SoK: Market Microstructure for Decentralized Prediction Markets (DePMs)

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Abstract. Abstract goes here.

1 Introduction

In late 2024, the United States was in the midst of a presidential election when the decentralized prediction market, Polymarket, broke through mainstream news coverage. Stories focused, in particular, on the fact that it offered odds more favourable to eventual winner Donald Trump than those reflected in conventional polls and forecasts. Polymarket's odds are not set by experts or pundits, instead it is effectively a betting market where odds are extrapolated from the prices of trades made in an open market (or somewhat open, as it was banned in many countries including the US).

As with traditional betting, whether online or through a bookie, prediction markets allow speculators to profit from correct forecasts. However the structure of a prediction market is different than traditional betting. One key difference is that prediction markets ease the process of moving in and out of bets before the event resolves, encouraging traders to place bets if they think the odds are over-stated or under-stated, and withdrawing profits if the odds realign with their view.

It would be easy to think that Polymarket's design is the most obvious, straight-forward way to deploy a decentralized prediction market (DePM) on a blockchain. However the central thesis of this systemization of knowledge (SoK) paper is that Polymarket found success in bucking the trend set by many previous attempts. DePMs were first given a few paragraphs in the Ethereum vision paper, released in late 2013 for the blockchain that would be deployed in 2015. Then two 2014 papers presented flushed out systems: a whitepaper called Truthcoin and an academic paper at WEIS (informally known as the 'Princeton DePM' because of author affiliation). Developed independently,[3] the two papers' designs

[3] The Princeton paper describes Truthcoin as being released while the paper was under review, and the Truthcoin FAQ mentions hearing about the Princeton paper but not having found the paper itself.

are vastly different, representing two different goalposts for how a DePM might look.

Early systems, like Augur and Gnosis closely resembled Truthcoin, while modern systems like Polymarket either resemble the Princeton DePM or use new solutions that resemble a hybrid of the two designs. Consider some examples. (1) In Truthcoin, the market creator is active in setting initial prices (*i.e.,* odds) for each option and risks its own money until enough traders balance the book. In the Princeton system, the market creator is passive and only generates complete sets of shares for every option. Polymarket uses the latter. (2) In Truthcoin, shares are created with an early version of an automated market maker (tweaks to this design by Gnosis led to Uniswap years later). In the Princeton DePM, shares are traded with an orderbook. In Polymarket, shares can be traded with either an AMM or an orderbook. (3) In Truthcoin, the blockchain decides event outcomes (*e.g.,* who won the election) through a reputation-based on-chain vote with slashing. In the Princeton paper, they are resolved through trusted arbiters acting as oracles. The Ethereum whitepaper suggests both. In Polymarket, oracles decide outcomes but the specific oracle used, UMA, operates under the hood through on-chain voting with slashing when outcomes are disputed.

Noticing these points of differences inspired us to ask what are all the design decisions involved in creating a DePM? We break the design into a 'modular workflow' with eight stages: underlying infrastructure, market topic, market mechanism, pricing, trading, market resolution, settling, and archiving. For each stage, we enumerate the possible designs and discuss competing trade-offs.

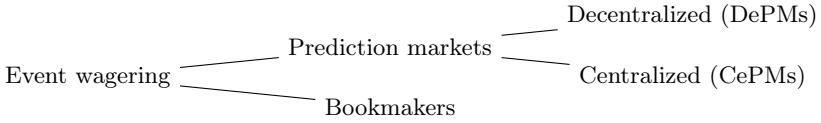
2 Preliminaries

2.1 Methodology

We obtained a collection of academic works on decentralized prediction markets, as well as various intersecting topics including (centralized) prediction markets, oracles, DeFi, and AMMs. We used our knowledge of the field, Google Scholar (search and cited by features), and citations within papers. Our library is available, sorted by topic, on Zotero.[4]. We also searched news sources for opinions and issues on leading decentralized prediction markets, such as polymarket. Finally, we informally monitored markets on popular markets but we did not conduct a systematic measurements as this paper is more concerned with the underlying mechanics than specific markets.

2.2 Taxonomy

Consider the following taxonomy of wagering systems:



[4] `tk`

Bookmakers versus prediction markets. A wager is a two-party contract with payouts based on the outcome of a future event. Consider Alice and Bob who wager on the same outcome of an event. With a bookmaker (or online betting), Alice's contract is different from Bob's contract in at least two regards: (i) it specifically names Alice as the counterparty and (ii) the payouts could be different if the odds changed between Alice's wager and Bob's. By contrast, in a prediction market contract (called a share), Alice and Bob hold identical contracts: (i) all contracts are between the market operator and whoever redeems the contract, and (ii) the payout is exactly the same (typically \$0 if incorrect and \$1 if correct). Odds are reflected in the price paid for a prediction market contract (*i.e.,* variable cost and fixed payout), while a bookmaker contract has a fixed cost and variable payout. Thus the key distinction is that prediction market shares are *fungible* and can be freely traded between participants, enabling a free market that communicates information to the public through share prices, trading volume, market depth, and other financial market metrics.

CePM versus DePM. The term *decentralized prediction market* originates from the Ethereum whitepaper and we abbreviate it DePM to match terms like DeFi (decentralized finance) or DePIN (decentralized physical infrastructure networks). The term *decentralized* in each of these is actually shorthand for both *decentralized* and *permissionless*, where permissionlessness is generally the more important way DePMs distingusih themsleves from centralized prediction markets (CePMs). Permissionlessness could extend itself to setting up markets, creating market shares, trading shares, closing the market, and withdrawing rewards, but not all systems will open up each of these operations (as we will explain in our modular framework). We say a system is DePM if at least one is permissionless.

2.3 Definitions

We define a market within a prediction-market system. In contrast to existing definitions, we abstract away details about how they are implemented. If the definitions are not clear, we refer the reader to Appendix C where we describe a specific market offered by Polymarket and map each term in the following definitions to this real world example.

Definition 1 (Market). *A (single) market is a tuple $M = (E, \Omega, J, R)$, where E is a well-defined uncertain event, Ω is a nonempty outcome space for E, J is a finite index set of contract labels ("shares"), and $R = (R_j)_{j \in J}$ are nonnegative payoff functions with $R_j : \Omega \to \mathbb{R}_{\geq 0}$. When M resolves to $\omega_M \in \Omega$, one unit of share $j \in J$ pays $R_j(\omega_M)$ (in units of $\mathcal{N}$ defined below).*

Definition 2 (Prediction–market system). *A prediction–market system is a tuple $\mathcal{S} = (\mathcal{M}, \mathcal{N}, \mathsf{Res})$, where $\mathcal{M}$ is a countable set of markets, $\mathcal{N}$ is a numeraire (unit of account), and $\mathsf{Res} = \{\mathrm{res}_M\}_{M \in \mathcal{M}}$ is a family of resolution registers such that, for each M with outcome space Ω_M, we have $\mathrm{res}_M \in \{\bot\} \cup \Omega_M$, res_M is initially $\bot$, and res_M transitions exactly once to some $\omega_M \in \Omega_M$.*

Remark (Arrow–Debreu Markets). For a market $M = (E, \Omega, J, R)$, suppose there exists a bijection $\iota : J \to \Omega$ and $R_j(\omega) \in \{0, 1\}$ with $\sum_{j \in J} R_j(\omega) = 1$ for all $\omega \in \Omega$. Then M is a winner–take–all (Arrow–Debreu) market: a unit claim of label j pays 1 iff the realized outcome equals $\iota(j)$, and 0 otherwise.

