Bai & Savov, 2016).

We expect Parallel Markets to be as decisive as prediction markets, where the leading outcome's price advantage typically widens over time (Coles & McAfee, 2007). Because the system's only selection criterion is the maximum price, only the relative prices of the highest-valued alternatives matter, making selection insensitive to a uniform over-optimism bias that would shift all prices together (Cowgill & Zitzewitz, 2015). In each period, the highest-valued alternatives also attract more trading and are therefore priced more precisely relative to each other. When too many choices are open in a given period, the platform can rank alternatives by price to make the highest-priced choices more visible and easier to trade.

The system also operationalizes "Skin in the Game," sharing both the risk and reward of a decision directly through market participation, rather than through the political negotiation and "theater" of voting that current DAO governance relies on (Ellinger et al., 2024). This replaces the coordination costs of polycentric governance with a single equilibrium price per decision: participants who support a bad choice bear a financial loss, which is precisely the graduated cost needed to discipline the "tragedy of the digital commons" (Li & Chen, 2024) and sustain participation.

Two scope conditions apply. First, the system rests on the efficient market hypothesis: equilibrium share prices are assumed to reflect underlying firm value (at least in relative terms), with conditional share prices reflecting expected discounted future cash flows under each choice. Since some real-world DAOs issue governance tokens with no residual cash-flow rights, the system is best suited to DAOs structured as tokenized equity. Second, the system adopts shareholder primacy, with market capitalization as its objective. Saesen et al. (2025) identify token price as a reliable ex-post indicator of DAO performance; Parallel Markets operationalizes this link ex-ante to ratify decisions that maximize market capitalization. This choice is not a dismissal of multi-dimensional goals like social utility, protocol resilience, stakeholder inclusivity, and ESG considerations, but isolates a clear, verifiable benchmark for assessing the system's performance. Future work may adapt the system to other valuation metrics, such as Tobin's q (Black et al., 2006), or to non-financial proxy measures of social utility.

1.4. Outline

This paper follows a Design Science Research (DSR) methodology (Hevner et al., 2004), consistent with recent DSR applications to market-mechanism design (Dong et al., 2022). It builds a collective decision-making artifact, evaluates it, and refines it based on evaluation findings. As a designed artifact, the Parallel Markets system must satisfy four requirements: an architecture that ratifies decisions without voting (RQ1), empirically demonstrated selection reliability (RQ2), a design remedy when reliability breaks down (RQ3), and formal guarantees on when that reliability holds (RQ4).

This section establishes the problem's relevance to research and practice.

Section 2 presents the artifact, the Parallel Markets system, instantiated as a working web application in Appendix A, i.e., design as proof by construction. This answers RQ1.

Section 3 develops the first evaluation method: a simulated DAO experiment, structured as a mutual fund, governed by shareholders using this system. This method can be used to test and evaluate other governance systems as well. Section 4 reports the experimental results, answering RQ2.

This experiment drives the design-as-search cycle: it identifies liquidity as the binding constraint and motivates a refined artifact. To address it, Section 5 uses bonding-curve contracts to supply counterparty-independent liquidity, introducing the Parallel Primary Markets system and answering RQ3.

Section 6 supplies the second evaluation, a formal incentive-compatibility analysis, consistent with Hevner et al.'s guidance to evaluate with multiple methods. It formally characterizes the conditions under which the selection mechanism selects the value-maximizing choice and resists manipulation, thereby answering RQ4.

Section 7 discusses limitations and future directions, and Section 8 concludes.

2. Solution

This section proposes Parallel Markets as the solution. We assume governance proceeds through repeated rounds of decision-making, and each round requires two functions: a mechanism to generate alternative decision choices, and a mechanism to select one among them. Accordingly, the Parallel Markets system structures each decision round into two stages: a suggestion period, during which participants propose decision choices, and a selection period, during which the system replicates the DAO's shares into a set of conditional shares for each choice. Participants trade these shares, exercising control rights by trading for or against each choice; the system then ratifies the highest-priced choice and voids and refunds trades on the rest. Transactions and prices thereby autonomously select the choice that maximizes the DAO's market capitalization, without an oracle and without a vote.

This two-stage design is consistent with the broader information-systems and DAO-governance literature, which decomposes collective decision-making into more granular stages that collapse into the same two functions. Kornish and Hutchison-Krupat (2017) note that information technologies have opened new forms of governance around "idea generation" (suggestion) and "idea selection." Zhao et al. (2022) propose four stages for DAO governance: idea generation, sentiment investigation, voting, and execution. Our suggestion and selection periods correspond to the first and third; we replace the third stage's voting mechanism with market-based selection. Li and Chen (2024) similarly identify proposal and voting as the core stages, among five, on which we focus.

2.1. Suggestion Periods

For suggestion, we rely on the crowd to generate decision choices. Majchrzak and Malhotra (2013) argue that the information system shapes crowdsourcing outcomes, with participation-architecture design determining the quality of ideas generated. Sakamoto and Bao (2011) used crowdsourcing for a social problem and found the crowd's best ideas to be as novel and useful as those from experts. Gottschlich and Hinz (2014) showed the effectiveness of crowdsourced, user-generated investment recommendations for stock-market investment decisions.

Here, each decision round starts with identifying a decision matter (an issue) according to some predetermined rules. This starts a suggestion period, during which one or multiple proposals can be submitted for the decision matter. A proposal can refer to a solution, a policy, a contract, a decision initiative, a decision choice, a decision address, a proposal address, a contract address, a policy address, among other things. Proposals can be submitted by managers, shareholders, investors, employees, an open crowd or a set of qualified proposers according to some predetermined rules. Financial and non-financial rewards can incentivize more and better proposals.

To incentivize original proposals and deter copycats, proposals may remain confidential until the end of the suggestion period. At that point, some or all proposals are revealed as decision choices. To limit the number of choices, the governance system filters out proposals that do not meet predetermined criteria (e.g., English language requirement). Proposals that satisfy these criteria are considered qualified and proceed as choices for the selection period. These choices represent alternative futures for the company. Figure 2-1 illustrates the steps in a single decision round under this configuration.

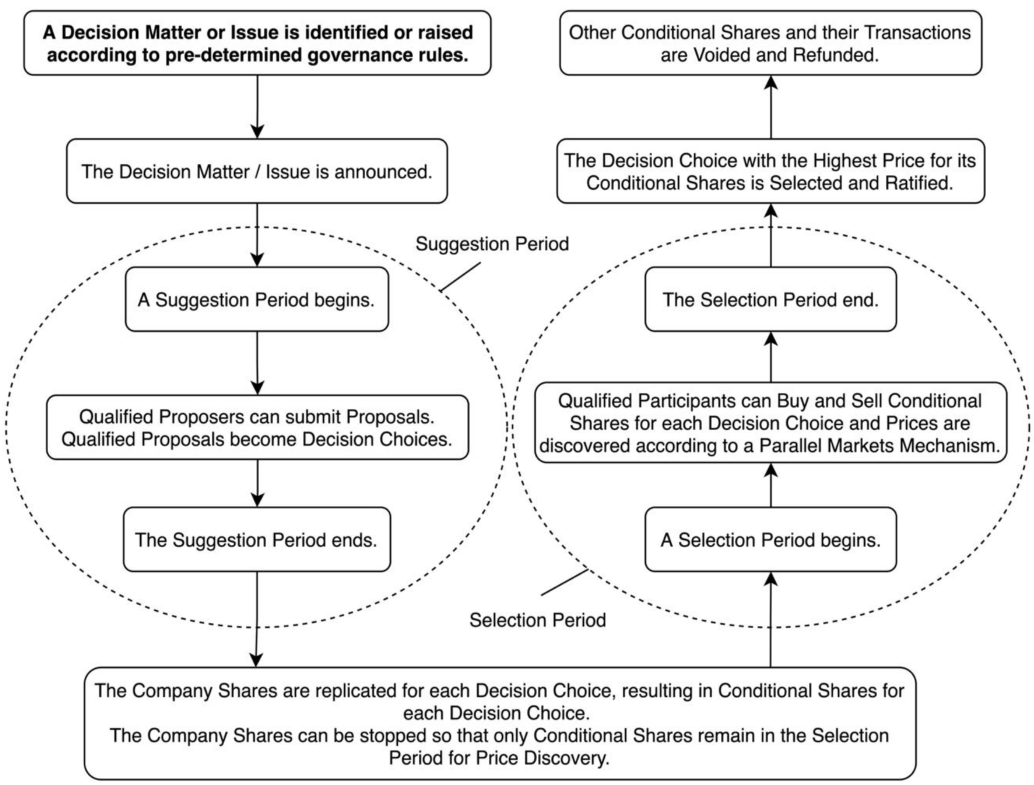


Figure 2-1. The Flowchart for the Parallel Markets System

In an alternative configuration, a decision round starts when a proposer proposes a qualified proposal (amendment) according to some predetermined rules. Then the qualified proposal becomes one choice, and “Status Quo” becomes another choice; there is therefore no suggestion period. Therefore, the selection period starts with two choices: “Accept” and “Reject”.

2.2. Selection Periods

To detect the best choice, ideally, we want to try each choice in a parallel universe and evaluate the value of the company under each choice. Then go back in time and pick the choice that would result in the highest value for the company. Unfortunately, it is not feasible yet. So, this section introduces a slightly different system called *Parallel Markets*.

According to this system, at the beginning of the selection period, the company ownership shares are replicated for each choice. These new shares are conditional on whether the choice is selected or not. Hence, they are referred to as conditional shares. Each shareholder will have the same number of conditional shares for each choice as they had for the (unconditional) company ownership shares immediately prior to replication. A set of conditional shares is converted to company ownership shares if its corresponding choice is selected at the end of the selection period.

After replicating company shares, a selection period begins and participants, investors, or traders can buy and sell the conditional shares for each choice in a separate market. These markets operate in parallel to discover the price for the conditional shares for each choice. People can trade the shares for each choice assuming that it will be implemented. Market prices can be determined through continuous double auctions, as described by Coles and McAfee (2007) and applied to e-commerce market design by Miyashita (2014). The resulting equilibrium prices reflect the expected values for the hypothetical futures of the company given all the available information. Figure 2-2 illustrates how prices of multiple conditional shares can change in parallel markets during two decision rounds.

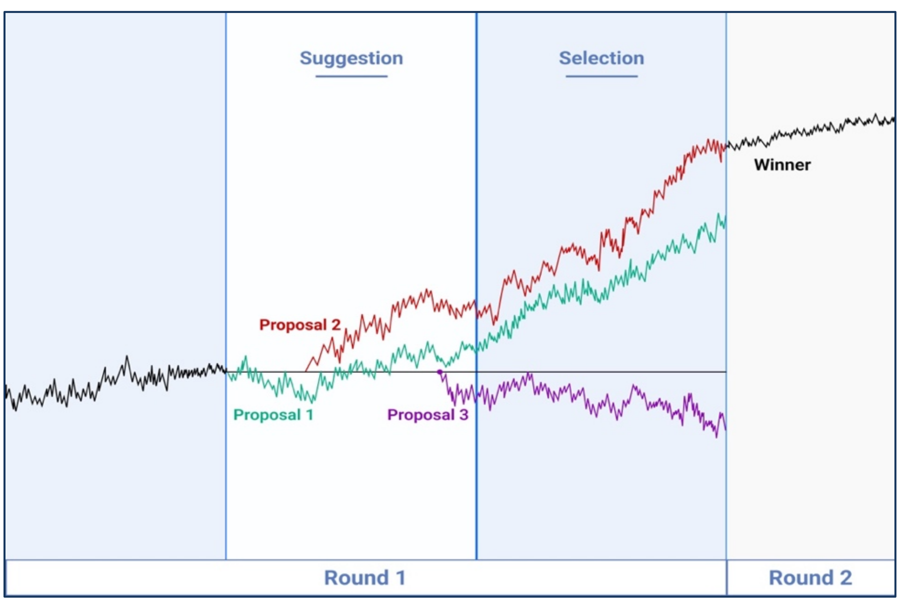


Figure 2-2. Decision rounds with the Parallel Markets system

After the selection period, the system autonomously makes the set of conditional shares with the highest price (or another measure of value) the (unconditional) ownership shares of the company and ratifies its corresponding choice as the effective decision. The system ensures a credible commitment that human agents cannot easily reverse. However, the conditional shares of other choices and their transactions are voided and refunded to their investors and traders. Voiding the non-winning choices limits the risk of buying precarious choices. This also mitigates manipulations like empty voting by ensuring that capital is only committed to the ratified reality. The numerical example in Appendix F shows how it works.

Liquidity

One challenge facing the Parallel Markets system is liquidity. Liquidity enables participants to make a transaction immediately without changing the price significantly (Coles & McAfee, 2007). On the other hand, a "thin market" with too few trades cannot effectively aggregate information (Healy et al., 2010). Markets need several participants and several trades to reach a meaningful equilibrium price for evaluation, whereas other evaluation mechanisms like rating and voting, only need one or two participants and one shot to result in a meaningful evaluation using an aggregation function (Blohm et al., 2011). Christiansen (2007) explained that Markets should have at least 16 participants to be efficient.

However Parallel Markets need multiple times more participants and trading activities to reach enough liquidity because multiple markets are running simultaneously, and each trader can meaningfully participate in one of them at any time. Therefore, the choices steal liquidity from each other. To mitigate this problem, we need to control the number of choices so as not to have too many low-quality ones, which could be time consuming and costly to evaluate. To this end, we can apply one or a combination of the following methods.

1. There can be a *fixed fee* for proposing each decision choice. This deters spam submissions, but too large of a fee may also deter risk-averse proposers to submit potentially superior proposals.

2. There can be a *betting contest* for suggestions. Proposers can pay to bet on their suggestions. Then the suggestions are sorted according to the payments. A larger betting amount indicates the proposer's higher confidence in their suggestion. Winning proposers can be rewarded proportional to their bets.

3. The proposers can be limited to shareholders. Particularly, only shareholders who *own more than a specific number of shares* (e.g. 1%) can suggest a decision choice. We already see that shareholder proposals are taken more seriously than the management proposals (Cvijanovic et al., 2019).

4. The decision choices can be *sorted based on the number of shares* their proposers have at the time.

	Filtering	Sorting
Per Choice	A *Fixed Fee* for each suggestion	*Betting Contest* for suggestions
Per Proposer	Proposers with more than 1% shares	Based on Proposers' shares

Table 2-1. The methods to control the number of choices

Accounting Technicalities

Another challenge for Parallel Markets is some accounting technicalities. An order or transaction can involve recalculating the available balances for each participant for each set of the conditional shares. Therefore, in addition to the cash balance, each person has two *conditional* balances associated with each choice. The *winning balance (W_i)* is realized if the choice (i) wins, and the *void balance (V_i)* is refunded if the choice (i) voids. The winning balance is the fund from selling conditional shares for a choice during the selection period. When a shareholder sells conditional shares for a choice, the transferred cash is not confirmed unless and until the choice wins. If the choice wins and its conditional shares are confirmed, its winning balances for all individuals are confirmed and added to their cash balances; otherwise, they are voided along with the choice's conditional shares. The winning balance cannot be cashed out or used to buy conditional shares for other choices, but it can be used to buy conditional shares for the same choice. Thus, during a selection period, the available balance for each person to buy choice i is calculated as follows:

$$A_i = B + W_i - \sum_k O_{ik} - \sum_{j \neq i} Ramp\left(\sum_k O_{jk} - W_j\right) \qquad (2-1)$$

Wherein, B is the individual's real cash balance and O_{ik} is the amount of money locked due to the person's buy order k on choice i. A buy order on a choice can use the cash balance as well as the winning balance for that choice. Since buy orders can use the cash balance, buy orders on other choices can also reduce the available balance on a choice. This happens when the total of buy orders on another choice (j) exceeds the winning balance (W_j) for that choice so they would take money from the cash balance B. The Ramp function reflects that. This ensures that there will never be a negative balance for any choice.

Another constraint is that during a selection period, an individual cannot withdraw their available balances, but he can withdraw their available balance on the winning choice at the end of the selection period.

However, during the selection period, we know exactly one choice will win and its winning balance will be confirmed. Thus, to facilitate withdrawal, we can let a person withdraw the minimum of their available balances across all choices. To this end, we normalize each individual's winning balances such that when an individual's winning balance for every choice is positive, the minimum of them is added to their cash balance and is deducted from all their conditional winning balances (W) so the individual's minimum winning balance across all choices becomes zero. In short, after each transaction, for the seller party:

$$min\{W_i | i \in All\ Choices\} > 0 \ \mapsto \ B \coloneqq B + min\{W_i\}\ ;\ \forall i: W_i \coloneqq W_i - min\{W_i\} \qquad (2-2)$$

It should be noted that this has an effect only if the person sells conditional shares for all choices, in which case, this facilitates the withdrawal of the minimum of the balances. However, this operation is not reversible, and once converted into a cash balance, it can be used only once to buy conditional shares.

Moreover, each person has a *Void Balance* (V_i) for each choice (i) when buying its conditional shares. The money an individual spends to buy conditional shares for a choice should be refunded if the choice and its conditional shares are voided. If the choice wins and its conditional shares are confirmed, its void balances (for all individuals) are discarded; otherwise, they are refunded and added to the cash balances. During a selection period, we know that each choice either wins or voids. Thus, we normalize each individual's balances for each choice so that either their winning balance or their void balance for that choice is zero. To this end, when both of an individual's conditional balances for a choice are positive, the minimum of them is added to the individual's cash balance and is deducted from both of their conditional balances so that one of them is always zero. In short, for each individual after each transaction for each choice:

$$min\{W_i, V_i\} > 0 \ \mapsto \ B \coloneqq B + min\{W_i, V_i\};\ W_i \coloneqq W_i - min\{W_i, V_i\}\ ;\ V_i \coloneqq V_i - min\{W_i, V_i\} \quad (2-3)$$

At the end of the selection period, the choice with the highest price wins (i=w) and becomes the effective decision. The distribution of conditional shares for the winner choice becomes the distribution of ownership shares for the company. The cash balance for each individual is updated according to:

$$B \coloneqq B + W_w + \sum_{j \neq w} V_j \qquad (2-4)$$

, where W_w is the individual's winning balance for the winning choice and V_j is their void balance for each choice j, which is not the winning choice.