System axioms (mechanism–agnostic). For every market $M = (E, \Omega, J, R) \in \mathcal{M}$ (with register res_M as in Definition 2):

1. **Issuance.** The system may increase the outstanding supply of any label $j \in J$ by any $q \geq 0$ subject to policy (unspecified here). Let $S_j(M) \geq 0$ denote the total outstanding supply of label j in M.
2. **Transfer.** Holdings of each label $j \in J$ are transferable between accounts; transfers conserve per–label totals $S_j(M)$.
3. **Burn/Cancel.** The system may decrease $S_j(M)$ via explicit burn/cancel operations according to policy (optionally allowed pre–resolution).
4. **Resolution.** The resolution register satisfies $\mathrm{res}_M \in \{\perp\} \cup \Omega$, is initially $\perp$, and transitions exactly once[5] to a realized outcome $\omega_M \in \Omega$.
5. **Settlement.** Once $\mathrm{res}_M = \omega_M \in \Omega$, any holder of q units of label $j \in J$ may redeem for $q \cdot R_j(\omega_M)$ units of the numeraire $\mathcal{N}$; redeemed units are removed from supply (burned).
6. **Conservation of liability.** Let $S_j^{\mathrm{pre}}(M)$ be the outstanding supply of label j immediately before settlement. The total settlement liability is

$$\mathsf{Liability}(M) \;=\; \sum_{j \in J} S_j^{\mathrm{pre}}(M)\, R_j(\omega_M) \;\in\; \mathbb{R}_{\geq 0},$$

   which equals the aggregate numeraire paid out if all outstanding units are redeemed.
7. **No pre–resolution obligation.** While $\mathrm{res}_M = \perp$, the system owes no cash payoff on holdings of (M, j) beyond recording balances and permitting issuance/transfer/burn per policy.

2.4 An Example of a Market

Before diving deep on the mechanics of decentralized prediction markets, we illustrate how markets work and provide value with a lighthearted example. On 3 Oct 2024, a trailer was released with press coverage of a new HBO documentary on Bitcoin to air about a week later on 8 Oct 2024. In an interview, the director stated, the film would question Satoshi's anonymous identity and, 'who we land

[5] Real world DePMs like Polymarket might resolve a market, receive a dispute of over the outcome, and resolve it differently after a process (see Section 3.5). In the definition, resolution refers to the final outcome only. An outcome is final when shares can be redeemed for payouts.

Date	Information	Market Impact	Hindsight Verdict
05 Oct	Partially redacted leaked email from an HBO executive implies Len Sassaman.	Immaterial	Fake
06 Oct	A long-dormant X account belonging to someone who had corrosponded with Sassaman on Twitter posted a new message stating they were interviewed for the documentary.	Immaterial	Fake
07 Oct	Widow of Sassaman states she was not interviewed.	Moderate	Truthful
07 Oct	CNN piece states director 'confronts' Satoshi suspect 'face-to-face' ruling out Sassaman, David Klieman, and Hal Finney.	Material	Truthful
07 Oct	Samson Mow, featured in the trailer, speculates it will name Adam Back, also featured heavily in the trailer	Material	Wrong but factual basis
07 Oct	End credits of documentary leaked featuring a tribute to Klieman.	Immaterial	Fake
07 Oct	Mow states Nick Szabo refused to discuss with director implying he was not 'confronted'.	Material	Truthful
08 Oct	Peter Todd confirms being confronted for documentary but unsure if he will be named.	Material	Truthful
08 Oct	Scene with Todd leaked but inconclusive if it is film's thesis.	Material	Truthful
08 Oct	Commenter on Polymarket claims to screen test and names Nick Szabo.	Immaterial	Fake
08 Oct	Fortune publishes movie review disclosing Todd is named	Very Significant	Truthful
08 Oct	Documentary airs and names Todd	Very Significant	Conclusive

Table 1. Over a few days, truthful and untruthful ('cheap talk') evidence was presented to traders. The market reacted to correct signals and effectively filtered out fake signals, demonstrating a beneficial feature of prediction markets.

on is unexpected and is going to result in a fair amount of controversy.' The next day, Polymarket setup a market for speculating on who the documentary would name, providing 15 names plus an 'other/multiple' option. A benefit of a decentralized prediction market is allowing niche topics for markets, unlikely to attract mainstream betting websites—in this case, attracting $44M USD in trading volume. Having an 'other' option is also critical after many markets have failed to fully articulate every eventuality and in this case, the winner, was not one of the original 15 names (see Section 3.2).

In game theory, cheap talk describes strategic misinformation or signalling aimed at shaping beliefs or prices, provided the cost of deception is outweighed by the potential payoff. This is well illustrated by what followed in the HBO Satoshi market as new pieces of evidence emerged, some real and some fake, with

some fakes relatively elaborate (professional appearing end-credits or hijacking a target's X.com account) as summarized in Table 1. Further details are provided in Appendix B.

Also of interest is how the prediction market did not seem to extract insider information which is in violation of what the theory would predict. The director did state he did not participate in the market and advised his team working on the film not to either. Friction for novice users is also perhaps high—web3 apps have a learning curve and if insiders were based in the US, access would require circumvention of Polymarket's geofencing. Perhaps these reasons kept insiders out of the market.

3 Modular Workflow

We now turn to the design landscape of DePMs and step through our modular workflow, summarized in Figure **??**. Some design decisions will be common issues for both centralized and decentralized prediction markets. We include these anyways for completeness. However we put the emphasis on discussing design decisions that are pertinent to the decentralization and permissionlessness of prediction markets.

3.1 Underlying Infrastructure

In theory, a decentralized and permissionless system might run on a system other than a blockchain, but blockchain technology underlays all known DePMs. Selecting a blockchain constitutes the initial design decision within our modular workflow. In selecting a blockchain, a set of desirable features include expressive smart contracts, low transactions fees, fast finality, guaranteed inclusion, and censorship resistance. The earliest research was in agreement that Bitcoin Script was not powerful enough to operate a DePM, and a separate chain (perhaps integrated with Bitcoin as a sidechain) would be required. Later Ethereum was deployed, providing general smart contracts, and most DePM activity moved to it. Much later, high fees on Ethereum caused the diversification of the VM-based blockchain space into numerous competing chains and layer 2 (L2) scalability solutions. As of today, the most active DePMs run on chains built to execute smart contracts (*e.g.,* EVM or WASM). Most no longer run on Ethereum but on either an Ethereum competitor (*e.g.,* Polygon or Solana) or an Ethereum L2 (*e.g.,* Arbitrum or Optimism).

Generally, there are no strong qualitative differences between the named blockchain options—it is a choice driven by fees, user base, and supporting infrastructure. In all cases, the logic of the prediction market operations is placed in smart contracts and the blockchain executes the contracts. A materially different approach is to put the prediction market logic into the blockchain rules themselves, either with a purpose-built blockchain or with a customized layer (called an L3) that uses custom rules but settles on a standard L1 or L2.

3.2 Market Topic

CePMs include the Iowa Electronic Markets, Kalshi, and PredictIt, as well as InTrade historically. These systems exercise control over what topics may form a market and thus are *permissioned* with respect to market topics. They also operate under regulations that may restrict markets to certain topics or fully ban operations in regulated jurisdictions [10].

By contrast, DePMs like Augur, Gnosis, and PlotX enable *permissionless* market creation by any user without centralized review. This removes the regulatory hook, enables niche topics that might not attract mainstream interest, and allows markets to be created without delay after real world events. However it can also lead to a greater incidence of malformed (or even malicious) market definitions, and unlawful topics, such as the 'assassination markets' which appeared on Augur in 2018. DePMs are generally web3 applications which means that a web-based user interface mediates transactions between the user and the underlying smart contracts. Market topic moderation could be implemented at the web3 layer (*e.g.,* Predictions.Global unlisted assignations markets from Augur's smart contracts) but this does not prevent users from building an alternative UI or directly transacting with the smart contracts. While DePMs have the option to operate permissionlessly, they may also choose to permission market creation while leaving other aspects permissionless. At the time of writing, Polymarket is considered a DePM and while market topics can be suggested by users, final approval is made by a Market Integrity Committee [12].

A *hybrid model* puts some controls on topic creation without centralizing it fully. For example, proposers may have to stake tokens to propose a market, and while the market is optimistically published, a review (either centralized or via an on-chain voting mechanism) could remove the market and/or slash the proposer.

Careful attention must be paid to both the general topic of the market and the 'fine-print' or exact predicate that decides the market. Table 2 provides several examples of pitfalls. A pitfall in the predicate means the market topic is acceptable but there is an issue with its exact specification (*e.g.,* a market about wearing a suit needs to define a suit). A pitfall in the topic means the topic itself is problematic, even if it is worded impeccably (*e.g.,* a Polymarket market about whether Polymarket will shut down is problematic because winners will not be paid if it does). The first pitfall, borderline categories, is very prominent with many other disputes, including whether enforcement against TikTok in the US

[6] Polymarket: 'Will Zelenskyy wear a suit before July?'
[7] Google Docs: Did President Zelenskyy wear a suit before July 2025?.
[8] Polymarket: 'Will Trump and Putin hug on Friday?'
[9] Polymarket: 'Will Volodymyr Zelenskyy be the 2022 TIME Person of the Year?'
[10] Polymarket: 'Astronomer Divorce Parlay'
[11] Polymarket: 'Fordow nuclear facility destroyed before July?'
[12] Polymarket: 'Was Barron involved in $DJT?'

Pitfall	Description
Borderline Categories [Def'n]	*Example*: A market on whether Zelensky would wear a suit was contested when he wore a single-breasted jacket with patch chest pockets and matching trousers.[6] Media equivocated on describing it as a suit.[7]
	Mitigation: Clearly state inclusion/exclusion criteria (*e.g.,* a subsequent market on a potential hug between Trump and Putin spent a paragraph defining a hug.[8])
Precedence Gaps [Def'n]	*Example*: A proposition bet on the colour of the 2014 Super Bowl 'Gatorade shower' was contested when the coach was showered twice with different colours [8]. A market on whether Zelensky would be 'the' 2022 TIME Person of the Year was contested when both Zelensky and the Spirit of Ukraine were named.[9]
	Mitigation: Parse the predicate for any statements needing explicit precedence (*e.g.,* first, majority, primary); or establish a payout rule for ties; or include an outcome for 'multiple.'
Hidden Presumptions [Def'n]	*Example*: A market concerning a divorce presumes the couple are married (as opposed to common law) which was unknown.[10]
	Mitigation: Parse the predicate for any presumptive statements and remove/address them.
No Ground Truth [Topic]	*Example*: A market on whether a US strike destroyed an Iranian nuclear facility was contested when each country reported different outcomes and no neutral third party was granted access to the site.[11] A market on whether Baron Trump was 'involved' in the $DJT memecoin lacked an authoritative source.[12]
	Mitigation: Avoid markets without ground truth sources; or include an additional option in the market for unverified.
Platform Coupling [Topic]	*Example*: Hypothetically, traders who correctly predict USDC will completely de-peg on a platform that pays out in USDC will receive a payout but it will be worthless (*cf.* [8]).
	Mitigation: Avoid markets that are self-referential, including topics on the platform itself and its numinaire.

Table 2. Some pitfalls that illustrate the difficulty in properly defining a prediction market topic. [Topic] is an issue with the topic itself and [Def'n] with the way the predicate is defined.

constitutes a ban,[13] or if finding debris from the Titan submersible constitutes it being found.[14]

These issues are not limited to DePMs and apply to event wagering in general, however some issues are more pronounced in DePMs. If market creation is permissionless, market creators may be amateurs and error-prone; may draft adversarial markets to trick traders; or duplicate existing markets, thinning out liquidity. CePMs have the latitude to organize, pause, or revise markets or ban users. DePMs may give themselves this latitude at the risk of appearing less per-

[13] Polymarket: 'TikTok banned in the US before May 2025?'
[14] Polymarket: 'Will the missing submarine be found by June 23?'

missionless. Further it seems inevitable that some markets will fall into a pitfall and DePMs have to carefully consider how dispute resolution will work while also appealing to blockchain enthusiasts.

Dealing with definitional pitfalls has been, to date, a trial and error process where market creators learn from past mistakes and ad hoc 'legalese' (e.g., a 'consensus of credible reporting' may be used to resolve markets) is copied from market to market. Future research could develop machine-checkable predicate specifications (precedence rules, ranked sources, time semantics, and default outcomes) and verify they are well-defined with model checking.

If issues in a market's topic or definition are uncovered while the market is still active, DePMs like Polymarket allow 'additional context' notes to be added. However these clarifications could alter the market ex post and also disadvantage traders who do not see the note. The latter can be mitigated by advertising that a note will be published, always publishing at the same time (*e.g.,* 5pm ET), and clearing standing limit orders from an orderbook before posting.

3.3 Share Structure and Pricing

The core requirement of a prediction market is that wagers are represented by fungible shares. The structure of shares typically falls into one of three categories and two variants (although more exotic structures are possible and explored in research). Consider a market with three possible outcomes: $\Omega = \{\mathsf{A}, \mathsf{B}, \mathsf{C}\}$.

The first structure we term *winner-take-all (WTA)* and is prominent on Iowa Electronic Markets and supported by Augur and Gnosis. A WTA market issues a share for each outcome $J = \{j_\mathsf{A}, j_\mathsf{B}, j_\mathsf{C}\}$. If the outcome is B, the share j_B pays \$1 (or one unit of numeraire $\mathcal{N}$) and the other shares pay \$0. For any $k \in \{\mathsf{A}, \mathsf{B}, \mathsf{C}\}$,

$$R_{j_\mathsf{k}}(\omega) = \begin{cases} 1, & \text{if } \omega = \mathsf{k}, \\ 0, & \text{otherwise.} \end{cases}$$

For a WTA market to be well-functioning, conditions must hold on outcome shares. (i) They should be *mutually exclusive* so no more than one share wins: $R_{j_\mathsf{k}}(\omega) R_{j_\ell}(\omega) = 0 \quad \forall \omega \in \Omega, \forall \mathsf{k} \neq \ell$; and (ii) they should be *complete* so at least one share wins: $\sum_{\mathsf{k} \in \Omega} R_{j_\mathsf{k}}(\omega) = 1 \quad \forall \omega \in \Omega$. If they are not mutually exclusive, the operator could be undercollateralized for making all payments. If they are incomplete, a deficient market might end with all participants receiving \$0. A consequence is that holding one share for each outcome is equivalent to holding \$1, a fact we will return to in the next section on trading.

In a WTA market, the price of a share (*e.g.,* $p(j_\mathsf{A}) = \$0.54$) is a proxy for the probability that the outcome will occur (*e.g.,* $\Pr[\omega = \mathsf{A}] = 54\%$). A common adage is the prices of each share sum to \$1.00 ignoring fees and discounting (*e.g.,* $p(j_\mathsf{A}) = \$0.54$, $p(j_\mathsf{B}) = \$0.23$, $p(j_\mathsf{C}) = \$0.23$) but this is imprecise. Shares (like anything) have two prices: a bid price (what a trader is willing to buy for) and an ask price (willing to sell for). If the sum of the bid prices exceeds \$1.00 or if the sum of ask prices are below \$1.00, arbitrageurs have an opportunity to secure risk-free profit through a trade that will erase the condition when fully

extracted. This means the sum of bids and sum of asks should result in the bid-ask spread straddling $1.00 but the amount of the spread could be arbitrarily large. So in user interfaces that display a single 'price' (*e.g.,* the last sale price or the midpoint between the best bid and the best ask), prices may indeed not sum to $1.00—this is not a market failure, just a misunderstanding.