3. Experimental Design

There have been several studies on crowdsourcing and user-generated content. However, the main novelty of this study is a new selection mechanism that relies on the equilibrium prices to select and ratify one choice out of many. Therefore, this section focuses on testing and experimenting with the evaluation and selection stage in the Parallel Markets system to demonstrate its feasibility and viability.

As a proof of concept, the Parallel Markets system is implemented in a web application and tested via online experimentation on *Amazon Mechanical Turk* (MTurk). MTurk is a web service that enables outsourcing or crowdsourcing simple tasks to human workers from all over the world (Davis & Lin, 2011). It provides a reasonable and cost-effective platform with diverse participants who are more representative of a real labor market than university students are (Mason & Watts, 2009). Appendix A presents the control panel and the important user pages in this web application. The web application includes an automated exchange that applies the Continuous Double Auction mechanism to match and clear buy and sell orders in each choice-market.

To evaluate the performance of a governance mechanism, instead of looking into the properties of the mechanism (e.g., fairness criteria), we look at the outcome of the mechanism hypothesizing that the quality of the outcome reflects the quality of the mechanism. This enables us to evaluate and compare governance mechanisms for real-world practice without trying to overcome the impossibility theorems.

Accordingly, we need to evaluate the quality of the outcomes of the process efficiently and objectively. In the real world, it takes a long time for a governance system to result in a measurable outcome, and even then, the quality of the outcome is affected by various factors and is mostly subjective. Therefore, here we define an artificial decision problem whose solutions can be objectively and immediately evaluated. This problem requires participants to make retroactive investment decisions as if they can time travel to the past. They should choose between different investment alternatives for a fictitious mutual fund at specific points in time. The mutual fund simulates a company with participants as its shareholders.

The evaluation criterion is therefore objective and pre-defined: a selection is correct if and only if the ratified choice is the one with the highest actual value, computed from historical asset prices. Because this ground truth is externally verifiable and free of rater subjectivity, system's performance is measured as the gap between the ratified choice's value and the ex-post value-maximizing choice, rather than against subjective quality ratings or inter-rater agreement.

This is a unique problem that has no practical application in the real world but has several desirable properties. First, the performance of the alternatives can be evaluated objectively without dealing with raters and inter-rater reliability issues. Particularly, historical prices have minimal measurement errors. Second, the solutions to this specific problem have only one dimension of quality (i.e., return) and there is no uncertainty or risk involved. Third, this is essentially an investment planning problem without the forecasting part. So, it does not require any expertise in financial forecasting, and thus laypeople (participants) can understand it and evaluate choices in a limited time. Decisions involving financial forecasts would require substantial knowledge and a long time to yield meaningful variations in performance.

We did not enable participants to chat or talk with each other, because a lack of interaction, isolated learning, and diversity can improve the accuracy of collective predictions or decisions (Hong et al., 2012). Moreover, in real-world market settings, it is hard to acquire any valuable information for free. Usually, people have conflicts of interest, and acquiring information is costly, so the (free) signals cannot be trusted. Hence, the lack of reliable communication in experiments is closer to reality. Participants have pseudonymous identities to closely replicate a real DAO environment.

The instructions presented to the participants are as follows:

<u>Imagine it is 1/1/2019</u> *and you have $5 cash balance plus 33.5 shares out of the one million shares in a mutual fund. On this day the mutual fund owns no asset other than $100,000 in cash, so each share is worth $0.10 at the beginning. The mutual fund will have the opportunity to invest during each of the next five months. The shareholders (including you) decide collectively where the mutual fund invests in each month. At the beginning of each month, there is a 10-minute selection period that results in one investment decision for the entire group in the entire month. At the end of each month, the mutual fund liquidates the investment, and then the investment process repeats.*

The first round takes place on January 1st, when your group has 10 minutes to select an investment portfolio or choose to hold onto the cash until the end of January. We then skip ahead to February 1st when the second round takes place and your group can reinvest the new fund's cash in a new investment portfolio or hold onto the cash until the end of February. Similarly, the third, fourth, and fifth rounds take place on March 1st, April 1st and May 1st respectively. Each month, the mutual fund can reinvest its cash in an effort to increase it or can hold onto its cash for the month. There are no transaction costs or fees.

<u>In the end,</u> *the total monetary value of the mutual fund (on June 1st) is calculated and you will see a short survey. If you stay in the game until the end and complete the survey, you will be paid your (individual)*

cash balance plus the dollar equivalent of your shares in the final mutual fund on June 1st, 2019. Your payoff will be at least \$5 and at most \$30 depending on your participation:

*Your payoff = Your cash balance + (Your number of shares) * (Final value of mutual fund) / (One Million)*

In addition, the participant with the highest final payoff will receive a \$20 bonus!

In each round, you can use historical data on websites such as CoinMarketCap to calculate the performance of each portfolio, which is the weighted average of the performance of its assets. If your group decides to hold cash for a month, the total value will not change (performance = 1). Please have a calculator or Excel sheet ready.

<u>*Selection Period*</u>***:*** *During each 10-minute round each person can trade (buy and sell) the shares of the mutual fund under different investment alternatives (choices). For each of these choices, you can sell your shares of the mutual fund, or you can use your cash balance to buy shares of the mutual fund for each choice. Hence, we call it Parallel Markets. There are no transaction costs or cancellation fees for trades.*

Your individual trades will result in one group decision each round. At the end of each round, the choice with the highest price is selected as the investment for that month. The transactions and shares for this choice are confirmed but the transactions and shares for other choices are voided as if they never existed. This reduces your risk if a choice's price declines. The shareholders of the selected choice will own the same number of shares for every choice in the next round, but of course, only one of those choices will be selected and confirmed.

<u>*Hint:*</u> *Each round, you should evaluate each choice and try to buy it at a price lower than its share value and sell it at a price higher than its share value. You can make money both ways if you estimate the share value for a choice. You want to sell the overpriced choices and buy the underpriced ones.*

4. Results

We recruited 69 participants from *MTurk* to participate in the experiment and 59 of them completed the experiment. This exceeds Christiansen's (2007) 16-participant threshold for market efficiency, and because each participant could trade in every parallel market in each round, the pool was effectively up to 69 potential participants per market.

There were five rounds with each round taking 10 minutes. There were between three and six choices in each round. Every round, the first choice (choice 0) was "*Holding Cash*". Table 4-1 presents the volume of transactions for each choice in each round. It also includes the total volume of transactions per round. The second round had the highest transaction volume ($338.83). The total sum of transaction volumes throughout the experiment was $1371.8.

	Rounds				
Choices	**1**	**2**	**3**	**4**	**5**
Holding Cash	$ 16.64	$ 140.92	$ 39.61	$ 46.76	$ 59.80
Portfolio 1	$ 117.01	$ 109.55	$ 24.18	$ 90.18	$ 83.08
Portfolio 2	$ 60.44	$ 52.01	$ 68.44	$ 35.00	$ 106.06
Portfolio 3	$ 81.20	$ 34.35	$ 6.99	$ 66.34	
Portfolio 4			$ 9.19	$ 40.39	
Portfolio 5			$ 68.66		
Volume per Round:	$ 276.29	$ 338.83	$ 220.07	$ 282.68	$ 253.93

Table 4-1. The transaction volumes for every choice in each round

Appendix B presents the choices shown to the participants in each round. Appendix C presents the subject-level analysis for the participation in the experiments.

During the first period, there were four choices including one choice for holding cash. The other three choices were three portfolios as Figure B-1 in Appendix B presents. See Figures B-1 to B-5 in Appendix B for the details of the portfolios and their performances at the ends of each period.

Figure 4-1 shows the results at the end of the first round. All bids for Hold Cash were cleared, leaving no unfulfilled bid. Among the remaining choices, both the last transaction price and the highest unfulfilled bid were highest for Portfolio 3, which also had the highest actual value; the system selected the value-maximizing choice. The mutual fund's value grew to $125,077 because Portfolio 3, the highest-priced choice, was ratified.

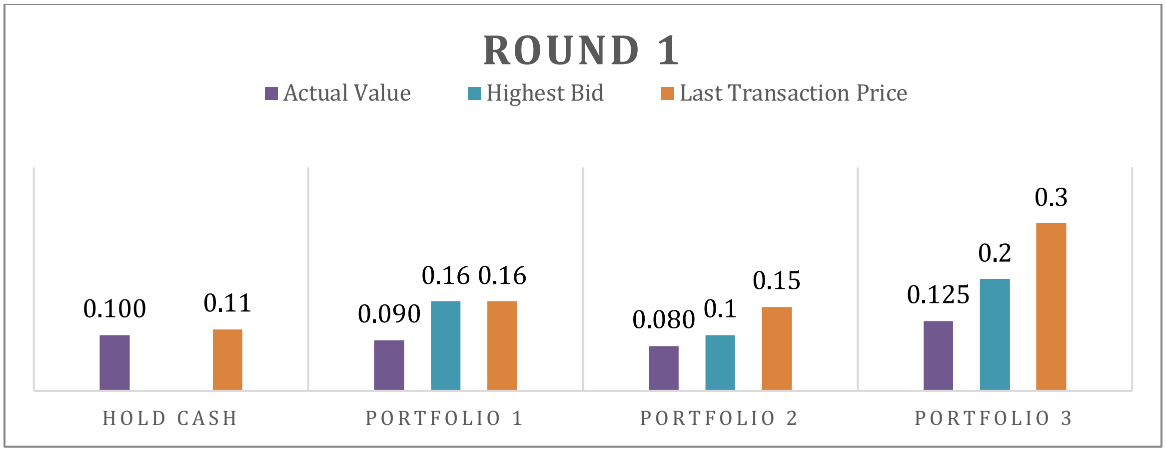


Figure 4-1. Results of the Parallel Markets at the end of the First Round

Figure 4-2 shows the results at the end of the second round. Portfolio 1 had the highest actual value, the highest last transaction price, and the highest bid, and was ratified accordingly. In both rounds the system was decisive: the highest price was far above the second highest.

These results demonstrate the system's functionality despite a small, financially inexperienced participant pool (MTurk workers), modest incentives (a few dollars per round), and short trading windows.

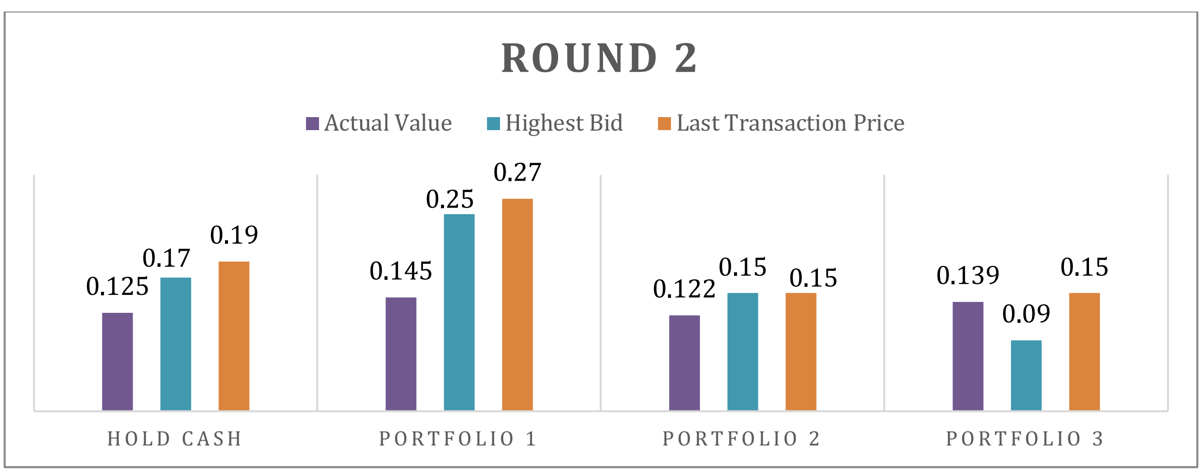


Figure 4-2. Results of the Parallel Markets at the end of the Second Round

Rounds 3–5 were designed to test the system's precision under near-identical top values. Because sufficient liquidity is defined relative to the precision required, this serves as an implicit liquidity stress test: the trading conditions adequate for widely separated values in Rounds 1–2 proved insufficient to reliably rank choices differing by only a few percentage points. This tests the system not by reducing liquidity directly, but by narrowing the value gap between choices.

As Figure 4-3 shows, round 3 had six choices, and Portfolios 1, 2, 4, and 5 were designed to have closely spaced actual values (0.162–0.166), so their last transaction prices clustered together as well. This illustrates that Parallel Markets can select a sub-optimal choice under low liquidity.

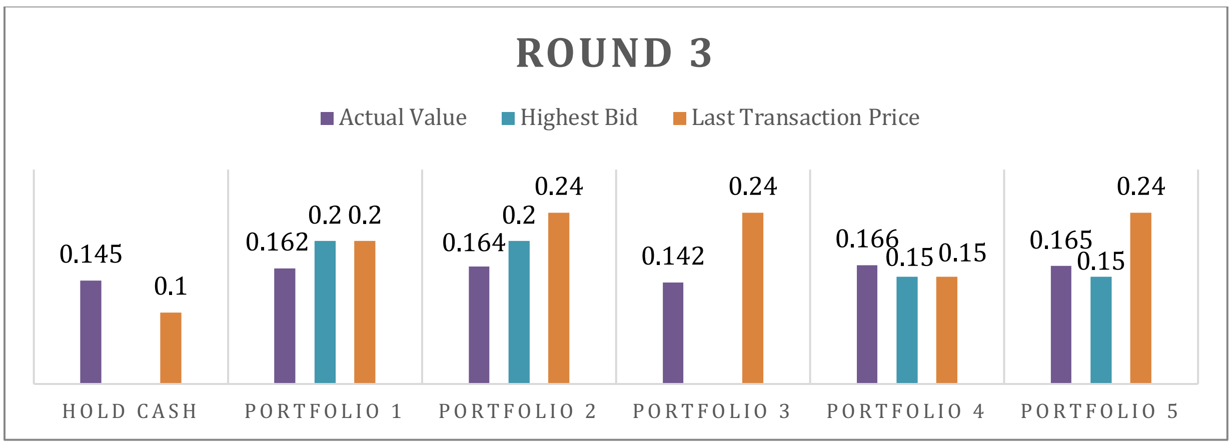


Figure 4-3. The results of the Parallel Markets at the end of the third round

Round 4 had five choices, again with several near-identical values (Figure 4-4). Portfolio 2, at the highest last transaction price (0.18), was ratified: the third-best choice by actual value, behind Portfolio 3 (0.186) and Portfolio 1 (0.178). This coincides with unusually thin trading: Portfolio 2 traded only $35.00, the lowest volume of any winning market across the three near-identical-value rounds (Table 4-1), compared to $68.66 and $83.08 in the winning markets of Rounds 3 and 5, respectively.

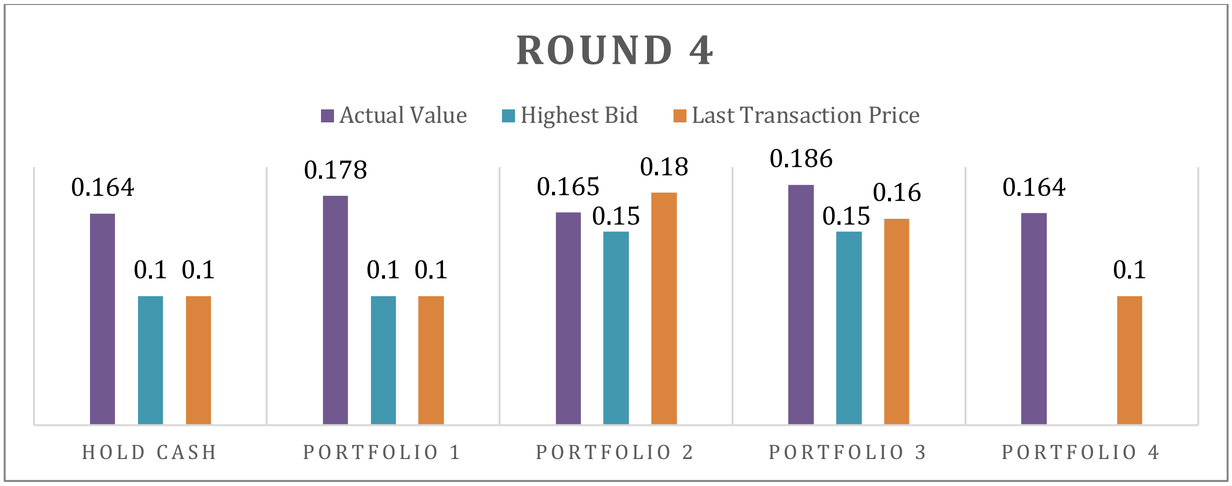


Figure 4-4. The Results of the Parallel Markets at the end of the Fourth Round

Figure 4-5 shows the fifth round's three choices, two of which (Portfolios 1 and 2) were designed to have closely matched values. Portfolio 1, at the highest last transaction price, was ratified, but Portfolio 2 had the higher actual value, a loss of about 2%. Possible explanations are that participant fatigue or attrition (from 69 to 59) contributed to thinning markets in the final round, though this was not directly measured and remains an open question.

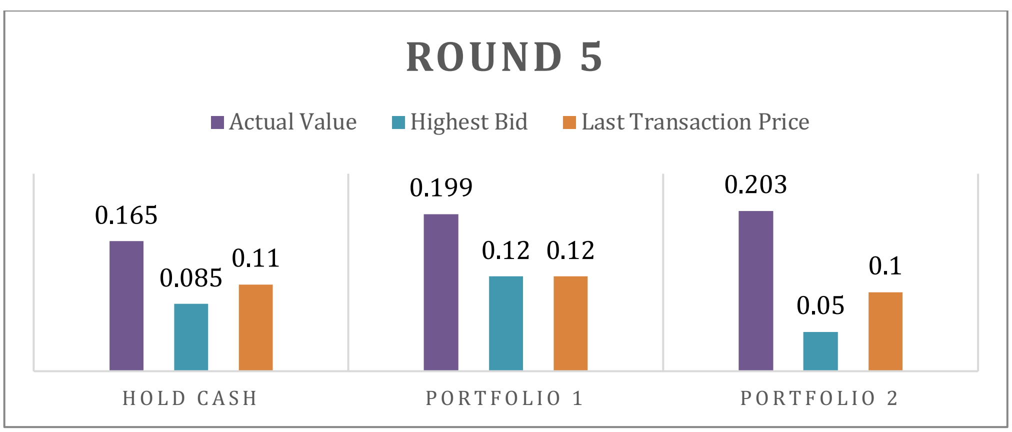


Figure 4-5. The Results of the Parallel Markets at the end of the Fifth Round

While the system accurately identifies value-maximizing choices when alternatives are distinct, performance degrades in Rounds 3–5. The selection gaps observed in Rounds 3, 4, and 5 trace to the low liquidity, exactly as the stress-test intended to reveal. With 59 remaining participants (of 69 recruited) who completed all rounds, split across multiple parallel trading markets, the effective depth of each market was insufficient. In these “thin” markets, even a single uninformed or “noise” trade can exert disproportionate pressure on the equilibrium price, leading to price-value divergence. Furthermore, narrow value margins between competing choices introduced “selection noise”, rendering the final ratification sensitive to minor volatility.

These results do not invalidate the Parallel Markets logic; rather, the stress test reveals liquidity as the binding constraint on exact selection. This dependence on liquid markets is a recognized challenge for such designs: Holographic Consensus, for instance, requires participants to stake on which proposals will pass, and concentrating sufficient stake across many concurrent proposals is a nontrivial coordination problem. The Parallel Markets system faces the same pressure but intensifies it by splitting trading volume across choice-conditional markets. This provides the empirical motivation for the Parallel Primary Markets system introduced next, which addresses the source directly: automated bonding curves supply continuous, counterparty-independent liquidity rather than relying on matched offers.

5. Parallel Primary Markets

The Parallel Markets system described in previous sections uses secondary markets to discover prices. Therefore, the number of shares outstanding is fixed. In such markets, each offer (order) should be cleared by counteroffer(s). This can stack up unfulfilled offers in queues. Therefore, it needs many offers to attain enough liquidity and discover prices accurately. This section introduces *Automated Primary Markets* as an alternative system to fulfill orders and discover prices without counteroffers or an exchange.

5.1. Automated Primary Markets

An Automated Primary Market system is similar to the *bonding-curve contracts* (Riady, 2018) but replaces the bondholders with shareholders who are the residual claimants and share the profits (dividends). The bonding-curve contracts underlying Automated Primary Markets can be formally specified, independent of platform, using model-driven DAO design methods such as DAOMod (Avanzo et al., 2026), which models token issuance and automated-market-maker mechanisms as first-class constructs prior to smart-contract implementation. This offers a path from the formal mechanism described here to a concrete, validated implementation.

Based on this mechanism, the company guarantees to buy and sell shares at price *f(s)*, which is an increasing function of the total number of shares outstanding (*s*) at any time. This can fulfill every order instantaneously by issuing and burning shares, thereby changing the number of shares outstanding. When a buy order is placed, the company automatically issues and sells out shares at the calculated price based on this function. This dilutes existing shares. When there is a sell order, the company buys back the shares at the calculated price and burns them. Therefore, the company itself can always provide full liquidity using Automated Primary Markets without trusting an exchange or any outside party.

Here, we use the same function *f(s)* for bidding and asking prices. Since the share price increases continuously according to this function, to buy Δs number of shares, the buyer should pay:

$$\Delta F = \int_{s_1}^{s_2} f(s) \,.\, ds = F(s_2) - F(s_1) \qquad (5-1)$$

Where s_1 is the initial number of shares outstanding and $s_2 = s_1 + \Delta s$ is the new number of shares after the purchase. *F(.)* is the indefinite integral of the price function *f(.)* and ΔF is the amount of the fund transferred to buy those shares. Similarly, when someone sells shares, the company buys them at price *f(s),* which decreases continuously as the number of shares outstanding decreases. Therefore, selling Δs number of shares will yield the seller $\Delta F = F(s_1) - F(s_2)$ in cash. We can set the constant for the indefinite integral such that $F(0) = 0$. Therefore, $F(s)$ is the amount of the company's capital fund when there are s shares outstanding. Figure 5-1 illustrates an example of such a price function and the resulting capital fund.

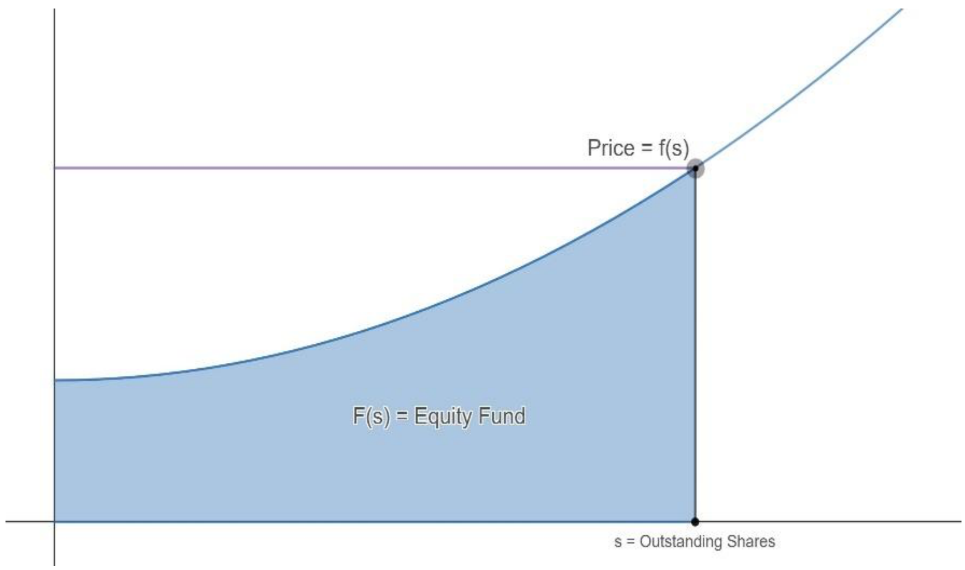


Figure 5-1. The number of shares outstanding determines price through price function f(s)

If we use the primary markets mechanism instead of secondary markets in the Parallel Markets system, constraint (2-1) is not required anymore, because with this new mechanism, there is no outstanding offer at any time, and each order is fulfilled instantaneously. The challenge is that the prices imposed by the price function *f(s)* should reflect the value of the company. Under this mechanism, the number of shares outstanding (and their price) depends on supply and demand, which in turn depend on the expected value of the company. Traders can buy and sell shares based on their perceived valuation of the shares, but when they buy (sell) shares, the number of shares outstanding increases (decreases), and thus the value of each share is diluted (enriched) if the value of the company stays constant. Therefore, the monotonicity of the price function makes the price even more sensitive to the value of the company because any deviation (if any) triggers two forces (s and $f(s)$) that can push the price toward equilibrium.

5.2. Parallel Primary Markets

Under the Parallel Primary Markets system, the price function is the same for all choices during each selection period, as Figure 5 – 2 shows. However, different choices have different expected values and returns (r_s and r_d) and this results in different equilibria for them. Therefore, they will have a different number of shares, reach different prices, and raise different amounts of funds. We expect the equilibrium prices of the choices to reflect their expected values. At least the choice with the highest price has the highest value.

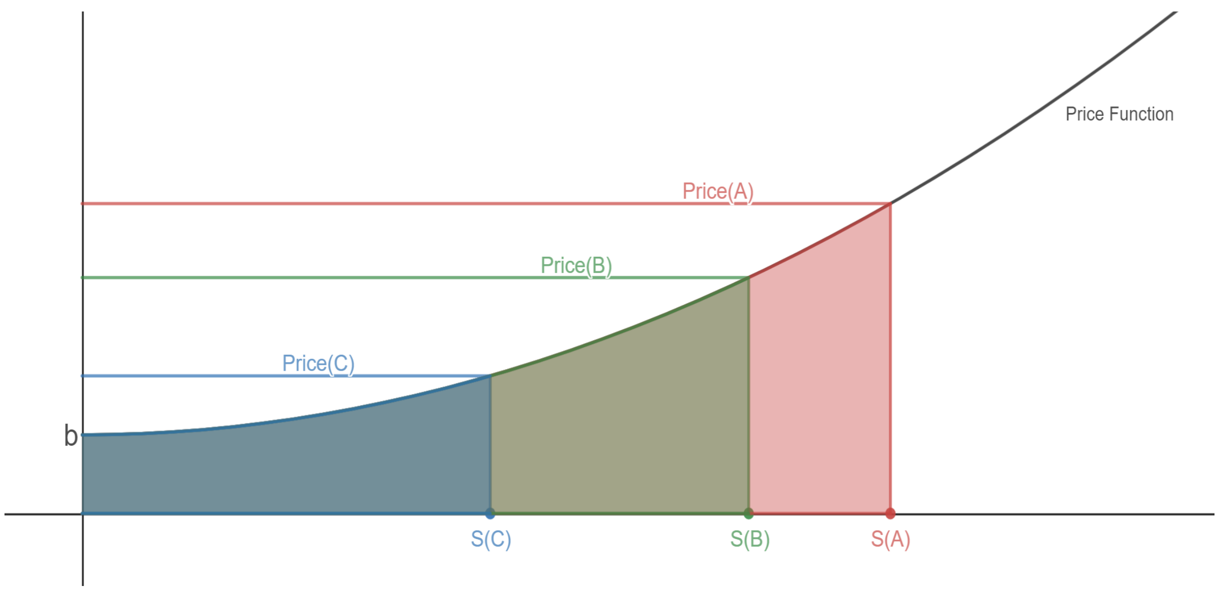


Figure 5-2. Parallel Primary Markets with three choices: S(.) denotes the number of shares outstanding and Price(.) denotes the equilibrium price for each choice.

When using automated primary markets, the orders are fulfilled instantaneously. Appendix D shows the transaction page for placing orders in the Parallel Primary Markets. Once a person places an order, the order is processed according to the flowchart shown in Figure 5-3. The numerical example in Appendix F shows how this system works.

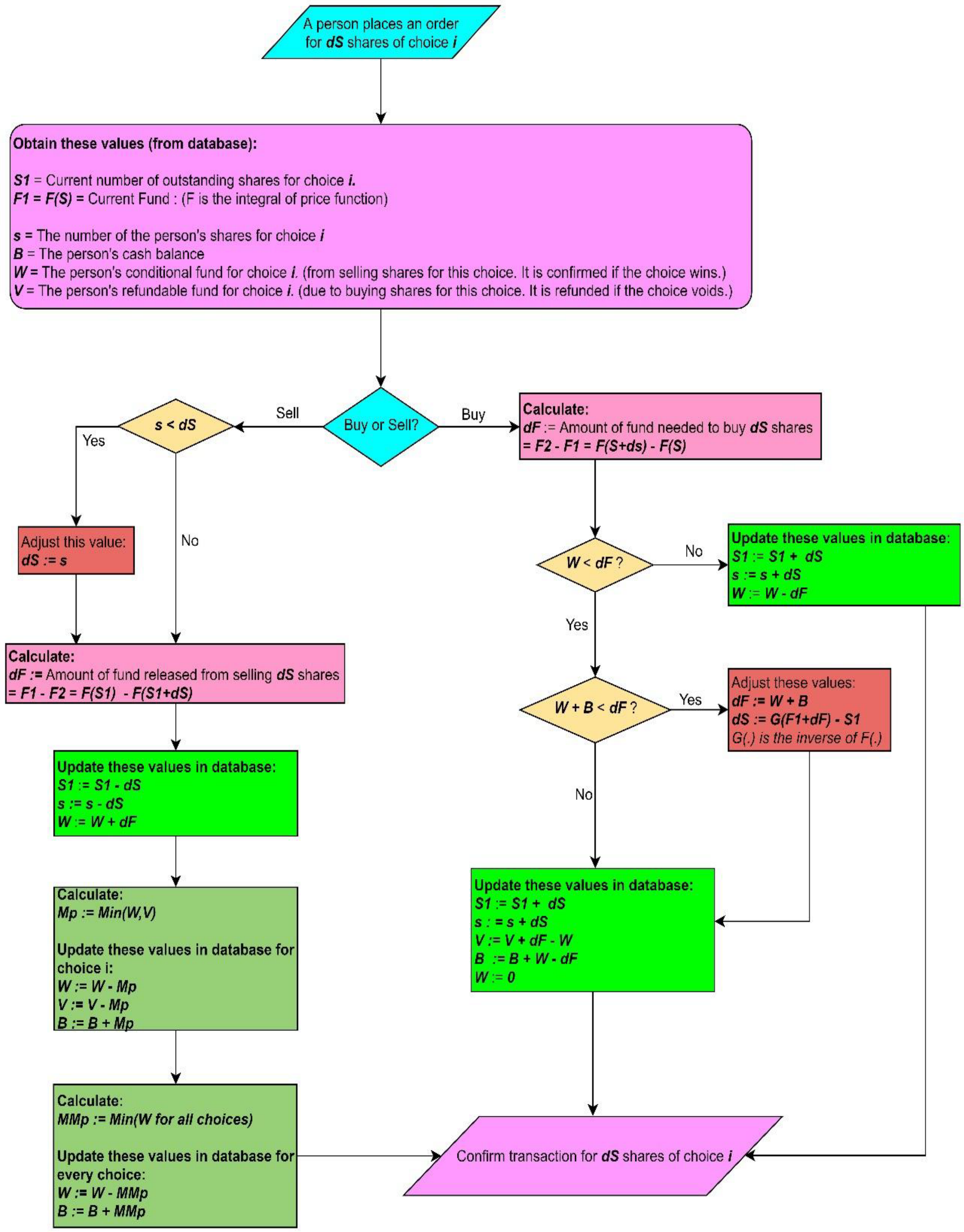


Figure 5-3. The flowchart for processing an order in the Parallel Primary Markets system

This figure shows an accounting process like what is described in Section 2. At the end of each selection period, the choice with the highest price wins and becomes the effective decision. The number of shares for this choice and their distribution among individuals become the number of shares outstanding for the company and their distribution. The winning balances (W_w) for the winner choice become cash, but its void balances (V_w) are discarded because its transactions are confirmed. On the other hand, the shares for other choices and their winning balances (W_i) are discarded, but their void balances (V_i) are refunded and added to their cash balances. Then the cash balance of each individual is updated based on Equation 2-4.

As before, we need to control the number of proposals in each round. To this end, the system can use two more methods in addition to the four methods discussed in Section 2:

5. The proposers can deposit funds to invest in their proposals at the beginning of the selection period before others. Then at the beginning of the selection period, the system sorts the choices based on their proposers' initial investments (or shares' initial prices). A larger initial investment indicates the proposer's higher confidence in their suggestion. Moreover, this rewards the proposers of superior suggestions by giving them the privilege to be the first to buy shares of their own choices.
6. The choices can be sorted based on the number of shares their proposers will have after the initial investment in their choices.

The funds collected for the winner choice are invested in the company, but the funds collected for the other choices (void balances) are returned.

The realization of profit or loss or distribution of dividends can be implemented via a transformation of the price function as discussed in the previous section. This will change the amount of the capital fund without changing the number of shares. This transformation can be executed at any time, but to avoid complications, it is better not to do this during the selection periods when there are multiple versions of the shares.

5.3. Financing with Equity

First, assume that the company raises funds only by issuing shares in the automated primary markets and receives an amount $F(s_e)$ of money by issuing s_e number of shares in a specific period. Then it invests this money in a profitable project with the expected future value of *FV* and expected *ROI* of r_s adjusted for inflation and risk premium. Therefore, $FV = (1+r_s) \,.\, F(s)$ is the expected future value of the company and its future cash flows. When there are *s* shares, the expected value of one share is:

$$v(s) = \frac{(1+r_s).F(s)}{s} \qquad (5-2)$$

Generally, rational participants buy shares when $v(s) > f(s)$ and sell shares when $v(s) < f(s)$. Therefore, in equilibrium, $v(s_e) = f(s_e)$ and the equilibrium is stable iff $v(s_e + \varepsilon) < f(s_e + \varepsilon)$ and $v(s_e - \varepsilon) > f(s_e - \varepsilon)$. In short, s_e is the stable equilibrium level iff $v(s) - f(s)$ is zero and strictly decreasing at $s = s_e$:

$$(1+r_s).\frac{F(s_e)}{s_e} - f(s_e) = 0 \qquad (5-3)$$

and,

$$(1+r_s).F(s_e) - (1+r_s).f(s_e).s_e + f'(s_e).s_e^2 > 0 \qquad (5-4)$$

Equation (5-3) as a differential equation characterizes the functions that satisfy the equation for all *s* and do NOT result in a nontrivial equilibrium point. Its solution is $f(s) = C.s^{r_s}$, where *C* is any constant. This function makes the participants neutral to buy or sell at any level of *s*. If $f(s) = C.s^h$ where $h \neq r_s$,then the only equilibrium point will be $s_e = 0$. This finding rules out using any power function in the Parallel Markets system because the price function *f(.)* should result in one *unique positive* and *stable* equilibrium price that can be used as the selection criterion in the governance system. Power functions are common in bonding-curve contracts (Riady, 2018).