The second structure we term a *yes-no bundle (YNB)* and YNB markets were prominent on InTrade and are currently prominent on Polymarket. A YNB market issues two shares for each outcome, a 'yes' and a 'no:' $J = \{j_{\mathsf{A_Y}}, j_{\mathsf{A_N}}, j_{\mathsf{B_Y}}, j_{\mathsf{B_N}}, j_{\mathsf{C_Y}}, j_{\mathsf{C_N}}\}$. For any $k \in \{\mathsf{A}, \mathsf{B}, \mathsf{C}\}$,

$$R_{j_{\mathsf{k_Y}}}(\omega) = \begin{cases} 1, & \text{if } \omega = \mathsf{k}, \\ 0, & \text{otherwise.} \end{cases} \qquad R_{j_{\mathsf{k_N}}}(\omega) = \begin{cases} 1, & \text{if } \omega \neq \mathsf{k}, \\ 0, & \text{otherwise.} \end{cases}$$

Each outcome-specific pair $\{j_{\mathsf{k_Y}}, j_{\mathsf{k_N}}\}$ constitutes a two-outcome WTA market (k vs. not-k). A YNB market is the union of these pairs, so the WTA exclusivity and completeness properties hold per pair. However exclusivity and completeness do not necessarily hold across all bundles, allowing more flexible markets. For example, a market on what words Trump will say in a congressional address included Bitcoin (no), beautiful at least 10 times (yes), and Canada (yes).[15] Multiple words can resolve to yes and the market does not need to include every possible word (or an 'other' category). Further if the market is already underway with active trades, the word list can be expanded before the speech with a YNB market, whereas a WTA market cannot be fairly altered once the market begins trading.

A variant of the YNB market is one where, even though it is not necessary, the share outcomes are in fact complete and exclusive. For example, the Satoshi/HBO YNB market from Section 2.4 was made exclusive and complete across bundles by including a bundle for the outcome: 'other/multiple.' We term this variant as *YNB negative risk (YNB-NR)*, a term introduced by Polymarket. Recall that in a WTA market, roughly speaking, the share prices sum to $1 (modulo the fine print about bid/ask spreads above). For a YNB-NR market, the Yes shares are the same as a WTA share and sum to $1, while the No shares will sum to $|\Omega| - 1$.

Further, in a YNB market, holding a No share for Hal Finney has the same payoff as holding a Yes share for every other candidate. Polymarket introduced a *negRisk* gadget that allows a trader to convert any No share into a portfolio of Yes shares for every other outcome. This enables traders to adjust their positions with less buying/selling on the markets, and also aligns prices between Yes and No markets with low friction arbitrage opportunities. Formally, a single No share has the equivalence (*i.e.,* same payoff ignoring fees and discounting):

$$j_{\mathsf{k_N}} \equiv \sum_{\ell \in \Omega \setminus \{\mathsf{k}\}} j_{\ell_{\mathsf{Y}}} \quad \text{for any } \mathsf{k} \in \Omega.$$

And multiple No shares can be converted into Yes shares plus cash:

[15] Polymarket: 'What will Trump say during address to Congress?'

$$\sum_{\ell \in \Omega \setminus \{\mathsf{k}\}} j_{\ell_{\mathsf{N}}} \equiv j_{\mathsf{k}_{\mathsf{Y}}} + \$1 \cdot (|\Omega| - 2)$$

The third structure is a market where the outcome is a quantity of interest (*e.g.,* a vote share, temperature, or price level) observed at a cutoff time. Termed a *linear* (often called *scalar*) market, there is only one share and its payout is what value the quantity takes on (perhaps normalized to the range $[0, 1]$ with rounding). As an example, in a market on Trump's popular vote, if the quantity is 49.8%, the share will pay \$0.498. Shares can also be sold in bundles with 'long' receiving \$0.498 and 'short' receiving (\$1-\$0.498).

Formally, if we let $X : \Omega \to \mathbb{R}$ be the observed quantity, and $[a, b]$ be an interval of values, then the linear share j_{lin} pays:

$$R_{j_{\text{lin}}}(\omega) = \begin{cases} 0, & X(\omega) \leq a, \\ \dfrac{X(\omega) - a}{b - a}, & a < X(\omega) < b, \\ 1, & X(\omega) \geq b. \end{cases}$$

While linear markets are supported by DePMs like Augur, Gnosis, and Omen, they are not frequently used. Even though Polymarket uses the Gnosis Conditional Tokens Framework (CTF) which supports linear markets, it instead approximates one by splitting the quantity into 'buckets' and running a YNB market for each bucket. This allows greater code-reuse and possibly avoid small edge cases over the exact resolution of the quantity (*e.g.,* off by 0.1 percentage disputes). However a problem with buckets is as follows: Alice estimates correctly that Trump will win the election with 49–51% of the popular vote. If there is a bucket for 45–49.9% and a bucket for 50–54.9%, Alice's forecast does not fit into a single bucket—she must buy both which dilutes her expected return on capital.

3.4 Trading

Bookie: bookie sets odds, takes opposite side of initial bets, eventually balances books and guaranteed profit, first trader can trade Complete set: bookie has no risk, just generates complete sets of shares for \$1, first trader sets a bid, or buys complete set and sets asks, second trader actually exchanges Both are bounded in profit: second trader by first trader's position, first trader by bookie's position

In section 3.4, we discuss options for trading prediction market shares. If the trading platform is on-chain, MEV protection.

3.5 Market Resolution

3.6 Settlement

timestamps and suppresion attacks

3.7 Archiving

4 Security and Adversarial Considerations

5 Regulatory and Ethical Considerations

6 Case Studies

7 Future Directions and Open Challenges

8 Conclusion

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A Modular Workflow

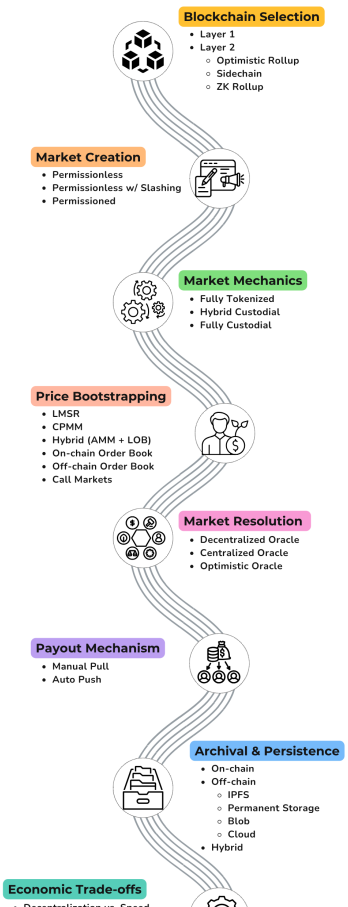
The modular workflow for DPMs, detailed in sub-sections A.1 through A.8 , outlines key components and decision pathways involved in platform development and operation. Initially, designers select an appropriate blockchain infrastructure, evaluating trade-offs between Layer-1 mainnet's decentralization and security versus Layer-2's cost and throughput efficiencies, considering bridging delays and associated security risks (Section A.1). Following this, market creation is structured by deciding on permissioned or permissionless market listing models (Section A.2). Next, the workflow addresses the tokenization of market outcomes (Section A.3) and implements suitable trading mechanisms such as automated market makers (AMMs), limit order books, or a hybrid combination of both (Section A.4). After market closure, the platform utilizes either centralized or decentralized oracle systems, including potential dispute resolution processes for contested outcomes (Section A.5). Subsequent stages involve selection of payout methods (automatic push or claim-based pull) and managing remaining funds or platform fees (Sections A.6). The market metadata archival is preserved on-chain logs or decentralized storage services such as IPFS and Arweave (Section A.7). Finally, economic trade-offs affect the popularity usability and adoption of the market (Section A.8). This modular workflow is visualized in Figure 1 below.