Monotonicity is another condition for the price function to be effective in the Parallel Primary Markets system. In particular, a larger s_e should indicate a larger r_s. That is:

$$\frac{\partial s_e}{\partial r_s} > 0 \qquad (5-5)$$

Now, assume *f(.)* is a linear function of shares outstanding: $f(s) = a.s + b$ and $F(s) = ½\, a.s^2 + b.s$, as Figure 5-4 illustrates. Then the equilibrium becomes:

$$s_e = \frac{2b.r_s}{a(1-r_s)} \;\;\Rightarrow\;\; f(s_e) = \frac{b(1+r_s)}{1-r_s} \;\;\Rightarrow\;\; F(s_e) = \frac{2b^2.r_s}{a(1-r_s)^2} \qquad (5-6)$$

It yields a valid equilibrium point for $0 < r_s < 1$, which would be the case for most investments. This also satisfies Equation (5 - 4) because the following is positive for $r_s < 1$:

$$\frac{a.s_e^2}{2} + bs_e + \frac{a.r_s.s_e^2}{2} + br_ss_e - (1+r_s).(as_e+b).s_e + \; a.s_e^2 = \frac{a.s_e^2}{2} - \frac{a.r_s.s_e^2}{2} = \frac{a.s_e^2}{2}(1-r_s) > 0$$

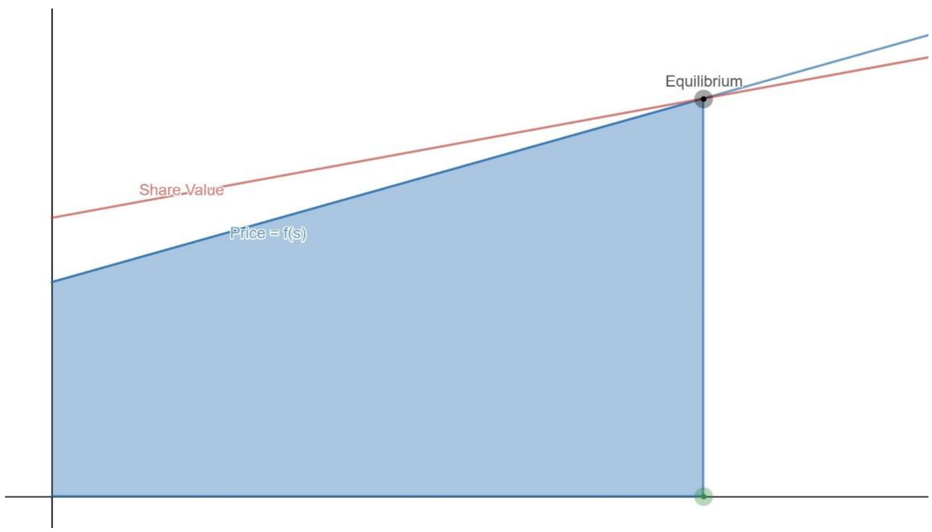


Figure 5-4. Equilibrium happens where the value per share equals the price of one share

However, if an investment has an expected *ROI* of more than 100% (adjusted for inflation and risk), the above answer results in unstable growth so that when more shares are issued the value of each share increases faster than its price. If we use $f(s) = a.s^2 + b$ and $F(s) = ⅓\, a.s^3 + b.s$, then:

$$s_e = \sqrt{\frac{3br_s}{a(2-r_s)}} \;\;\Rightarrow\;\; f(s_e) = \frac{2b(r_s+1)}{(2-r_s)} \;\;\Rightarrow\;\; F(s_e) = \frac{1}{3}\sqrt{\frac{1}{a}\left(\frac{3br_s}{2-r_s}\right)^3} + b\sqrt{\frac{3br_s}{a(2-r_s)}} \qquad (5-7)$$

This is a unique, positive, and stable equilibrium for $0 < r_s < 2$, which means *ROI* of less than 200%, because, Equation (5-4) holds for $r_s < 2$:

$$(1+r_s)\left(\frac{a}{3}s_e^3 + bs_e\right) - (1+r_s)(as_e^3 + bs_e) + \; 2as_e^3 = \left(\frac{4}{3}as_e^3 - \frac{2}{3}ar_ss_e^3\right) = \frac{2}{3}as_e^3(2-r_s) > 0$$

5.4. Financing with Debt

While the above functions can be used for experimentation, in reality, such a company has to use debt to be able to invest in long-term projects. In particular, our company needs to keep its capital fund *F(s)* mostly liquid to be able to buy back shares upon sell orders. Thus, assume the company borrows principal *D* and pays interest of d_i on it and expects an *ROI* of d_r on it. Thus, the expected net *ROI* for debt is: $r_d = d_r - d_i$. The company may also invest the fund *F(s)* in current assets, but most likely its *ROI* will be smaller (i.e., $r_s < r_d$). As a result, $FV = (1+r_s).F(s) + r_d.D$ is the expected future value of the company and its future cash flows. When there are *s* shares, the expected value of one share is:

$$v(s \mid D) = \frac{(1+r_s).F(s) + r_d.D}{s} \qquad (5-8)$$

As before, s_e is the stable equilibrium iff $v(s) - f(s)$ is zero and strictly decreasing at $s = s_e$:

$$(1+r_s).F(s_e) + r_d.D = s_e.f(s_e) \qquad (5-9)$$

$$(1+r_s).F(s_e) - (1+r_s).f(s_e).s_e + f'(s_e).s_e^2 > 0 \qquad (5-10)$$

Again, the first differential equation characterizes the functions that have all *s* as equilibrium points. Its solution is the same as before: $f(s) = C.s^{r_s}$, where *C* is any constant. But if $f(s) = a.s + b$, then we have $F(s) = ½\, a.s^2 + b.s$ and:

$$s_e = \frac{b.r_s + \sqrt{b^2.r_s^2 + 2a(1-r_s).r_d.D}}{a(1-r_s)} \;\Rightarrow\; f(s_e) = \frac{b + \sqrt{b^2.r_s^2 + 2a(1-r_s).r_d.D}}{(1-r_s)} \qquad (5-11)$$

It is the only equilibrium because the negative sign before radical always results in a negative value for s_e. This satisfies all the conditions when $0 \le r_s < 1$ and $0 < r_d$, both of which are likely in practice. The long term investment yields $r_d.D$, and r_s is the return on current assets. If $r_d.D > 0$ and we hold cash for $F(s_e)$, then $r_s = 0$ and we will have:

$$s_e = \sqrt{\frac{2r_d.D}{a}} \;\Rightarrow\; f(s_e) = \sqrt{2a.r_d.D} + b \;\Rightarrow\; F(s_e) = r_d.D + b\sqrt{\frac{2r_d.D}{a}} \qquad (5-12)$$

If $r_d.D > 0$ and $0 \le r_s < 1$, we can use a proportional function (i.e., $b = 0$), which yields:

$$s_e = \sqrt{\frac{2r_d.D}{a(1-r_s)}} \;\Rightarrow\; f(s_e) = \sqrt{\frac{2a.r_d.D}{(1-r_s)}} \;\Rightarrow\; F(s_e) = \frac{r_d.D}{(1-r_s)} \qquad (5-13)$$

If $f(s) = a.s^2 + b$ as Figure 5-5 shows, then $F(s) = ⅓\, a.s^3 + b.s$, and:

$$a(2-r_s).s_e^3 - 3r_s b.s_e - 3r_d.D = 0 \qquad (5-14)$$

yielding a depressed cubic equation with $p = \frac{-3r_s.b}{a(2-r_s)}$ and $q = \frac{-3r_d.D}{a(2-r_s)}$. It results in the following discriminant:

$$\Delta = 4b^3.r_s^3 - 9a(2-r_s).r_d^2.D^2 \qquad (5-15)$$

When it is less than zero, the only real root becomes the equilibrium point:

$$s_e = \sqrt[3]{\frac{3r_d.D}{2a(2-r_s)}}.\left\{\sqrt[3]{1+\sqrt{1-\frac{4(r_s b)^3}{9a(r_d.D)^2.(2-r_s)}}}+\sqrt[3]{1-\sqrt{1-\frac{4(r_s b)^3}{9a(r_d.D)^2.(2-r_s)}}}\right\} \qquad (5-16)$$

and the other roots are complex.

When the discriminant is zero, the equilibrium point is:

$$s_e = \frac{3D.r_d}{b.r_s} \qquad (5-17)$$

whereas the other root (double root) is negative and thus not feasible ($s_2^* = s_3^* = \frac{-3D.r_d}{2b.r_s} < 0$).

When $\Delta > 0$, there are three real roots, but only one of them is positive ($s_e > \frac{3D.r_d}{b.r_s} > 0$), which becomes the equilibrium. The other two roots are always negative and thus not feasible as Figure 5-6 illustrates. It can be shown that in every case for small enough *s*, the value is more than the price ($v(s) - f(s) > 0$). Therefore, Inequality 5-10 holds when they meet on the positive side, thereby making the equilibrium stable.

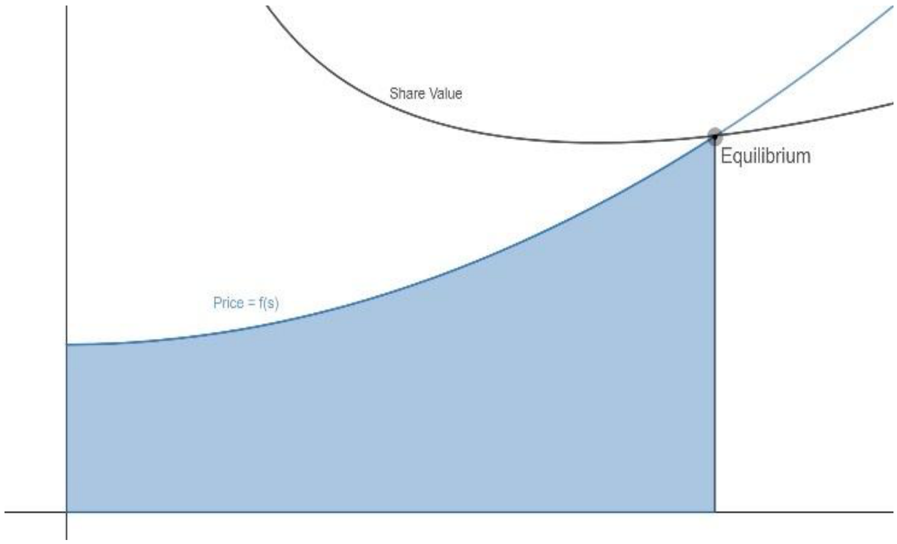


Figure 5-5. The equilibrium point is where the quadratic share price equals share value (with debt).

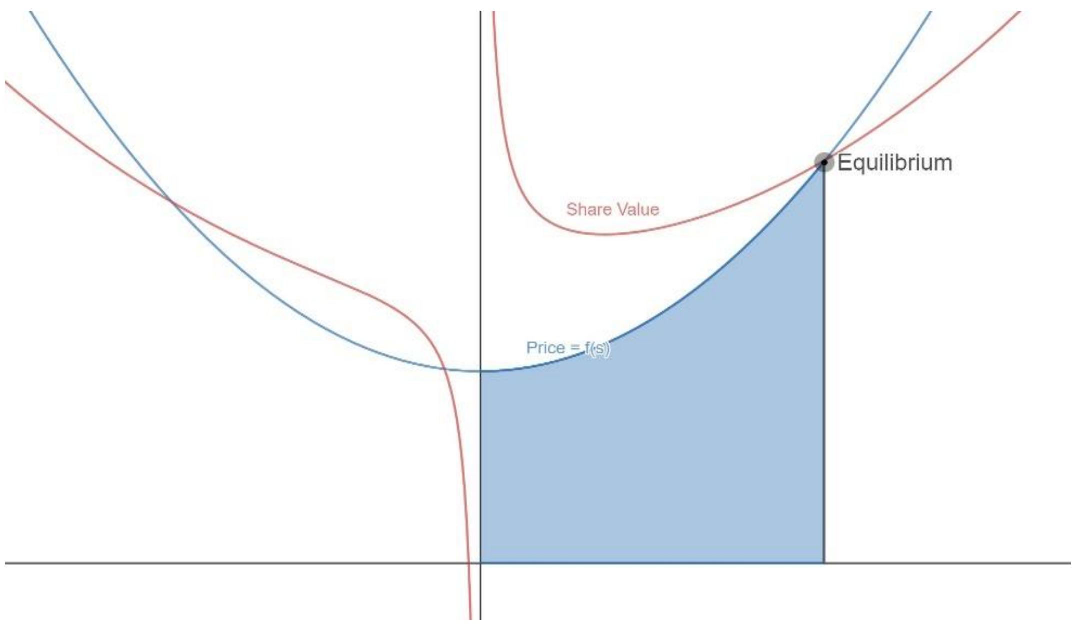


Figure 5-6. The equilibrium point is the unique positive solution for the quadratic share price (with debt).

5.5. Changes in Capital Fund

Generally, the amount of capital fund can change via three channels: (1) issuing and burning shares for buy and sell orders, (2) distribution of dividends and liquidation, and (3) realization of profits and losses.

The first channel changes the number of shares, s, according to the change in the capital fund, such that when someone invests ΔF into the company, Δs shares are issued where $\Delta s = s_2 - s_1 = F^{-1}(F_2) - F^{-1}(F_1)$. Here, F_1 is the initial capital fund, and $F_2 = F_1 + \Delta F$ is the new fund after issuing the shares. When someone sells Δs shares we have $\Delta F < 0$ and $\Delta s < 0$. Now, assume $f(s) = a.s + b$ and $F(s) = ½\, a.s^2 + b.s$, and the company currently has s_1 number of shares and $F_1 = F(s_1)$ funds. If someone invests ΔF in the company, the new number of shares will be:

$$s_2 = \frac{-b + \sqrt{b^2 + 2a(F_1 + \Delta F)}}{a} = \frac{-b + \sqrt{(as_1 + b)^2 + 2a\Delta F}}{a} = \sqrt{\left(\frac{f(s_1)}{a}\right)^2 + \frac{2\Delta F}{a}} - \beta \qquad (5-18)$$

, wherein $\beta = b/a$ is the ratio of b to a. Of course, no more than s_1 exists to be sold. Therefore, the minimum level of ΔF is $-F_1 = -F(s_1)$, which results in $s_2=0$. The second way that the capital fund can change is through the payment of dividends or distribution of funds to the shareholders. When the amount of capital changes due to factors other than changing shares, the price function can be adjusted to reflect the change in the fund. To implement such changes, we use proper transformations to adjust the price function f(.). Such transformations are discussed next when dealing with the third channel of changes.

The third channel through which the capital fund can change is profit and loss. When there is profit, it can be distributed as a dividend to the shareholders, but what if they do not want to cash out all their profit? What if there is a loss? We need a systematic approach to deal with such changes in the capital fund. We have to adjust $f(s)$ (and $F(s)$) to reflect the new level of the fund without changing the number of shares. Here, we suggest two transformations to adjust $f(s)$; the first one holds the current price constant ($p_{new} = p_{old}$) as well as the number of shares outstanding. The other one holds the equilibrium level of shares constant ($s_{e,new} = s_{e,old}$) as well as the number of shares outstanding.

***Holding the price constant*:** This makes $(s_o , f(s_o))$ the pivot point where s_o is the current number of shares outstanding and $f(s_o)$ is the current price. So, the new price function results in the same price at the current level of shares outstanding: $f_{new}(s_o) = f(s_o)$. Imposing $F_{new}(s_o) = F(s_o) + \Delta F$ will result:

$$\int_0^{s_o} f_{new}(s)\,.\,ds = \int_0^{s_o} f(s).\,ds + \Delta F \qquad (5-19)$$

This inevitably changes the equilibrium if the expectations (r_s , r_d) remain the same. Therefore, after the change in the fund, there will be transactions, and the number of shares outstanding will move toward the new equilibrium. Now, if $f(s) = a.s + b$ and $F(s) = ½\ a.s^2 + b.s$, then we have $f_{new}(s) = a'.s + b'$, where:

$$a' = a - \frac{2\Delta F}{s_o^2} \quad and \quad b' = b + \frac{2\Delta F}{s_o} \tag{5-20}$$

But, this is limited to $\Delta F < ½\ a.s_o^2$, when realizing a profit and to $(-\Delta F) < ½\ b.s_o$, when realizing a loss; because we need $a' > 0$ and $b' > 0$ to have a valid equilibrium. When we realize large profits or profits in several periods, the coefficient *a* decreases very fast and the price function quickly becomes flat. Similarly, if we realize large losses or multiple losses, the intercept *b* decreases quickly and becomes zero, which means no equilibrium when there is no debt. Figure 5-7 shows this transformation and its limitations. In this figure, the red triangle is the increase in capital fund (ΔF).

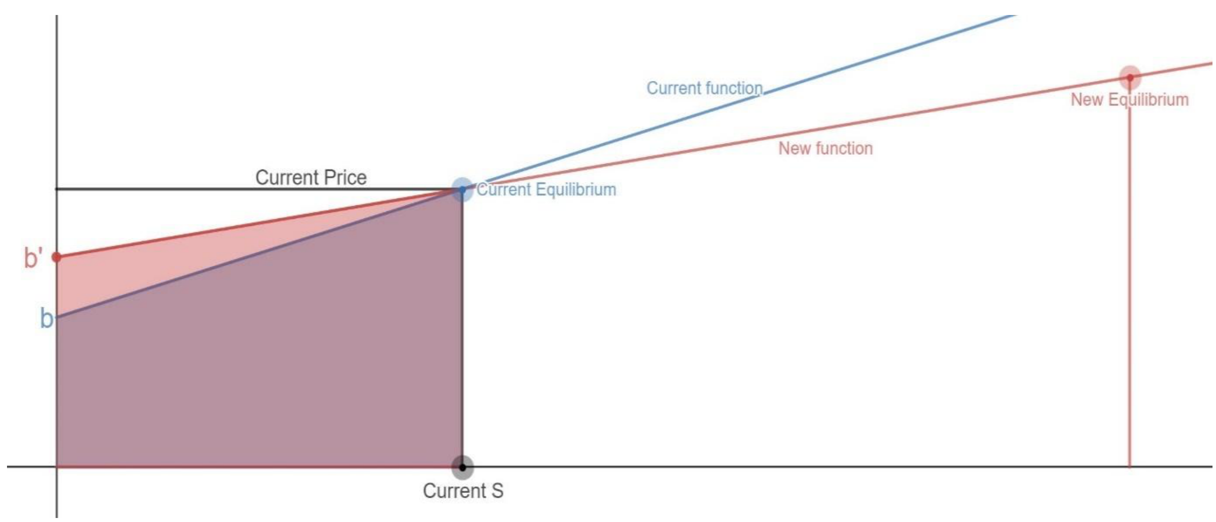


Figure 5-7. Transformation holding the (linear) price constant but letting the equilibrium point move

The limitations on the fund will be much less restrictive if we use $f(s) = a.s^2 + b$ and $F(s) = ⅓\ a.s^3 + b.s$. In that case, $f_{new}(s) = a'.s^2 + b'$, where:

$$a' = a - \frac{3}{2}.\frac{\Delta F}{s_o^3} \quad and \quad b' = b + \frac{3}{2}.\frac{\Delta F}{s_o} \tag{5-21}$$

This is limited to $\Delta F < ⅔\ a.s_o^3$, when realizing a profit and to $(-\Delta F) < ⅔\ b.s_o$, when realizing a loss. This can provide a much wider window than the linear limitation. Figure 5-8 shows this transformation and its limitations. In this figure, the red area is the increase in capital fund (ΔF).

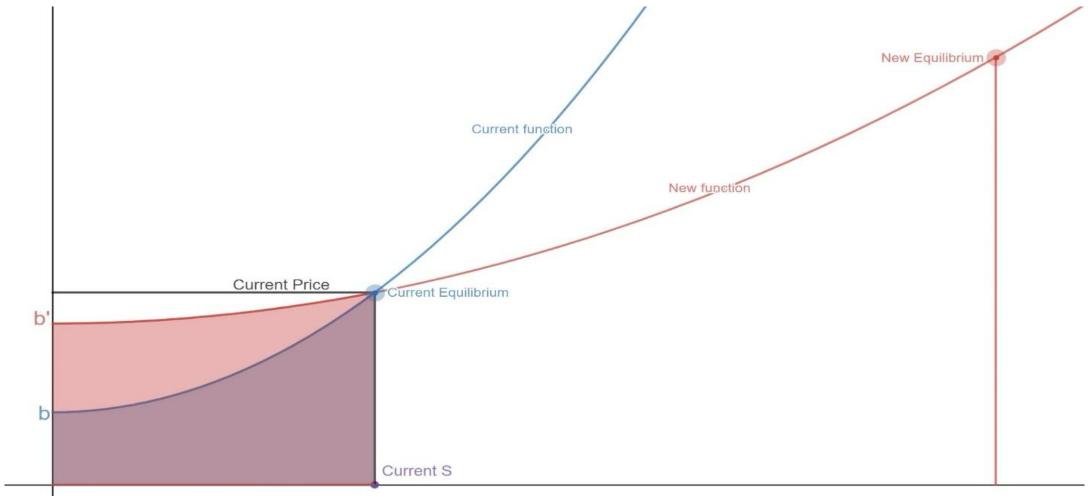


Figure 5-8. Transformation holding the (quadratic) price constant but letting the equilibrium point move

***Holding the equilibrium constant*:** The above transformations can change the equilibrium point, which might not be desirable in some situations. Moreover, they have constraints on the amount of change in the fund. So here, we suggest transformations that implement the fund change while keeping the equilibrium level constant, assuming stable expectations.

When there is no debt, the transformation is a simple multiplication, so it multiplies *f(.)* by the ratio of the new capital fund to the old capital fund: $f_{new}(s) = (1+\gamma).f_{old}(s)$, wherein $1+\gamma = F_2 / F_1$ is the realized return for the fund. The *multiplicative* transformation changes the share price to reflect the new amount of capital fund without changing the number of shares outstanding or its equilibrium level. It can easily be proven that this is the only transformation that satisfies these criteria per Equation (5-3). This transformation can change the fund to any non-negative amount with no limitation. For the linear and quadratic functions, it will yield $a' = (1+\gamma).a$ and $b' = (1+\gamma).b$, where a' and b' are the new values of the parameters. This will adjust the amount of capital without changing the number of shares or β, the ratio of b to a. Figure 5-9 depicts an example of such a transformation with the red area representing the added fund. The transformation can be written as follows:

$$[a'b'] \equiv \begin{bmatrix} 1+\gamma & 0 \\ 0 & 1+\gamma \end{bmatrix} [a\ b\ ] \qquad (5-22)$$

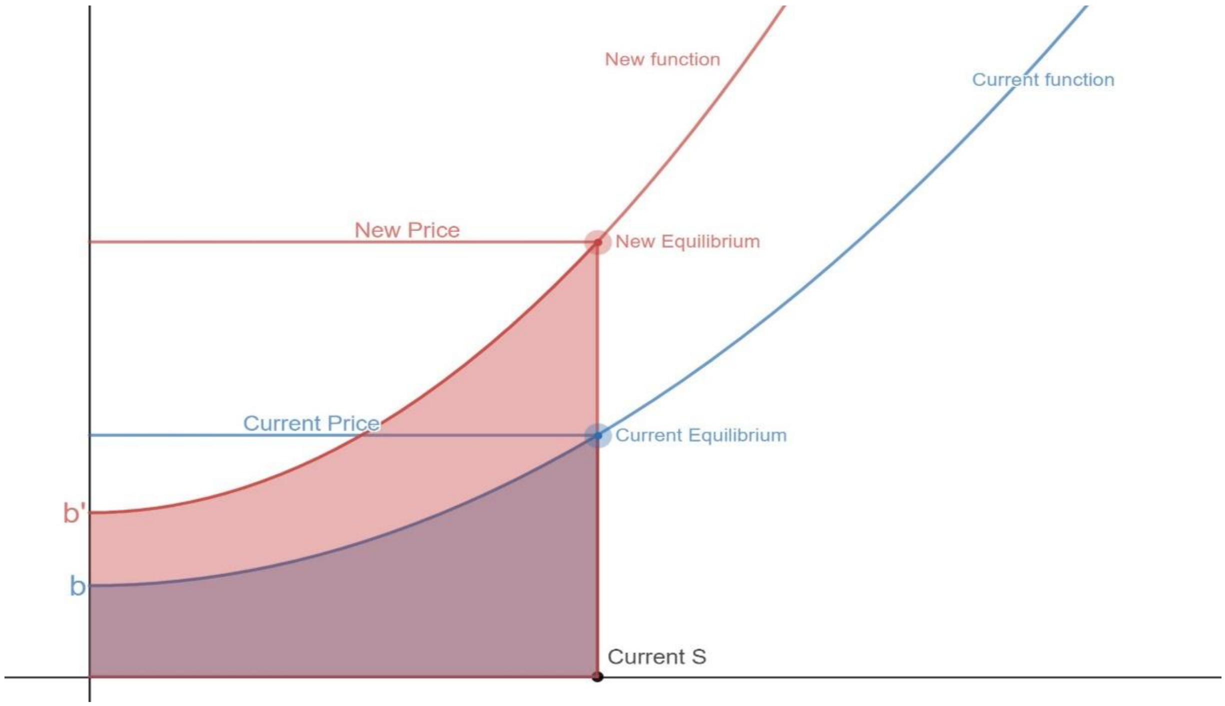


Figure 5-9. Transformation holding the equilibrium shares constant but letting the price change

However, if there is debt, and $r_d.D > 0$, this transformation can change the equilibrium level s_e according to Equation (5-11). To analyze this situation, we focus on linear price functions. For the linear price function, generally, the transformation should satisfy the following constraint to implement a fund increase:

$$F_2 = (1+\gamma) * F_1 \Rightarrow \tfrac{1}{2}\, a'.s_o^2 + b'.s_o = (1+\gamma).(\tfrac{1}{2}\, a.s_o^2 + b.s_o) \;\Rightarrow\; a'.(s_o + 2\beta') = (1+\gamma).a.(s_o + 2\beta) \quad (5 - 23)$$

This constraint can be satisfied by the following class of transformations for linear price functions:

$$\begin{bmatrix} a' \\ b' \end{bmatrix} \equiv \begin{bmatrix} 1+\gamma-\eta & 0 \\ \eta.s_o/2 & 1+\gamma \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \qquad (5-24)$$

We need to find the η that results in the same equilibrium level as before the transformation. To this end, we assume that the current number of shares outstanding is at the equilibrium level ($s_o = s_e$) and it should be equal to the new equilibrium level s'_e , which per Equation (5-11) yields:

$$s'_e = s_o \quad \Rightarrow \quad b'.r_s + \sqrt{b'^2.r_s^2 + 2a'.(1-r_s).r_d.D} = a'.s_o.(1-r_s)$$

$$\Rightarrow \quad a'.s_o{}^2.(1-r_s) - 2b'.s_o.r_s - 2r_d.D = 0 \qquad (5-25)$$

Now we use the general transformation (5 - 24) to state a' and b' as functions of a, b, and η:

$$a\,.(1+\gamma-\eta).s_o^2.(1-r_s)-a.\eta.s_o^2.r_s-2b(1+\gamma)s_o.r_s\ -2r_d.D=0 \qquad (5-26)$$

Therefore, we have:

$$\eta=(1+\gamma)(1-r_s-\frac{2br_s}{as_o})-\frac{2r_dD}{as_o^2} \qquad (5-27)$$

, where γ is the realized return and a and b are the current parameter values. Also r_s and $r_d.D$ are the net expected returns for the capital fund and the debt respectively. If $r_dD=0$, then $s_o=s_e=\frac{2b.r_s}{a(1-r_s)}$ and thus $\eta=0$ per Equation (5 - 27). If there is no return on the capital fund ($r_s=0$), then $s_o=s_e=\sqrt{\frac{2r_d.D}{a}}$ per Equation (5 - 26) and thus $\eta=\gamma$, which yields:

$$\begin{bmatrix}a'\\b'\end{bmatrix}\equiv\begin{bmatrix}1 & 0\\ \gamma.s_o/2 & 1+\gamma\end{bmatrix}\begin{bmatrix}a\\b\end{bmatrix} \qquad (5-28)$$

When $r_dD>0$ and $r_s>0$, we may approximate their values by the realized returns on equity and debt, which should satisfy:

$$\gamma=\widetilde{r_s}+\frac{\widetilde{r_d}D}{F(s_o)}$$

The numerical example in Appendix F demonstrates how such a system works.

6. Incentive-Compatibility of the Mechanisms

This section establishes the incentive properties of the Parallel Markets mechanisms in Sections 2 and 5. We show that the void-and-refund rule makes each parallel market price its conditional shares at the share's value conditional on implementation; that the resulting ratification is value-maximizing; and that the mechanism eliminates purely financial manipulation, while the secondary-market variant's resistance to private-benefit manipulation is bounded by liquidity.

Markets aggregate dispersed information more efficiently than voting or polling (Hayek, 1945), and decision markets extend this logic by having participants trade conditional claims tied to future outcomes (Hanson, 2002), but they require an external oracle to verify which outcome occurred. Parallel Markets removes this requirement by tying each conditional share's payoff to the firm's own future value rather than to an externally verified event. This substitution requires a formal argument that prices remain correct and selection remains efficient; this section supplies that argument and the conditions under which it fails.

Setup. A decision has K mutually exclusive choices indexed $i \in \{1,\dots,K\}$. Choice i, if ratified, yields firm value V_i, the present value of the firm's cumulative future expected cash flows under i. This value is exogenous to the conditional share prices. At the start of the selection period the mechanism replicates ownership into K sets of conditional shares. A conditional share of choice i becomes an ownership share worth $v_i = V_i / N_i$ if i wins (where N_i is the number of outstanding conditional shares of i), and its purchase is voided and refunded if i loses. The ratified choice is $w = \text{argmax}_i\, p_i$.

The refund rule eliminates probability weighting. Consider a risk-neutral trader who buys one conditional share of i at price p_i. The position has two outcomes: if i wins, the trader holds an asset worth v_i having paid p_i, for net payoff $v_i - p_i$; if i loses, the purchase is voided and refunded, for net payoff 0. The expected payoff is therefore $E[\pi_i] = \Pr(i \text{ wins}) \cdot (v_i - p_i)$. Because the losing state is costless, the sign of the expected payoff is independent of Pr(i wins) whenever that probability is positive. A trader buys whenever $v_i > p_i$ and sells whenever $v_i < p_i$, regardless of how likely i is to be ratified.

Proposition 1 (Conditional pricing). In any competitive equilibrium of market i with positive ratification probability, the no-arbitrage conditional share price satisfies $p_i = v_i$. That is, each parallel market prices its share at the firm's per-share value conditional on that choice being implemented, independent of the choice's winning probability.

Proof sketch. Assume each market has sufficient informed liquidity: informed traders with capital who can take either side (an assumption Proposition 3 later relaxes). If $p_i < v_i$, every informed trader strictly prefers to buy, raising p_i; if $p_i > v_i$, every informed trader strictly prefers to sell, lowering p_i. The only price admitting no profitable deviation is $p_i = v_i$. The refund rule removes Pr(i wins) from the first-order condition, so the result holds market by market.

"Sufficient informed liquidity" is relative to the task: resolving a value gap of size $\Delta_{ij} = |v_i - v_j|$ requires trading precise enough to distinguish prices within Δ_{ij}; the same market that is liquid enough to separate widely spaced values may be insufficiently liquid to separate near-identical ones.

This property distinguishes Parallel Markets from prediction markets, whose unconditional prices conflate value with win-probability. Voiding non-winning markets makes each price a conditional value estimate, recovering Hanson's (2002) decision-market logic without an external oracle.

A known impossibility result appears to stand against Proposition 1. Othman and Sandholm (2010) prove that decision markets operating under the deterministic max-price rule are inherently manipulable: a trader can profit by inflating the price of a suboptimal action even with correct beliefs, because selection makes prices self-referential: price determines the action, the action shifts the success probability, and that probability determines the payoff. Their result does not apply here, for a structural reason. In their model each conditional contract pays out on a binary success event whose probability the chosen action itself moves, so a trader who pushes the price toward their belief can come to regret it once the action is taken. In Parallel Markets the conditional share instead pays the firm's value v_i under choice i, a quantity exogenous to the share price (Setup); selection changes which market settles, not the payoff v_i within it. The self-referential channel that drives their impossibility is therefore absent; the loop terminates at an exogenous v_i. This exogeneity is the load-bearing assumption: Proposition 1 prices a value that the selection price does not feed back into, rather than eliciting a self-affecting probability. Their result and Proposition 3 below also concern different manipulations: theirs, probability manipulation under endogenous outcomes, eliminated here by construction; ours, private-benefit manipulation, bounded rather than eliminated.

Proposition 2 (Selection efficiency). If $p_i = v_i$ for all i, the ratified choice $w = \text{argmax}_i\, p_i = \text{argmax}_i\, v_i$ maximizes per-share firm value. Under secondary-market replication, N_i is identical across choices (it is constant), so this is equivalent to $w = \text{argmax}_i\, V_i$: the mechanism ratifies the value-maximizing decision.

In Parallel Primary Markets, Proposition 1 corresponds to the equilibrium condition of Equation (5-3), $v(s_e) = f(s_e)$: the bonding-curve price equals value per share at equilibrium supply s_e. Because f is strictly increasing, each choice has a unique s_e and the equilibrium prices are directly comparable across choices, so selection by argmax price returns the value-maximizing choice.

Some critics hold that markets are themselves open to gaming: participants can transfer money between accounts and trade with themselves to move the price (Blume et al., 2010). This concern does not withstand scrutiny of order matching mechanism. In a central exchange clearing homogeneous claims, orders clear against the best counteroffers in the book, not against chosen counterparties. A participant trying to trade far from equilibrium first clears the asks or bids closest to equilibrium, not their own resting orders at the target price; trading with oneself or an accomplice at a non-equilibrium price is possible only outside the market, which does not move the market price. To move the price inside the market, a manipulator must absorb the cost of clearing every counteroffer up to the desired price.

This theoretical prediction is consistent with experimental evidence. Hanson et al. (2006) found that manipulation attempts in experimental markets do not degrade price accuracy: when other traders are sufficiently informed and free to enter, they profit by trading against apparent manipulation. Hanson and Oprea (2009) and Newman (2012) report the same in prediction markets, and experienced traders earn higher returns by trading against such biases (Cowgill & Zitzewitz, 2015). Speculative markets reward informed traders who push prices toward true value and penalize those who push prices away from it.

The same logic holds formally in Parallel Markets. Suppose a manipulator tries to make an inferior choice i (with v_i below the true optimum) win by buying its conditional shares up to a price $p_i > v_i$. The position pays $v_i - p_i < 0$ precisely in the state where the manipulation succeeds (i wins) and pays 0 when it fails (refund). The manipulator bears a loss exactly when they achieve their aim, while informed traders profit by selling into the inflated price, pushing it back toward v_i. Within each self-referential market, financial manipulation is thus self-penalizing.

Proposition 3 (Bounded manipulation-resistance). Let a participant derive a private, non-share benefit B_i from the ratification of choice i (e.g., appointment, control rents). Manipulating i to victory requires absorbing a trading loss $L_i(\lambda)$ increasing in market liquidity λ. The mechanism resists manipulation if and only if $B_i < L_i(\lambda)$. As λ grows, L_i grows without bound, so resistance rises monotonically with liquidity; in thin markets L_i is small, and manipulation by sufficiently motivated insiders becomes feasible.