A.1 Underlying Blockchain Infrastructure

The base blockchain layer (Layer-1 vs. Layer-2) impacts transaction fees, finality guarantees, throughput, and censorship resistance for DPMs, influencing the efficiency and reliability of each stage within the DPM modular workflow. Selecting the underlying blockchain infrastructure constitutes the initial design decision within the modular workflow for DPMs.

Ethereum Layer-1 (L1) mainnet uses proof-of-stake consensus with explicit finality at approximately 13-minute intervals post-Merge, incurring transaction fees typically between $1 and $20 and supporting throughput of around 15–30 transactions per second (TPS) [12]. The relatively higher fees and limited throughput can restrict frequent trading activities and real-time market responsiveness within the DPM modular workflow.

Bitcoin's proof-of-work consensus results in probabilistic finality, generally confirmed after around 60 minutes, with throughput



around 7 TPS and fees from $1 to $5, impacting the settlement timing and reliability of outcome reporting and payouts in DPMs [8]. Ethereum's implementation of proposer/builder separation (PBS) and fair-ordering protocols addresses maximal extractable value (MEV) risks, mitigating transaction front-running and block reordering threats that could compromise fairness within market trading and resolution stages [9].

Layer-2 (L2) solutions, including optimistic and Zero Knowledge (ZK) rollups, reduce fees to few cents per transaction and improve throughput to thousands of TPS, facilitating high-frequency trading and timely market resolution. Optimistic rollups introduce withdrawal delays of around 7 days due to fraud-proof verification, complicating liquidity management and affecting timely payouts in the market settlement stage. ZK rollups, using validity proofs, offer quicker withdrawal options, beneficial for improving liquidity availability in the workflow [18]. However, the centralization of sequencers in some L2 platforms like Arbitrum introduces potential censorship issues, partially mitigated by reducing forced-inclusion delays from 24 to 4 hours, thereby influencing market openness and fairness during trading and settlement phases [3].

Bitcoin's simpler architecture provides resistance to blockchain reorganizations but lacks detailed MEV mitigation, potentially exposing prediction markets to transaction ordering vulnerabilities. Bridging infrastructure connecting L1 and L2 platforms introduces additional latency, complexity, and security risks, potentially disrupting seamless market transitions between layers. Multisig custodians and relay validators involved in bridging have historically been susceptible to financial exploits, highlighting critical risks to asset safety and liquidity flow within the modular workflow of DPMs.

Table 3 below summarizes the performance and decentralization characteristics of blockchain infrastructures relevant to the DPM modular workflow. These infrastructure characteristics shape the feasibility of subsequent market design elements, including market setup and initialization.

Explicit finality mechanisms, such as Ethereum's proof-of-stake consensus, provide certainty regarding transaction irreversibility after a specific period, enabling precise timing for market settlements and payouts [12]. In contrast, probabilistic finality, characteristic of Bitcoin's proof-of-work, introduces uncertainty, requiring multiple block confirmations, thereby delaying final market outcomes and associated payout distributions [8].

Table 3. Comparative Attributes of Blockchain Infra for DPM Platforms

Attribute	**Ethereum Mainnet**	**Polygon**	**Bitcoin**
Transaction Latency	∼12–15 sec/block; ∼13 min finality	∼2–5 sec/block	∼10 min/block; ∼60 min finality
Bridging Delays	∼7 days (Optimistic Rollups)	∼30 min–3 hrs (Checkpointing)	∼60 min (Sidechains)
Transaction Costs	High ($1–20+ per tx)	Very low ($0.01–0.05 per tx)	Moderate-high ($1–5+ per tx)
Throughput (TPS)	∼15–30 TPS	∼7,000 TPS (peak)	∼7 TPS
Validator Decentralization	High (∼600,000 validators)	Moderate (∼100–150 validators)	High (large miner base)
Censorship Resistance	High (MEV risk present)	Moderate (checkpoint risk)	High (minimal MEV risk)

A.2 Market Setup and Initialization

Market setup and initialization choices influence censorship resistance, regulatory compliance, and operational effectiveness of DPMs.

Permissionless Models: In permissionless setups, such as Augur, any user can initiate markets without centralized oversight, enabling maximum censorship resistance and innovation [10]. This openness creates potential regulatory challenges, illustrated by Augur's "assassination markets" controversy, where third-party moderation efforts (e.g., Predictions.Global) were limited in effectiveness. Economic penalties like validity and no-show reporter bonds address malicious or ambiguous market creation. Permissionless setups typically encourage standardized event templates to minimize ambiguity, though custom markets remain allowed. Collateral selection often involves endogenous (native) tokens (e.g., ETH for Augur), introducing volatility risk and regulatory complexity, balanced by potential hedging benefits when outcomes correlate with token value [25] [26].

Hybrid Governance Models (Permissionless with Centralized Slashing): Hybrid models allow permissionless market creation combined with centralized oversight mechanisms. Platforms like Polymarket use entities such as a Market Integrity Committee to enforce compliance and penalize markets violating rules [12] [10]. This partially decentralizes market listing but maintains centralized control, creating regulatory accountability and single points of control. Hybrid platforms also leverage standardized event templates to maintain clarity and reduce dispute risk, supplemented by custom market oversight. Collateral choices generally include stablecoins, reducing volatility exposure and regulatory uncertainty compared to endogenous tokens.

Permissioned Models: Fully permissioned setups, including Kalshi and PredictIt, require internal or regulatory reviews before listing markets, significantly reducing regulatory and operational risks by limiting ambiguous or unlawful

markets [8]. Market proposals typically use standardized event templates to ensure unambiguous resolution, supported by rigorous internal review. Collateral is generally stablecoins or fiat currency, minimizing volatility and simplifying regulatory compliance. Strict implementation of KYC/AML protocols further reduces regulatory exposure, though it introduces operational overhead and restricts market diversity [10].

Table 4 summarizes operational implications for each market setup, guiding stakeholders in selecting appropriate governance models based on desired censorship resistance, compliance requirements, and collateral management.

Table 4. Comparative Evaluation of Market Creation and Permission Models

Market Setup	**Benefits**	**Drawbacks**	**Platforms**
Permissionless	Open participation, censorship resistance, flexible collateral (endogenous tokens)	Regulatory risks, potential misuse, collateral volatility exposure	Augur, PlotX, Gnosis
Permissionless with Slashing	Openness balanced by centralized enforcement, stable collateral (stablecoins)	Centralized oversight, regulatory accountability	Polymarket, UMA*
Permissioned	Compliance, controlled market environment, stable collateral (stablecoins, fiat)	Limited diversity, lower censorship resistance, operational overhead	Kalshi, PredictIt, Stox

*UMA is not a DPM in the traditional sense; it is mentioned here due to its Permissionless with Slashing model usage.

A.3 Market Mechanics and Share Custodianship

Market mechanics and share custodianship directly influence the operational efficiency, liquidity, and decentralization of DPMs.

Binary markets offer intuitive simplicity and consolidated liquidity, facilitating hedging via straightforward YES/NO token pairs, as exemplified by Polymarket's ERC-1155 tokens redeemable for $1 upon outcome resolution [25] [17] This binary structure enables users to hedge risks akin to insurance instruments, although extensive hedging activities by risk-averse participants can temporarily distort prices, potentially diverging from true event probabilities until arbitraged by informed traders [16].