Proposition 3 locates the mechanism's vulnerability precisely. The Parallel Secondary Markets system neutralizes manipulation motivated by share value alone, but not manipulation motivated by private benefits exceeding the (liquidity-dependent) cost of moving the price. This is the market analogue of Roe's (2004) observation that market discipline limits managerial shirking but does not deter small-scale extraction, and it formalizes why liquidity is the binding constraint: the same thinness that compresses differentiation between choices also lowers the cost of private-benefit manipulation. Parallel Primary Markets addresses the counterparty-availability source of thinness by supplying continuous liquidity (Section 5), so L_i is then governed by the bonding-curve slope rather than by order-book depth. Under a bonding curve, moving the price from equilibrium to a target requires depositing the integral of the price function (the area F under f between the two supplies), so the manipulation cost L_i is F evaluated over that interval. A steeper f makes F rise faster, raising L_i for any given price distortion; this is the precise sense in which the Parallel Primary Markets system strengthens manipulation resistance, and, in Othman and Sandholm's (2010) terms, shrinks manipulability by raising the cost of moving the price.

The liquidity dependence in Proposition 3 fits a broader pattern in the literature comparing markets to voting and rating. Blohm et al. (2011) found rating to be more effective than trading, but benchmarked ratings against other expert ratings rather than an independent objective criterion, thereby posing a methodological bias in favor of rating. Moreover, their experiments were small-scale; voting and rating can work well in small groups, whereas markets require sufficient liquidity, as Blohm et al. acknowledge. The comparison reverses at scale: as markets grow more liquid, they become more accurate, while voting and rating become more susceptible to free-riding and manipulation (Cvijanovic et al., 2019). Markets also improve over time, since informed traders survive and exert more influence while uninformed traders incur losses and exit. Such an evolutionary correction is absent under voting and rating.

7. Limitations and Future Research

The experiment has several limitations. The participant pool was small (69 participants), the selection period short, and the rewards modest. The decision task was a retroactive investment-allocation choice, which is atypical of governance problems. This design supports internal validity, since the controlled task isolates the mechanism's selection logic from confounds, but it threatens external and ecological validity, since retroactive investment allocation is not a problem most real DAOs face. The experiment further tests generic shareholder-value selection under a corporate framing; DAO-specific behavioral factors such as token-holder apathy, whale-identity effects, Sybil attacks, and on-chain transaction costs were outside the experimental design and remain untested.

The formal manipulation-resistance result (Proposition 3) is similarly untested empirically: the experiment included no adversarial manipulators, so Proposition 3 should be read as a game-theoretic property, not an experimentally confirmed one. Future research should test Parallel Markets in more realistic DAO settings and introduce adversarial conditions to test manipulation resistance directly.

A related open question is participant motivation and sustainability. Unlike token-based or NFT-based participation rewards, which attract uninformed, low-quality participation and can signal negatively to investors (Saesen et al., 2025), Parallel Markets ties participation directly to financial exposure: traders profit by moving prices toward true value and lose by moving them away. This "skin in the game" (Ellinger et al., 2024) is self-selecting for informed participation and, in principle, self-sustaining, since informed traders accumulate capital and influence while uninformed traders exit. Whether this incentive sustains participation at the scale and over the horizon real DAOs require is an empirical question this study does not resolve and is a priority for field validation.

While this study offers a proof of concept, future research should compare the performance of Parallel Markets against voting mechanisms directly. The experimental design could include four governance systems: Parallel Markets, Parallel Primary Markets, plurality voting, and approval voting. Each system is tested across three independent groups, with participants randomly assigned to the 12 groups.

For Parallel Primary Markets, Appendix E presents modified instructions, but its logic may still be too complex for ordinary MTurk subjects to grasp within a short experimental session. Rigorous evaluation may instead require a hybrid simulation-experimentation design: train machine-learning models on empirical data to imitate human subjects with bounded rationality, then use these virtual agents to simulate the system's performance.

Beyond this paper's experimental scope, technical feasibility of Parallel Primary Markets has been demonstrated independently: the ParaLead project (paralead.org) implements the system in Solidity smart contracts, currently deployed on an Ethereum testnet. This establishes technical feasibility; behavioral validation remains an open question for future research. However, DAO adoption has proven to be challenging in practice (Xie & Tsang, 2025).

Two open design questions deserve dedicated study. First, how long should a selection period run before the ranking of top choices stabilizes? Second, what threshold of token holdings, if any, should govern proposal rights? Too high a threshold limits diversity and inclusivity; too low a threshold invites low-quality proposals that fragment liquidity across too many parallel markets, slowing convergence to equilibrium prices. Both questions point to the same underlying design principle: several of the system's parameters (trading-period length, proposal thresholds) may benefit from adaptive rules that respond to market conditions: lengthening or raising thresholds when volatility is high or submission volume runs high. Specifying and testing such rules is left to future research.

Although this paper is focused on DAO governance, extending market-based ratification to broader constitutional and institutional settings constitutes a promising direction for future research. This extension follows naturally from a view of constitutional and institutional design as an engineering discipline grounded in mechanism design and systems engineering (Armani, 2026).

8. Conclusion

The contributions of this paper are fourfold, corresponding to RQ1 through RQ4.

First, it introduces Parallel Markets, a voting-free governance system that uses market equilibrium prices to autonomously ratify decisions, mitigating the agency conflicts, rational apathy, and whale dominance inherent in token-based voting.

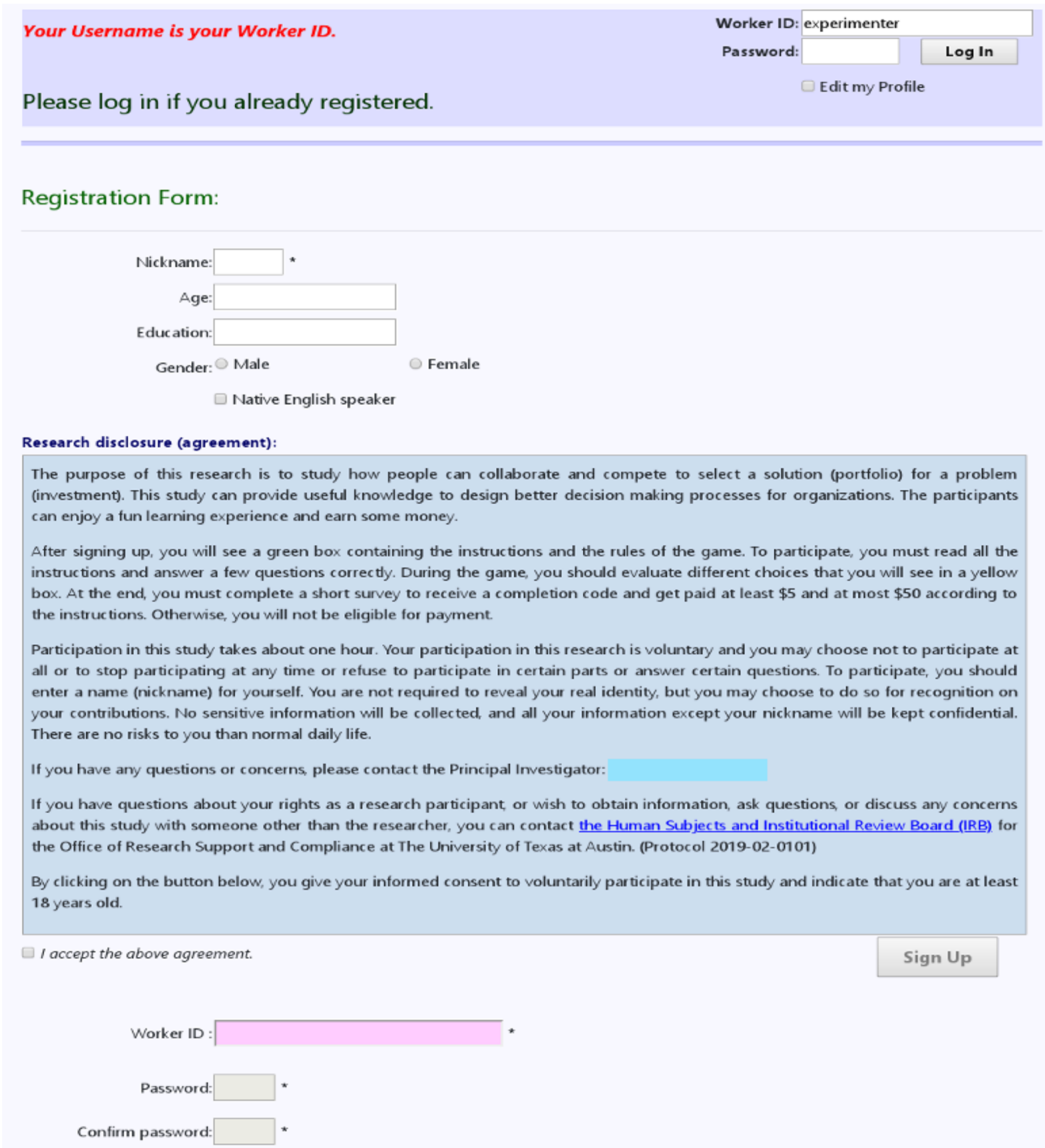
Second, it provides experimental evidence that the system selects the value-maximizing choice under normal value separation, and that under a deliberate liquidity-ceiling stress test with near-identical top choices, selection accuracy degrades, with the largest deviations coinciding with the thinnest trading volume, thereby indicating liquidity, not mechanism logic, as the source of the residual error.

Third, it introduces Parallel Primary Markets, combining the core architecture with bonding-curve contracts to alleviate this liquidity dependence and accelerate decision-making in thinner markets.

Fourth, it formally characterizes the mechanism's incentive properties, showing that conditional share prices reflect underlying value independent of winning probabilities, that the resulting ratification is value-maximizing, and that resistance to manipulation holds only when a manipulator's private benefit stays below the liquidity-dependent cost of moving the price.

Appendix A

This section explains the web application that serves as a platform to conduct experiments on governance systems. Figure A-1 illustrates the login/registration page on the web application. It also shows the consent form approved by IRB (protocol 2019-02-0101).


Your Username is your Worker ID.

Worker ID: experimenter

Password: Log In

Edit my Profile

Please log in if you already registered.

Registration Form:

Nickname: *

Age:

Education:

Gender: Male Female

Native English speaker

Research disclosure (agreement):

The purpose of this research is to study how people can collaborate and compete to select a solution (portfolio) for a problem (investment). This study can provide useful knowledge to design better decision making processes for organizations. The participants can enjoy a fun learning experience and earn some money.

After signing up, you will see a green box containing the instructions and the rules of the game. To participate, you must read all the instructions and answer a few questions correctly. During the game, you should evaluate different choices that you will see in a yellow box. At the end, you must complete a short survey to receive a completion code and get paid at least $5 and at most $50 according to the instructions. Otherwise, you will not be eligible for payment.

Participation in this study takes about one hour. Your participation in this research is voluntary and you may choose not to participate at all or to stop participating at any time or refuse to participate in certain parts or answer certain questions. To participate, you should enter a name (nickname) for yourself. You are not required to reveal your real identity, but you may choose to do so for recognition on your contributions. No sensitive information will be collected, and all your information except your nickname will be kept confidential. There are no risks to you than normal daily life.

If you have any questions or concerns, please contact the Principal Investigator:

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher, you can contact the Human Subjects and Institutional Review Board (IRB) for the Office of Research Support and Compliance at The University of Texas at Austin. (Protocol 2019-02-0101)

By clicking on the button below, you give your informed consent to voluntarily participate in this study and indicate that you are at least 18 years old.

I accept the above agreement.

Sign Up

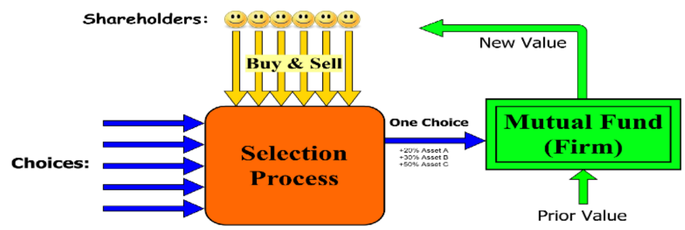
Worker ID : *

Password: *

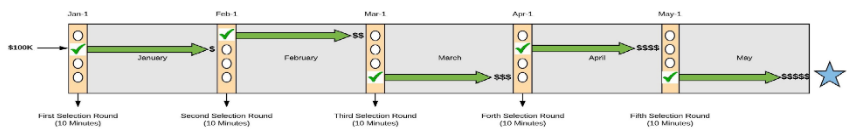
Confirm password: *

Figure A-1. The First Page of the Application Letting User to Log In and Sign Up.

Figure A-2 shows the visual directions for the participants. It complements the instructions.



TimeLine:



Perfromance of one Portfolio (One Choice):

Example: If on Jan 1st the firm invests 30% of its cash on coin A and 70% on coin B, then on Feb 1st this is the amount it will have:

$$Value_{Feb1} = Value_{Jan1} * \left[0.3 * \frac{Price(A)_{Feb1}}{Price(A)_{Jan1}} + 0.7 * \frac{Price(B)_{Feb1}}{Price(B)_{Jan1}}\right]$$

Share Value (for Each Choice):

$$Value\ of\ One\ Share = \frac{Final\ Value\ of\ Mutual\ Fund}{Number\ of\ Outstanding\ Shares}$$

The Prices:

	1-Jan-2019	1-Feb-2019	1-Mar-2019	1-Apr-2019	1-May-2019	1-Jun-2019
Bitcoin (BTC)	3746.71	3460.55	3853.76	4105.36	5,350.91	8,573.84
EOS	2.57	2.32	3.54	4.17	4.83	8.52
Ethereum (ETH)	133.42	107.15	136.84	141.47	162.19	268.43
Ripple (XRP)	0.352512	0.310839	0.315066	0.309195	0.30949	0.438711
LTC (Litecoin)	30.46	31.72	46.24	60.77	74.3	114.47
Cardano (ADA)	0.040984	0.038441	0.043112	0.069651	0.070338	0.089462
NEM (XEM)	0.064185	0.040572	0.042631	0.055242	0.056169	0.098231
TRON (TRX)	0.018892	0.025325	0.023878	0.023507	0.023969	0.03306
Lisk (LSK)	1.35	1.12	1.22	1.72	1.74	2.08
Verge (XVG)	0.006851	0.005936	0.00597	0.007476	0.00748	0.009996

How to Navigate CoinMarketCap.com:

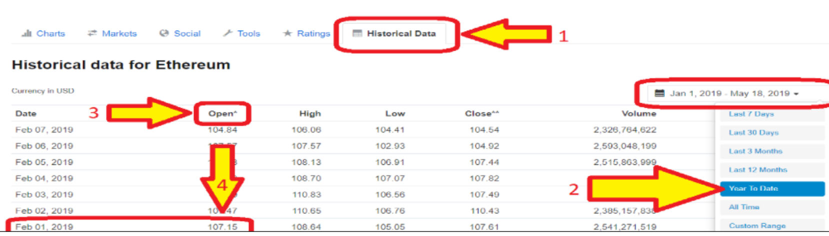


Figure A-2. Visual Directions for Participants

Figure A-3 shows the trading page. This page enables each participant to buy and sell the shares of the company under different choices. They can see the prices for the previous transactions. They can also see the existing offers that they or other participants have made. They can submit new buy or sell orders for the shares of the company under each choice.

Figure A-3. Trading page for participants in the parallel secondary markets governance system

Figure A-4 shows the control panel of the application. In this panel, the experimenter can set up the parameters to define a decentralized governance system and schedule it to run at a specific time. Once it goes live it allows people to register to participate in solving a specific problem. Then, after recruiting participants it starts enforcing the decentralized governance rules on the participants.

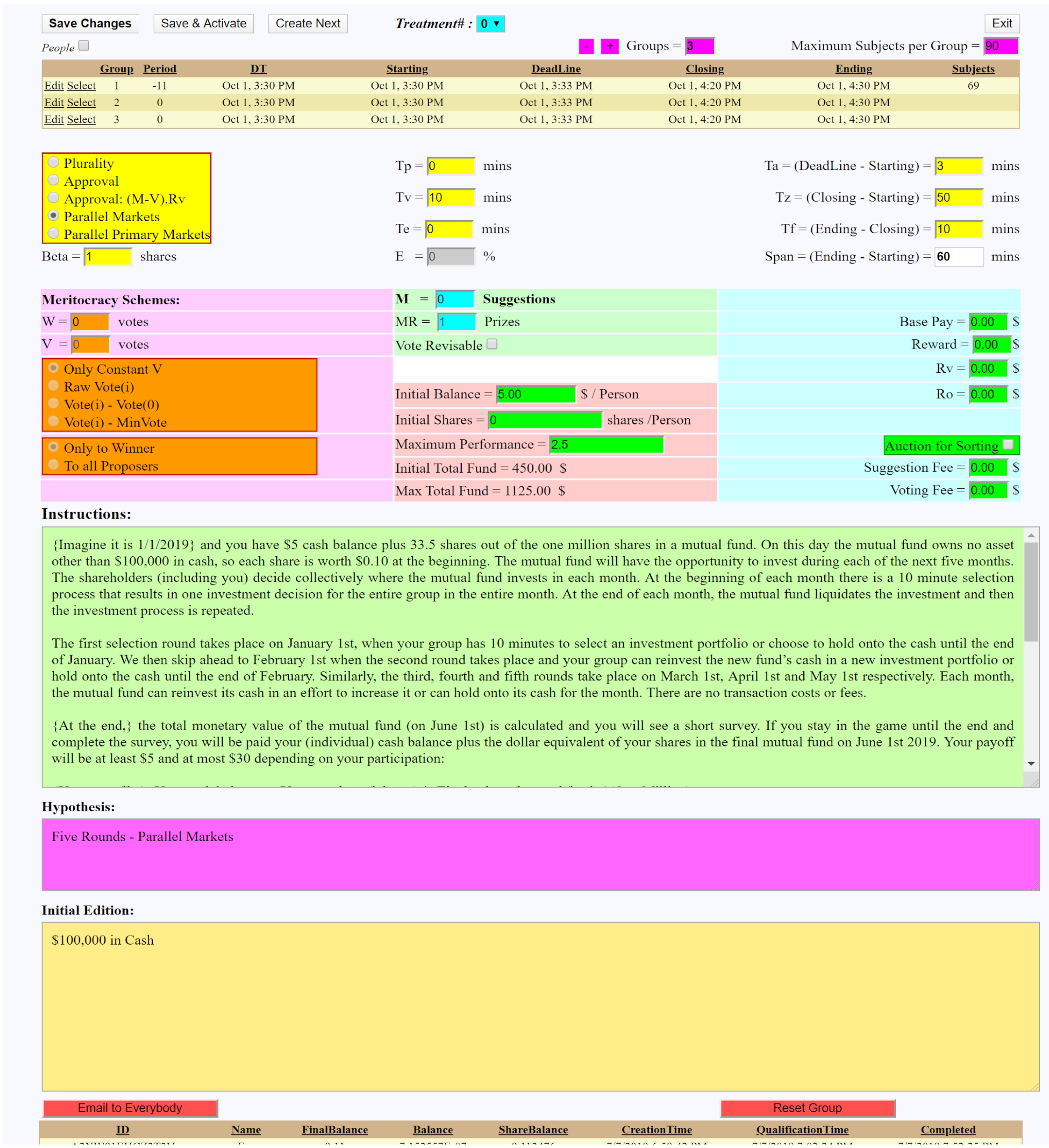


Figure A-4. Control Panel for the Experimenter

Appendix B

This appendix reports the portfolio details and results for all five rounds. Figures B-1 to B-5 show the end-of-round screen for each round, one row per choice. The Hold Cash row's bracketed number is the fund's current dollar value, carried forward from the previous round's winning choice; an accompanying calculation shows that choice, its performance, and how it updated the fund value. Each other choice's bracketed number is the performance multiplier the fund would earn if that choice were selected. The parenthetical figures are each choice's live market data: last transaction price, lowest sell offer, and highest buy offer. It is the last transaction price that the system uses to ratify the winner.

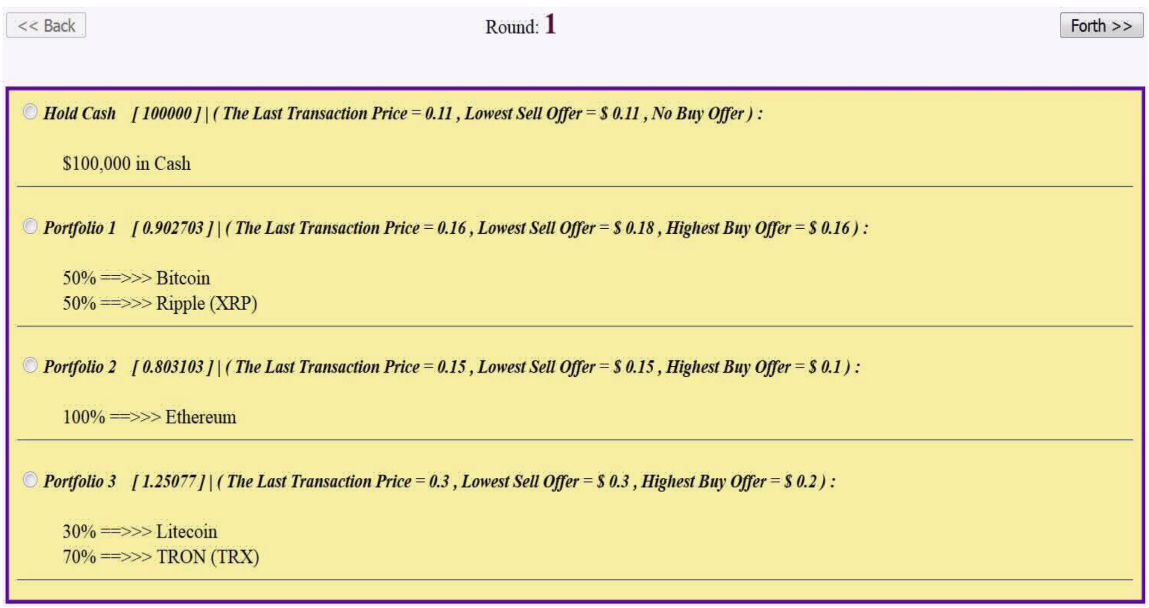


Figure **B**-1. Alternative Choices (Markets) in the First Round

Hold Cash   [125077] | (The Last Transaction Price = 0.19 , Lowest Sell Offer = $ 0.18 , Highest Buy Offer = $ 0.17) :

$125,077.00 in cash

Calculation:

The investment choice selected on January 1st:

30% ==>>> Litecoin
70% ==>>> TRON (TRX)

Its performance was 1.250770
Prior value of the mutual fund (on January 1st) was $100,000.00
*New Value = Prior Value * Performance = $125,077.00*

Portfolio 1   [1.15606] | (The Last Transaction Price = 0.27 , Lowest Sell Offer = $ 0.27 , Highest Buy Offer = $ 0.25) :

40% ==>>> Bitcoin
20% ==>>> EOS
40% ==>>> Ripple (XRP)

Portfolio 2   [0.975869] | (The Last Transaction Price = 0.15 , Lowest Sell Offer = $ 0.18 , Highest Buy Offer = $ 0.15) :

20% ==>>> Ripple (XRP)
50% ==>>> TRON (TRX)
30% ==>>> Verge (XVG)

Portfolio 3   [1.10862] | (The Last Transaction Price = 0.15 , Lowest Sell Offer = $ 0.18 , Highest Buy Offer = $ 0.09) :

60% ==>>> Cardano (ADA)
40% ==>>> Lisk

Figure B-2. The Alternative Choices (Markets) in the Second Round

Hold Cash [144597] | (The Last Transaction Price = 0.1 , Lowest Sell Offer = $ 0.1 , No Buy Offer) :

$144,596.80 in cash

Calculation:

The investment choice selected on February 1st:

40% ==>>> Bitcoin
20% ==>>> EOS
40% ==>>> Ripple (XRP)

Its performance was 1.156062
Prior value of the mutual fund (on February 1st) was $125,077.00
*New Value = Prior Value * Performance = $144,596.80*

Portfolio 1 [1.11992] | (The Last Transaction Price = 0.2 , Lowest Sell Offer = $ 0.23 , Highest Buy Offer = $ 0.2) :

70% ==>>> EOS
30% ==>>> TRON (TRX)

Portfolio 2 [1.13445] | (The Last Transaction Price = 0.24 , Lowest Sell Offer = $ 0.24 , Highest Buy Offer = $ 0.2) :

70% ==>>> Bitcoin
30% ==>>> NEM (XEM)

Portfolio 3 [0.982605] | (The Last Transaction Price = 0.24 , Lowest Sell Offer = $ 0.15 , No Buy Offer) :

50% ==>>> Ripple (XRP)
30% ==>>> TRON (TRX)

Portfolio 4 [1.14988] | (The Last Transaction Price = 0.15 , Lowest Sell Offer = $ 0.23 , Highest Buy Offer = $ 0.15) :

50% ==>>> TRON (TRX)
20% ==>>> Lisk
30% ==>>> Verge (XVG)

Portfolio 5 [1.14066] | (The Last Transaction Price = 0.24 , Lowest Sell Offer = $ 0.24 , Highest Buy Offer = $ 0.15) :

10% ==>>> EOS
10% ==>>> Ethereum
40% ==>>> LiteCoin
40% ==>>> TRON (TRX)

Figure B-3. The Alternative Choices (Markets) in the Third Round

Hold Cash [164037] | (The Last Transaction Price = 0.1 , Lowest Sell Offer = $ 0.15 , Highest Buy Offer = $ 0.1) :

$164,037.20 in cash

Calculation:

The investment choice selected on March 1st:

70% ==>>> Bitcoin
30% ==>>> NEM (XEM)

Its performance was 1.134446
Prior value of the mutual fund (on March 1st) was $144,596.80
*New Value = Prior Value * Performance = $164,037.20*

Portfolio 1 [1.0822] | (The Last Transaction Price = 0.1 , Lowest Sell Offer = $ 0.15 , Highest Buy Offer = $ 0.1) :

50% ==>>> Ethereum (ETH)
30% ==>>> NEM (XEM)
20% ==>>> TRON (TRX)

Portfolio 2 [1.00375] | (The Last Transaction Price = 0.18 , Lowest Sell Offer = $ 0.19 , Highest Buy Offer = $ 0.15) :

33% ==>>> Ripple (XRP)
33% ==>>> Cardano (ADA)
34% ==>>> Verge (XVG)

Portfolio 3 [1.13595] | (The Last Transaction Price = 0.16 , Lowest Sell Offer = $ 0.16 , Highest Buy Offer = $ 0.15) :

30% ==>>> Ethereum (ETH)
40% ==>>> LiteCoin
30% ==>>> Cardano (ADA)

Portfolio 4 [1.00054] | (The Last Transaction Price = 0.1 , Lowest Sell Offer = $ 0.15 , No Buy Offer) :

100% ==>>> Verge (XVG)

Figure B-4. The Alternative Choices (Markets) in the Fourth Round


Hold Cash [164653] | (The Last Transaction Price = 0.11 , Lowest Sell Offer = $ 0.11 , Highest Buy Offer = $ 0.085) :

$164,652.70 in cash

Calculation:

The investment choice selected on April 1st:

33% ==>>> Ripple (XRP)
33% ==>>> Cardano (ADA)
34% ==>>> Verge (XVG)

Its performance was 1.003752
Prior value of the mutual fund (on April 1st) was $164,037.20
*New Value = Prior Value * Performance = $164,652.70*

Portfolio 1 [1.20687] | (The Last Transaction Price = 0.12 , Lowest Sell Offer = $ 0.13 , Highest Buy Offer = $ 0.12) :

15% ==>>> Cardano (ADA)
85% ==>>> Lisk

Portfolio 2 [1.23364] | (The Last Transaction Price = 0.1 , Lowest Sell Offer = $ 0.1 , Highest Buy Offer = $ 0.05) :

50% ==>>> Cardano (ADA)
50% ==>>> Lisk

Figure B-5. The Alternative Choices (Markets) in the Fifth Round

Appendix C

There were two surveys, one before and one after the trading game. At first 69 subjects participated and did the first survey (i.e., treatment delivery), but 10 of them abandoned the experiment before the end (i.e., attrition = 14.5%). The remaining 59 participants stayed until the end and completed the final survey (i.e., treatment adherence). Their average age was 35 and 31% of them were female and 95% were English speakers. The older participants were less likely to speak English (*ρ=-.48*). On average, it took a participant 8.2 minutes to answer the first survey and 4.3 minutes to answer the final survey. The times taken to do the surveys were positively correlated (*ρ=.57*) and also were affected by the age and language of the participants. It took the older participants longer times to finish the surveys after controlling for language. The English speakers did the first survey significantly faster, but language had no significant effect on the time taken to finish the final survey. Table C-1 presents the OLS regression coefficient estimates obtained by IBM® SPSS®. Figure C-1 illustrates the path diagram for the Structural Equation Model (SEM).

Dependent Variable	Predictor	Coefficient	Standard Error	Standardized *β*	*P*
First Survey (in seconds)	*English*	-419*	226	-.26	.07
	Age	8.0*	4.8	.23	.1
*N=59 , df (for residuals)= 56 , R^2=.42 , F = 5.92*** (p=.005)*					
Final Survey (in seconds)	*English*	5.07	77.1	.01	.95
	Age	5.02***	1.64	.42	.003
*N=59 , df (for residuals)= 56 , R^2=.42 , F = 5.94*** (p=.005)*					

Table C-1. OLS coefficient estimates for the model on the survey times (* ≡ p <0.1, *** ≡ p <0.01)

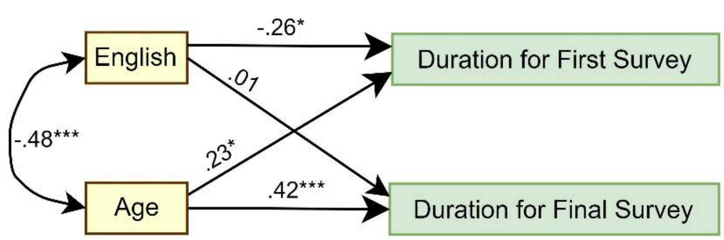


Figure C-1. Path diagram with standardized estimates for the survey times (* ≡ p <0.1, *** ≡ p <0.01)

To measure how well the participants understood the instructions, the first survey included two questions as manifests for the Comprehension construct:

Comprehension1: *Are the instructions clear and understandable?*

[1 = Very confusing…10 = Completely clear and easy to understand]

Comprehension2: *How well did you comprehend the rules of the game?*

[1 = I could not understand them at all…10 = I understood them completely]

The average responses to these two questions were 8.5 and 8.7 respectively and they were positively correlated ($\rho=.74$), supporting that they reflect the same latent variable. To measure the participant' financial knowledge, the first survey included two questions as manifests for the Knowledge construct:

Knowledge1: *What do you think is your level of expertise in the financial markets?*

[1=Never heard of it … 10= A professional trader]

Knowledge2: *How do you compare yourself to others in terms of financial literacy?*

[1=Everybody knows better than me …. 10= I know better than 99% of people]

The average responses to the above questions were 5.51 and 5.51 respectively and they were positively correlated ($\rho=.8$), supporting that they reflect the same latent variable.

The first hypothesis (H1) is that Knowledge (in financial markets) is positively associated with Comprehension (of the instructions). That is because the instructions included financial terms (e.g. mutual fund, shares, etc.), and participants with financial knowledge can better understand financial terms.

The second hypothesis (H2) is that being an English speaker is positively associated with higher Comprehension. It is obvious because the instructions were in English.

The third hypothesis (H3) is that people who reported to have more financial knowledge expected to earn more rewards in the experiments. That is because they are more confident. To measure expected earning, the first survey included this question:

Expected Earnings: *How much do you think you will earn in this game?*

.$5 .$5-$7 .$7-$10 .$10-$13 .$13-$16 .$16-$20 .$20-$25 .$25-$30 .$30-$40 .$40-$50

The choices ranged from \$5 to \$50 and the participants on average chose the 4th choice, which is between \$10 and \$13.

The fourth hypothesis (H4) is that Comprehension is positively associated with giving the correct answer to a check question about the instructions. The first survey included this check question:

> <u>Correctness</u>: *How many rounds are there in the game?*
>
> *[1 = One… 10 = Ten]*

The correct answer is five. If the subject gave a wrong response, the program prompted them to read the instructions carefully and recorded this mistake as level zero for a check. Only five out of 59 participants (8.5%) provided an incorrect response.[1]

The fifth and sixth (H5 & H6) hypotheses are that Comprehension and Knowledge are positively associated with the Final Balance respectively. The final balance was the sum of the cash balance and the cash value of the number of shares each participant owned at the end. The average final balance for a participant was \$11.68 and the sum of the final balances for 59 participants was \$689.28.

The seventh and eighth (H7 & H8) hypotheses are that Comprehension and Knowledge are positively associated with the Transaction Volume respectively. The transaction volume was the sum of the absolute volumes (in dollars) of the transactions each participant made throughout the game. The absolute volume for each transaction is the price times the number of shares transacted. On average each participant made total transactions of \$44.72 in volume and the sum of transaction volumes in the game was \$1319.24 for the 59 participants and \$1371.8 for all 69 participants.

To test these hypotheses, IBM® SPSS® AMOS 26.0 was used. We included age and gender as control variables in the SEM. Table C-2 provides the estimated coefficients and their *p* values, and Figure C-2 provides the path diagram with the standardized coefficients (β) for the complete SEM in AMOS.

Performing backward elimination results in a more parsimonious (reduced) model with better fitness statistics. Table C-3 shows the coefficients for the reduced model and Figure C-3 presents the standardized estimates of its SEM path diagram.