In contrast, combinatorial markets, which enable complex bets on interdependent outcomes, significantly enhance theoretical information aggregation by capturing correlations and conditional probabilities but impose exponential computational complexity (#P-hard for LMSR market makers) and cognitive burdens on users [6] [7]. Thus, combinatorial markets have remained largely experimental, given the difficulty in matching trades efficiently without algorithmic support and substantial fragmentation of liquidity (Pennock & Sami, 2007).

Markets inherently start with zero traders, necessitating careful liquidity bootstrapping to avoid under-collateralization and price manipulation. Safe market initialization requires at least two traders with opposing views (or one trader matched by an automated market maker) to create balanced, fully collateralized initial positions. This balanced issuance is critical to avoid under-collateralization and ensure meaningful initial price discovery; for instance, Polymarket only mints YES and NO shares simultaneously upon matched buyer-seller orders that sum exactly to $1 collateral [8]. Similarly, Augur mandates traders to initially collateralize all outcomes fully, thus guaranteeing solvent market conditions from inception [25].

Custodianship models significantly affect decentralization, regulatory visibility, and systemic trust. Fully tokenized on-chain shares (ERC-20/ERC-1155) maximize decentralization and composability within broader DeFi ecosystems. Conversely, centralized custodial models, though enabling simpler KYC/AML integration, inherently risk censorship and unilateral asset control, undermining core decentralized principles [10]. Polymarket notably adopted more centralized custodianship following regulatory enforcement by the CFTC, underscoring the practical impacts of regulatory pressures on market design [20]. Table 5 below summarizes custodianship models, highlighting their implications for composability, decentralization, and systemic trust.

Table 5. Comparative Analysis of Custody Models for Outcome Tokenization

Custody Model	**Composability**	**Regulatory Visibility**	**Systemic Trust & Risk**	**Decentralization**	**Examples**
Fully Tokenized (ERC-20 / ERC-1155)	High (DeFi interoperability)	High (public)	Smart-contract reliant	High	Augur, Gnosis
Hybrid Custodial	Moderate	Moderate-high (KYC/AML)	Partial central reliance	Moderate	Polymarket, UMA
Fully Centralized	Low (none)	Low visibility, high control	Centralized, censorship risk	Low	Kalshi, PredictIt

A.4 Price Bootstrapping and Liquidity Mechanisms

Price bootstrapping and liquidity provision enable initial price formation and continuous trading in DPMs. Automated Market Makers (AMMs) address the bootstrapping challenge by providing immediate liquidity and initial price setting without requiring initial trading counterparties. The Logarithmic Market Scoring Rule (LMSR), introduced by [16], utilizes a convex cost function: FORMULA REMOVED where b>0 defines liquidity depth [23]. LMSR adjusts instantaneous outcome prices using a softmax function to maintain valid probability distributions. LMSR limits liquidity provider losses to a maximum of $b \ln N$ for a market with N outcomes, providing a known loss boundary [7]. Selecting the liquidity

parameter b presents practical challenges; inappropriate values can result in either excessive price sensitivity or limited market responsiveness [16]. Constant Product Market Makers (CPMM), such as those based on the invariant:

$$x \cdot y = k$$

manage liquidity by holding two token reserves, with outcome prices determined by the ratio of these reserves [1]. Arbitrage ensures prices generally sum to a valid probability distribution. However, CPMMs expose liquidity providers to divergence loss (impermanent loss), where large shifts in outcome probabilities leave providers holding primarily the less valuable tokens at resolution [5]. Unlike LMSR, CPMM does not limit potential losses, thus introducing additional financial risk despite operational simplicity and compatibility with decentralized finance (DeFi) protocols. Hybrid models integrating AMMs with limit order books (LOBs), as implemented by platforms like Polymarket, combine continuous liquidity provided by AMMs with liquidity precision offered by order books [12]. These hybrid systems facilitate arbitrage-driven adjustments that stabilize market prices and maintain accurate probability reflections, balancing AMM simplicity with order book responsiveness.

Alternative liquidity mechanisms, including pure on-chain order books and periodic call markets, introduce distinct trade-offs, which are detailed in Table 1. Pure on-chain order books offer precise pricing but encounter issues related to transaction latency and high gas fees, whereas off-chain order books mitigate these problems at the expense of decentralization [8]. Call markets aggregate trades at regular intervals to improve liquidity but face latency issues and potential arbitrage vulnerabilities due to delayed execution [11].

Table 6 contrasts liquidity mechanisms used in decentralized prediction markets by evaluating their risk characteristics, price formation methods, and operational attributes. Each mechanism presents unique trade-offs, balancing liquidity provider risks, system complexity, arbitrage vulnerabilities, and operational efficiency.

Table 6. Comparative Analysis of Liquidity Mechanisms

Liquidity Mechanism	**Loss Limitation**	**Price Formation**	**Complexity**	**Arbitrage Exposure**	**Operational Latency**
LMSR	Yes	Softmax pricing	Moderate	Moderate	Low
CPMM	No	Reserve ratios	Low	High	Low
Hybrid (AMM + LOB)	Partial	Mixed	High	Moderate	Low to Moderate
On-chain Order Book	No	Order matching	High	Moderate	High
Off-chain Order Book	No	Order matching	Moderate	Moderate	Low
Call Markets	No	Batch matching	Moderate	High	Moderate to High

A.5 Market Resolution and Dispute Models

Market resolution and dispute models are essential for accurate and fair settlement in DPMs, directly affecting market credibility and operational continuity. Single-trusted entity models utilize a single oracle, such as the Associated Press, enabling efficient and rapid finalization. However, reliance on a single entity introduces centralization risks, including vulnerability to bribery and biased reporting [12]. Economic deterrents like escrow bonds may not prevent manipulation if potential gains surpass the penalties.

Decentralized oracle collectives distribute decision-making across multiple oracles. Chainlink aggregates data from independent nodes using median or majority votes, with nodes required to stake tokens, incentivizing accuracy and penalizing errors. MakerDAO uses governance-based collectives, electing trusted data feeders through community governance to enhance transparency and reduce individual collusion risks [12]. These collectives, however, experience higher latency and complexity and remain susceptible to coordinated manipulation and governance capture. UMA's Data Verification Mechanism (DVM) dynamically calculates stakes based on the Cost of Corruption versus Profit from Corruption, aiming to ensure corruption costs always exceed potential profits [19]. Realitio employs a tiered dispute escalation process, resolving uncontested outcomes swiftly while disputed cases escalate to external arbitrators like Kleros, balancing speed and decentralization.

Self-settling models depend entirely on internal incentives to align reporter behaviour around Schelling points. Augur exemplifies this, with REP tokens staked to encourage reporting consistent with the majority's expectations. Disputes trigger increased staking requirements and potentially protocol forks, reinforcing truthful reporting through economic incentives [25]. Yet, these mechanisms are vulnerable to coordinated bribery and external manipulation, especially when attackers exploit side-bet strategies [13]. An attacker-defender payoff matrix clearly illustrates these economic vulnerabilities, highlighting equilibrium conditions shaped by manipulation costs and incentives.

Table 7 provides a comparative evaluation of oracle types, outlining operational characteristics, specific risks, and representative examples. It succinctly differentiates between single trusted entities, decentralized oracle collectives, and self-settling oracles by highlighting advantages such as decentralization levels and inherent vulnerabilities like susceptibility to bribery.

Table 8 presents a detailed incentive compatibility payoff matrix for Augur's REP staking mechanism. It describes four distinct situations with different combinations of attacker and honest stakes, and potential rewards if an attacker succeeds versus consequences if defenders successfully prevent the attack. The first scenario shows stability when no attack occurs and reporting remains honest, generating standard rewards. In the second scenario, a small attacker stake versus a larger honest stake renders attacks unlikely due to limited attacker profitability. However, in scenarios with higher attacker stakes or significant external bets, the table demonstrates potential attacker profitability, making bribery eco-

Table 7. Comparative Evaluation of Market Resolution Types

Oracle Type	Pros	Cons	Examples
Single Trusted Entity	Fast resolution; clear accountability	Single failure point; high censorship risk	Associated Press, Chainlink
Decentralized Oracle Collective	Distributed trust; censorship resistance	Higher complexity; risk of collusion	UMA, Realitio, MakerDAO
Self-Settling (Schelling-Point)	No external trust; economic incentives	Vulnerable to bribery; fork complexity	Augur, Truthcoin, Kleros

nomically viable and possibly leading to the breakdown of the Schelling point equilibrium.

Table 8. Oracle Incentive Compatibility Payoff Matrix (Example: Augur REP Game)

Scenario	Attacker Stake (A)	Honest Stake (H)	Attacker Reward if Successful	Defender Reward if Successful	Equilibrium Result
No Attack, Honest Majority	\$0	\$1,000,000	\$0	\$0 (normal fees)	Honest Reporting Stable
Attack, Low Attacker Stake	\$500,000	\$1,000,000	\$10,000,000	Attacker's stake (slashed)	Honest Reporting Stable (Attack Unlikely)
Attack, High Attacker Stake	\$1,500,000	\$1,000,000	\$10,000,000	Attacker's stake (slashed)	Attacker Profitable (Bribe Possible)
Coordinated Side-Bet Bribery	\$2,000,000	\$1,000,000	\$20,000,000 (external bets)	Attacker's stake (slashed)	Attack Profitable (Schelling Point Fails)

To mitigate vulnerabilities identified in Table 6, designers can implement thresholds for stake escalation and require proportionally larger attacker stakes relative to honest stakes to disrupt equilibrium [25]. Additionally, periodic audits or community-based moderation processes may deter coordinated attacks, reinforcing equilibrium stability [12].

A.6 Payout and Redemption Mechanisms

DPMs commonly implement push or pull payout mechanisms, each presenting distinct trade-offs. Push payout models automatically distribute winnings once market outcomes are resolved, reducing user interaction requirements. However, they face scalability and cost constraints due to increased gas usage, especially in scenarios involving numerous recipients [12]. Polymarket uses a hybrid model on the Polygon network with USDC that mimics push mechanisms via meta-transactions, effectively removing direct user gas fee payments [20] Castle Capital, 2024). Conversely, Augur utilizes a pull mechanism, requiring users to manu-

ally redeem tokens to collect payouts. This approach prioritizes decentralization but increases the complexity and cost associated with claiming rewards [24].

Gasless redemption mechanisms aim to improve usability by eliminating user gas fees, typically relying on third-party relayers to cover transaction costs. Such mechanisms enhance accessibility but introduce dependencies on centralized components, creating potential points of failure or censorship (Castle Capital, 2024).

Time-bounded redemption windows set deadlines for payout claims, aiming to reduce inefficiencies caused by permanently locked collateral. These mechanisms can enhance capital utilization but raise ethical and regulatory concerns, including issues related to unclaimed property regulations and user fairness [12]. Major platforms like Augur and Polymarket generally favor open-ended claims to uphold continuous user rights.

Surplus management deals with residual funds from unclaimed or locked winnings. Permanent locking maintains explicit user ownership at the expense of economic efficiency over time, exemplified by Augur's approach [12]. Redistribution methods periodically allocate surplus to liquidity providers or active users, increasing capital efficiency but potentially creating incentives to abandon minor balances intentionally. Governance-controlled treasuries allow directed surplus management, balancing efficiency against the risk of centralized governance influence and regulatory attention [2].

Table 9 compares surplus management methods in decentralized prediction markets, evaluating their economic efficiency, ethical considerations, and regulatory implications. It identifies trade-offs between preserving explicit user ownership and maximizing capital efficiency, highlighting potential governance risks and compliance requirements for different mechanisms.

A.7 Archival, Transparency, and Meta-Data Persistence

Archival, transparency, and metadata persistence within DPMs ensure verifiable and accessible records, directly impacting market integrity and governance processes.

Critical metadata, such as market states, transaction histories, and resolution outcomes, inherently benefit from blockchain immutability and cryptographic verification [10], [12]. Augur v2 stores metadata, including user profit/loss computations, directly on-chain, providing immediate access without external archives. This design increases transparency but also results in higher transaction costs and larger blockchain state size [14].

Off-chain metadata - including market descriptions, resolution criteria, and user-generated content - are typically stored in decentralized storage solutions due to blockchain capacity constraints [4]. IPFS (InterPlanetary File System) employs peer-to-peer, content-addressable storage using cryptographic hashes, verifying content authenticity through immutable identifiers. IPFS's availability depends on node operators maintaining persistent storage through pinning, without central points of failure [22]. Arweave offers an economic incentive structure

Table 9. Comparative Evaluation of Surplus Management Mechanisms

Mechanism	Description	Economic Efficiency	Ethical Considerations	Regulatory Implications	Example Platforms
Permanent Locking	Surplus funds locked indefinitely post-resolution	Low	Maintains explicit user ownership	Low regulatory risk	Augur, Gnosis
Redistribution to LPs/Stakers	Surplus periodically redistributed to liquidity providers	High	May incentivize intentional abandonment	Moderate, potential property concerns	UMA, Realitio
Governance-controlled Treasury	Surplus directed by governance structures	Moderate–High	Potential governance influence risk	Moderate–High, regulatory attention	Polymarket, SX Network
Burning Tokens	Surplus tokens destroyed to reduce supply	Moderate–High	Minimal ethical concerns	Moderate, regulatory stance uncertain	Truthcoin (theoretical)
Returning to Original Funders	Surplus returned to initial market creators	Moderate	Risks manipulation incentives	High, KYC and AML compliance concerns	Kalshi

combined with a "blockweave" architecture for permanent data storage, providing perpetual availability and resistance to censorship [28].

Recent updates to Ethereum, such as proto-danksharding, provide ephemeral "blob" storage. These storage blobs temporarily allow for large metadata availability and cryptographic verification. However, their short-term nature necessitates subsequent migration to persistent storage solutions [14].

The archival model chosen by a DPM influences governance outcomes and resilience against manipulation. Persistent archival supports retrospective audits critical for resolving disputes and maintaining accountability of oracle activities [12]. Decentralized archival mechanisms prevent centralized control from suppressing or altering market data, enabling community-driven governance or protocol forks when required [28].

Table 10 compares archival methods such as blockchain storage, IPFS, Arweave, Ethereum blob storage, and hybrid models. It details each method's durability, authenticity, and accessibility, highlighting their distinct operational trade-offs and cost implications for decentralized prediction markets.

A.8 Economic Trade-Offs in DPM Design

The design of DPMs involves inherent economic trade-offs affecting platform adoption, integrity, and resilience. This analysis examines these trade-offs across four dimensions: decentralization versus speed, liquidity versus capital efficiency, incentive robustness versus usability, and expressiveness versus composability, with agility noted as an additional consideration.