[1] The check question was not included as an item for Comprehension because the correlation was not large enough. (i.e. no convergent validity)

Association	Coefficient	Standard Error	Standardized β	p
Construct: Comprehension → Comp1	1***	0	.778	<.001
Construct: Comprehension → Comp2	1.145***	.204	.953	<.001
Construct: Knowledge → Know1	1***	0	.899	<.001
Construct: Knowledge → Know2	1.005***	.145	.882	<.001
H1: Knowledge → Comprehension	.374***	.108	.551	<.001
H2: English-Speaking → Comprehension	1.063	.747	.185	.155
H3: Knowledge → Expected Earnings	.422***	.143	.391	.003
H4: Comprehension → Correctness	5.121*	2.754	.252	.063
H5: Comprehension → Final Balance	.281	.368	.136	.445
H6: Knowledge → Final Balance	.04	.254	.028	.876
H7: Comprehension → Transaction Volume	3.982	8.534	.083	.641
H8: Knowledge → Transaction Volume	2.881	5.895	.088	.625
Control: Age → Comprehension	-.007	.016	-.06	.643
Control: Gender → Comprehension	-.143	.323	-.052	.657
Control: Age → Knowledge	-.03	.024	-.169	.207
Control: Gender → Knowledge	-1.048*	.543	-.26	.054
N=59 , df = 36 , χ^2 = 42.63 (p=.21) , CMIN = 42.63 , RMR = 20.3 , GFI = .89 , CFI = .96 , RMSEA = .06				

Table C-2. Path coefficient estimates for the complete SEM w/ latent variables (* ≡ p <0.1, *** ≡ p <0.01)

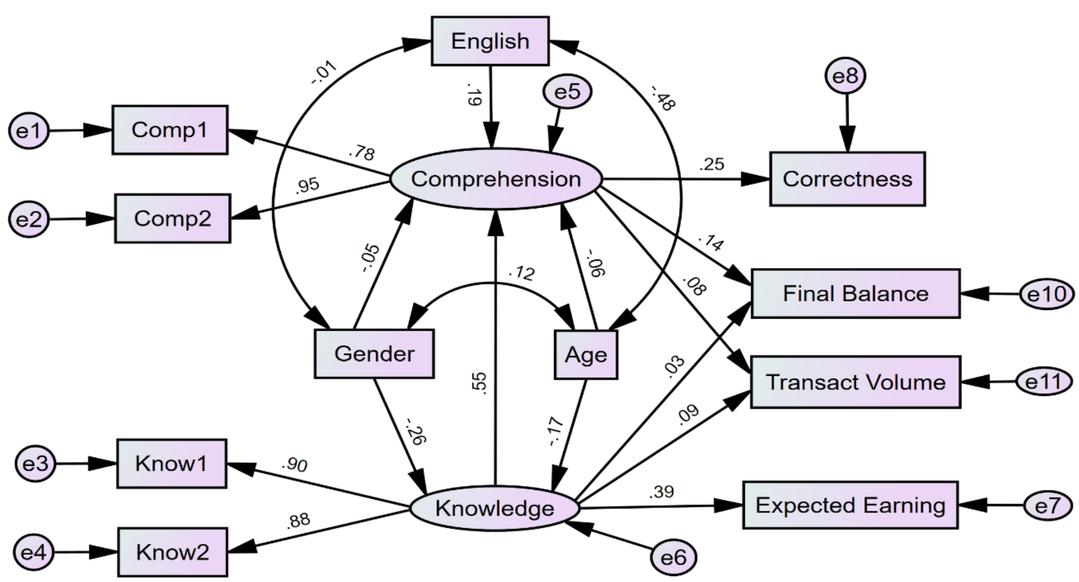


Figure C-2. Path diagram with the standardized estimates for the complete SEM in AMOS

Association	Coefficient	Standard Error	Standardized β	p
Construct: Comprehension → Comp1	1***	0	.767	<.001
Construct: Comprehension → Comp2	1.169***	.220	.962	<.001
Construct: Knowledge → Know1	1***	0	.895	<.001
Construct: Knowledge → Know2	1.011***	.146	.885	<.001
H1: Knowledge → Comprehension	.389***	.108	.581	<.001
H2: English-Speaking → Comprehension	1.236*	.662	.220	.062
H3: Knowledge → Expected Earnings	.423***	.144	.392	.003
H4: Comprehension → Correctness	5.018*	2.793	.242	.072
Control: Gender → Knowledge	-1.163**	.543	-.289	.032
N=59 , df = 18 , χ^2 = 17.89 (p=.46) , CMIN = 17.89 , RMR = 2.16 , GFI = .93 , CFI = 1.00 , RMSEA = 0				

Table C-3. Path coefficient estimates for reduced model w/ latent variables (* ≡ p <0.1, ** ≡ p <0.05, *** ≡ p <0.01)

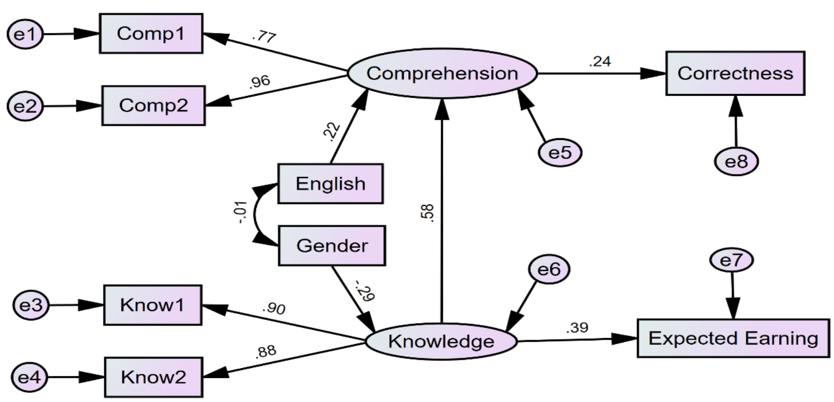


Figure C-3. Path diagram with the standardized estimates for the reduced model in AMOS

The control variables had no effect, except gender (male=0, female=1) had a negative effect on knowledge, meaning that women on average reported being less knowledgeable than men in financial markets. The results supported hypotheses H1 to H4 but did not support hypotheses H5 to H8. Naturally, we expect that the subjects with more knowledge about the financial markets and more understanding of the game should make more transactions and gain a larger final balance. However, they did not do that. This points us to the main shortcoming of these experiments. Perhaps, the amounts of rewards were not large enough to incentivize participants to trade more, especially in a calculated manner. However, those who engaged in more trading should have made more profit. So, I hypothesize (H9) that higher transaction volume is positively associated with a larger final balance for each participant. Furthermore, in the previous section, we saw that in the final rounds the choices were underpriced. Therefore, those who made more buying than selling in the last two rounds should have higher final balances. To measure that, I defined this variable for each participant:

Net volume in the last two periods = Volume of Buy Transactions – Volume of Sell Transactions

, and I hypothesize (H10) that higher net volume in the last two periods is positively associated with the final balance. Now I define three more variables as the answers to three questions in the final survey:

Ease: *Was the game easy to follow?*

[1 = No it was very confusing … 10 = Yes it was completely clear and easy]

Quality: *How were the overall quality of the game and the website?*

[1 = Very poor … 10 = Very effective]

Final Rating: *The final outcome is as follows. Please rate it.*

[1 = The worst possible outcome … 10 = The best outcome with maximum profit]

(Below this question they saw the final winner choice.)

The average response levels were 6.4, 7.4, and 5.6 for the Ease, Quality, and Final Rating respectively. The next hypothesis (H11) is that those who perceived the game to be easier to follow made more transactions. That is because they should have found it easier to engage in trades. Similarly, I hypothesize (H12) that those who have perceived the game and website to have higher quality, have made more transactions. That is because a higher-quality website would facilitate trading more effectively. The next hypothesis (H13) is that higher (perceived) quality of the website is positively associated with the perceived ease of following the game. That is because a higher quality website would make it easier for the participants to follow the game and its process. Also, those who perceived the game to be of higher quality should have perceived the outcome of the game of higher quality as well. So, I hypothesize (H14) that the higher perceived quality of the game is positively associated with the higher ratings for the final outcome.

To test the above hypotheses, I included age and gender as control variables and estimated the path coefficients using AMOS. Backward elimination results in a reduced model with significant coefficients as Table C-4 presents. Figure C-4 illustrates the path diagram for the reduced model.

The results supported hypotheses H9, H10, H12, H13, and H14 but not H11, implying that *the perceived ease of the game* does not lead to more trading. Again, that can be ascribed to the small rewards for trading. Among the control variables, age had negative associations with *Ease* and *Transaction Volume*, implying that older participants found the game harder to follow and made fewer transactions. Also, gender had a positive association with the net transaction volume in the last two periods. That means, women were more likely to buy the underpriced shares at the end.

Association	Coefficient	Standard Error	Standardized β	p
H9: Transaction Volume → Final Balance	.01**	.004	.23	.031
H10: Net Volume Last Periods → Final Balance	.145***	.029	.54	<.001
H12: Quality → Transaction Volume	6.35*	3.39	.23	.061
H13: Quality → Ease	.555***	.12	.48	<.001
H14: Quality → Final Rating	.359***	.11	.4	<.001
Control: Age → Ease	-.087***	.026	-.35	<.001
Control: Age → Transaction Volume	-1.32*	.73	-.22	.07
Control: Gender → Net Volume Last Periods	4.42*	2.62	.22	.092
N=59 , df = 19 , χ^2 = 19.36 (p=.43) , CMIN = 19.36 , RMR = 30.28 , GFI = .93 , CFI = .995 , RMSEA = .018				

Table C-4. Path coefficient estimates for reduced model w/ final measures (* ≡ p <0.1, ** ≡ p <0.05, *** ≡ p <0.01)

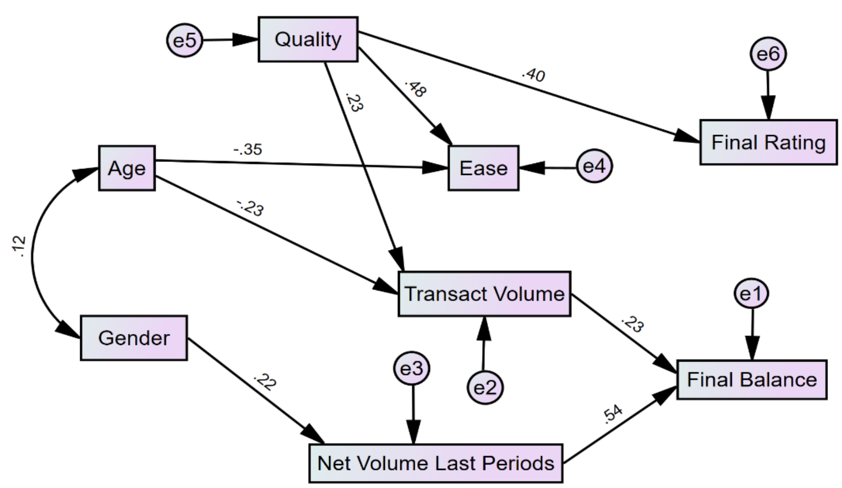


Figure C-4. Path diagram with the standardized estimates for the reduced model with the final measures

Overall, the findings are not surprising, but they are limited due to the small sample size and small incentives for active participation.

Appendix D

Figure D-1 presents the transaction page for the participants in the Parallel Primary Markets.

Figure D-1. The transaction page for participants in the Parallel Primary Markets

Appendix E

Experiments for the Parallel Primary Markets will be different from the experiments for the parallel secondary markets. As Appendix D shows, the trading page does not have open orders or offers anymore. The instructions are also different. The following are the instructions we suggest for experimenting with the Parallel Primary Markets system. It uses a linear price function and multiplicative transformation, but one can easily modify it to use quadratic or other price functions and other transformations.

<u>*Imagine it is 1/1/2019*</u> *and you have $10 cash, which you can invest in a mutual fund (*company*). At the beginning of this day, the* company *has no assets or cash, but it can raise funds in five rounds. Each round is 10 minutes at the beginning of one of five months. The first 10-minute round takes place on January 1st. During this round, you and others can buy shares of the* company *and supply funds for it. Then an algorithm selects where the* company *invests for January for the entire group. The computer calculates the return for January and skips ahead to February 1st when the second 10-minute round takes place. Then, again, you and others can buy more shares or sell your shares. This process repeats. Similarly, the third, fourth, and fifth rounds take place on March 1st, April 1st and May 1st.*

<u>*Choices:*</u> *The investment choices in each round include "holding cash" and a few portfolios of cryptocurrencies. At the beginning of each month, the selection algorithm selects to invest in one of the suggested portfolios or "hold cash" until the end of the month. Then the* company *applies the selected choice to the funds collected for that choice but returns the funds collected for all other choices. So, the shares are "conditional" shares depending on whether their choice is selected. At the end of each month, the* company *liquidates the investment and obtains cash if it was a portfolio. Then, the group can decide to reinvest the new cash in an effort to grow it or hold onto it for the upcoming month.*

<u>*Selection Algorithm:*</u> *During each 10-minute round you and others can buy and sell shares of the* company *for each choice assuming that the choice will be selected. Your transactions will result in one price for each choice at the end of each round, and then the choice with the highest price is selected as the investment for that month. The transactions and shares for this choice are confirmed but the transactions and shares for other choices are voided and the payments are returned. This reduces your risk if a choice's price declines. In the next round, the shareholders of the selected choice will own the same number of shares for every choice, but of course, only one of those choices will be selected and confirmed at the end. There are no transaction costs or fees.*

<u>*In the end*</u>*, the total monetary value of the* company *(on June 1st) is calculated and you will see a short survey. If you stay in the game until the end and complete the survey, you will be paid your (individual)*

cash balance plus the dollar equivalent of your shares in the final company. *Your payoff will be at least \$10 and at most \$30 depending on your participation:*

Your payoff =

*Your cash balance + (Your number of shares) * (Final value of the* company*) / (Final number of shares)*

In addition, the participant with the highest final payoff will receive a \$20 bonus!

<u>*Hint:*</u> *Each round, you should evaluate each choice and buy its shares if its price is lower than its share value and sell its shares if its price is higher than its share value. You can make money both ways if you estimate the share value for a choice. You want to sell the overpriced choices and buy the underpriced ones. You can use historical data on websites such as CoinMarketCap to calculate the performance of each portfolio, which is the weighted average of the performance of its assets. If the algorithm selects to hold cash for a month, the total value will not change (performance = 1). Please have a calculator or Excel sheet ready.*

<u>*Share Price:*</u> *The* company *uses the price function (Price = a+b.S) to determine the share price as an increasing function of the number of shares outstanding (S). For every buy order, the* company *issues shares at the calculated price at that time, and for every sell order, the* company *buys back shares at the calculated price at that time. The values of a and b are determined at the beginning of each round. In the first round a=1 and b=1, therefore: Price = 1+S.*

Meanwhile, as S continuously changes, the price also continuously changes and thus the average price is a little different from the beginning price for each transaction.

At the end of each month, the computer adjusts the price function to reflect the new amount of the funds. To this end, the parameters a and b are multiplied by the realized performance of the investment. Then the investment process repeats using the new price function.

Appendix F

Imagine company X has one million outstanding (ownership) shares, and its CEO retires next month. Conventionally, the board of directors would find and select the next CEO. However, the Parallel Markets system can find and select the next CEO as follows:

The platform opens a submission page allowing any shareholder with at least 1% of shares (qualified proposers) to propose a CEO candidate. The suggestion period starts and lasts one week.

During the suggestion period, four qualified shareholders, each proposes a candidate. So, in total there are four candidates: Allen, Bernard, Cody, and Diana. The suggestion period ends.

The platform replicates the company shares for each possible CEO. Therefore, the one million company shares become four million conditional shares: one million X-if-Allen, one million X-if-Bernard, one million X-if-Cody, and one million X-if-Diana. A conditional share becomes a company share if and only if its corresponding candidate is selected as the CEO. Then the selection period starts and lasts one week.

During the selection period, traders, shareholders, and speculators can buy and sell conditional shares for each choice. Essentially each conditional share represents a possible future for the company.

The Parallel Primary Markets system executes and fulfills the orders instantaneously using a price function (Figure 5-1). To fulfill buy/sell orders, conditional shares are issued/burned and the number of shares outstanding changes for each conditional share (Figure 5-2). Fulfilling the orders will change the prices and result in price discovery for the conditional shares for each choice in a different market.

Many investors know Diana has an excellent work record and experience. She is committed to improving efficiency, and the company will be more profitable if she becomes the CEO. Therefore, many investors buy X-if-Diana and as a result, the price of the conditional shares for X-if-Diana increases and becomes the highest price ($1490 per share).

On the other hand, people know that Bernard has used the corporate jet for his trips in his last company. He spends a lot of corporate money on luxury hotels. Therefore, many people believe the company will be less profitable if Bernard becomes the CEO. As a result, the price of X-if-Bernard goes down ($900 per share).

At the end of the selection period, X-if-Diana has the highest price for its conditional shares and is selected and ratified as the effective decision and is announced to the public.

Therefore, the conditional shares of X-if-Diana become the company shares X and their conditional shareholders become the shareholders of the company X.

On the other hand, the other three conditional shares and their corresponding transactions are voided and the funds invested in them will be returned to their investors and traders.

Change in funds with price function: Now assume that we use this price function to discover prices:

$f(S) = (S^2 / 10^9 + 50)$ dollars. ($a=10^{-9}$, $b=50$)

During the selection period, X-if-Diana reaches 1.2 million conditional shares, with price \$1490 at the end of the selection period. Since it is the highest among the four choices, it becomes the company shares X. The total capital fund becomes:

$F(S) = S^3 / (3*10^9) + 50*S = \$636$ million

After Diana becomes the CEO, the company shares (X) are issued or burned to fulfill the orders based on the price function. After one month, due to some economic conditions, several shareholders sell their shares and the price of the company shares goes down to \$1260 and thus the number of shares outstanding goes down to 1.1 million shares ($= \sqrt{10^9 * 1210}$) and the total capital fund becomes: \$498.67 million.

Then, shortly after that, \$40 million profit is realized and is deposited into the company bank account. This profit adds to the capital fund of the company making it \$538.67 million. To reflect this change in the capital fund, the price function can be adjusted in different ways such as:

I. One can adjust the price function while holding the price constant (Figure 5-8). To this end, Equation 5-21 may be used wherein we have $a=10^{-9}$ and $b=50$, and $s_0 = 1.1$ million company shares. Thus, the new price function is: $f_2(S) = 0.955 \times S^2 / 10^9 + 104.6$, because:

$$a' = 10^{-9} - 3/2 * (40*10^6) / (1.13 * 10^{18}) = .9549 * 10^{-9}$$

$$b' = 50 + 3/2 * (40*10^6) / (1.1 * 10^6) = 50 + 3/2 * (40) / (1.1) = 104.545$$

II. One can multiply the price function by the ratio 538.67 / 498.67 to obtain the new price function:

$f_2(S) = (1.08 * S^2 / 10^9 + 54)$ dollars

This retains the equilibrium number of shares, but changes the current price of the shares X, making it jump as Figure 5-9 shows.

After the price function is adjusted, the new price function is used to execute the orders and issue or burn company shares and conditional shares during the selection period.

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used Claude (Anthropic) to improve grammar and prose, and to identify errors and inconsistencies in the manuscript (e.g., numbering, terminology). After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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