A fundamental trade-off occurs between decentralization and execution speed. Fully decentralized DPMs, such as early Augur versions, achieve censorship re-

Table 10. Comparative Evaluation of Archival Methods for Decentralized Prediction Markets

Archival Method	**Description**	**Durability & Persistence**	**Authenticity & Integrity**	**Accessibility & Discovery**	**Example Platforms**
Blockchain On-chain Storage	Directly store metadata and outcomes on-chain (e.g., Ethereum).	Extremely high (immutable, perpetual)	High authenticity (cryptographic guarantees)	Excellent (immediate, global nodes)	Augur (partial), Gnosis
IPFS (Inter-Planetary File System)	Decentralized, peer-to-peer, content-addressable storage.	Medium (requires community pinning)	High (content hashes provide tamper-evidence)	Good (distributed nodes, variable retrieval speeds)	Augur, Polymarket
Arweave Permanent Storage	Blockchain-based storage with economic incentives for permanent retention.	Very high (economically incentivized permanence)	Very high (blockchain-backed immutability)	High (permanent, redundant node distribution)	Mirror.xyz, RedStone Oracles (experimental)
Ethereum Blob Storage	Temporary large-data storage via Ethereum blobs (proto-danksharding).	Low (temporary, ephemeral data availability)	High (cryptographic authenticity guaranteed short-term)	Moderate (short-term retrieval from Ethereum nodes)	Ethereum L2s (Optimism, Arbitrum)
Centralized Cloud Storage	Traditional cloud services (AWS, Google Cloud).	Variable (single point of failure risk)	Low–moderate (trust reliant on centralized operator)	High (fast retrieval, easy indexing)	Early centralized prediction platforms
Hybrid Storage Model	Combination: blockchain on-chain pointers plus decentralized or permanent storage.	High (leverages strengths of multiple methods)	High (on-chain hashes guarantee authenticity)	Very high (multiple redundancy points, robust discovery)	Polymarket, UMA

sistance but experience latency and high transaction costs due to reliance on Ethereum's mainnet [8] [24]. Hybrid models, including Polymarket, employ off-chain order matching and on-chain settlements or dedicated sidechains to increase throughput and improve usability, albeit with the addition of trust assumptions and centralization risks [12]. Layer-2 technologies like state channels and rollups offer alternative methods to balance decentralization and performance [21].

Liquidity provision versus capital efficiency presents another critical trade-off. Automated market makers (AMMs), such as Hansonian market scoring rules or constant product market makers (CPMM), deliver continuous liquidity by committing substantial collateral, reducing capital efficiency [16] [1]. Conversely, order-book-based models maximize capital efficiency by avoiding idle capital but can encounter liquidity issues and impaired price discovery, as noted in Augur v1 markets [27]. Platforms like Gnosis address some of these challenges through conditional markets that dynamically allocate capital among outcomes [15].

Incentive robustness and usability reflect another key trade-off. Augur's multi-stage dispute mechanisms and token staking enhance manipulation resistance but complicate user experience and slow resolution processes [24] [12]. In contrast, simplified oracle solutions, such as UMA's optimistic oracle, offer streamlined resolution processes but carry greater risks of manipulation. Hierarchical or two-tiered dispute frameworks (e.g., Pisa watchtowers) seek to address these issues by maintaining manipulation resistance while minimizing complexity [21].

Expressiveness versus composability represents an additional design dimension. Highly expressive combinatorial market structures, such as those enabled by Gnosis's Conditional Tokens, allow detailed market configurations but reduce interoperability and composability with other decentralized finance (DeFi) systems due to technical complexity [15]. Simpler binary or categorical markets increase interoperability and composability but sacrifice detailed market structuring capabilities.

B Satoshi HBO Market

C Example instantiation of formal definitions

In section 2.4, we discussed an example market concerning who the HBO documentary 'Money Electric' would name as Satoshi Nakamoto. In this section, we will see how this fits the definitions of a market, prediction market system, and the Arrow–Debreau special case. As discussed in Section 3.3, Polymarket employs a market mechanism we call a yes/no bundle (YNB), as opposed to winner-take-all (WTA). YNB requires an extra step in the definitions so we will do a first pass with a simplified WTA submarket, and then add the full YNB market.

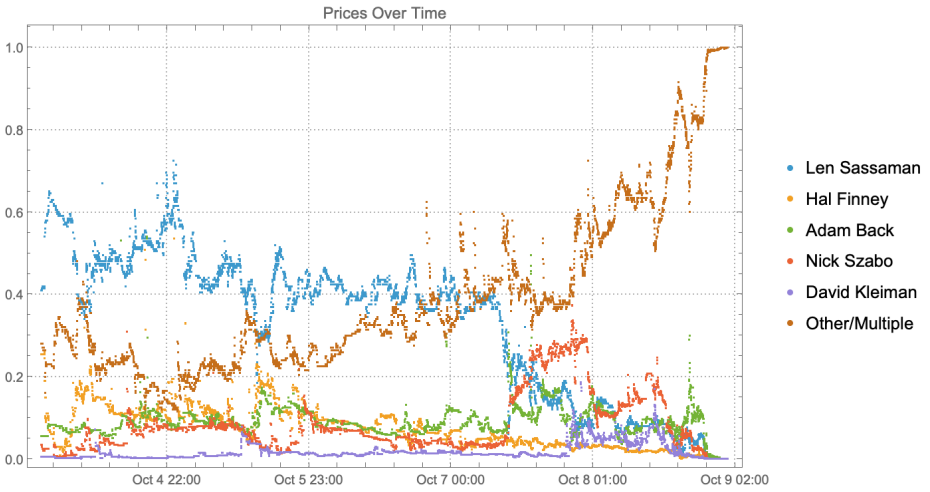


Fig. 2. The price movements for 6 leading candidates in the Polymarket market for who would be named as Satoshi Nakamoto in the HBO documentary 'Money Electric' which aired the evening of October 8.

C.1 Pass 1: Single WTA Market

Consider a simplified market that questions whether one specific candidate, *e.g.,* Hal Finney, is named as Satoshi: yes or no. If through unforeseen circumstances, who the documentary names is not verifiable by the air date, the market resolves to no.

Recall Definition 1 of a market:

Definition 3 (Market). *A (single) market is a tuple* $M = (E, \Omega, J, R)$*, where* E *is a well-defined uncertain event,* Ω *is a nonempty outcome space for* E*,* J *is a finite index set of contract labels ("shares"), and* $R = (R_j)_{j \in J}$ *are nonnegative payoff functions with* $R_j : \Omega \to \mathbb{R}_{\geq 0}$*. We assume* $|J| \geq |\Omega|$ *and we require* outcome distinguishability *on* Ω*:*

$$\forall\, \omega \neq \omega' \in \Omega \;\; \exists\, j \in J : \;\; R_j(\omega) \neq R_j(\omega').$$

When M *resolves to* $\omega_M \in \Omega$*, one unit of share* $j \in J$ *pays* $R_j(\omega_M)$ *(in units of* $\mathcal{N}$ *defined below).*

Event E is whether or not Hal Finney is named as Satoshi in the documentary.

Ω is the set of resolution outcomes the market recognizes for E—the labels the system can publish at settlement. For this Hal-only binary market the outcome space is $\Omega = \{\mathsf{True}, \mathsf{False}\}$. Here True means the documentary (per the market's stated criteria) identifies Hal Finney as Satoshi; False aggregates all other possibilities (Hal not named, someone else named, no one named, the film does not air, or the identification is not verifiable by the resolution deadline).

We require that Ω contain no redundant labels. A label is redundant if it does not change at least one contract's payoff: $\omega \sim \omega' \iff \forall j \in J,\ R_j(\omega) = R_j(\omega')$. For example, "Hal is named and it is raining" and "Hal is named and it is not raining" are distinct real-world states, but they cannot both appear in Ω since they both map to True. The restriction can be written as:

$$\forall\, \omega \neq \omega' \in \Omega \ \ \exists\, j \in J :\ R_j(\omega) \neq R_j(\omega').$$

In a prediction market, there are a set of shares. If we label them and add them all to an index set, that set is J. For this example, $J = \{\mathsf{YES}, \mathsf{NO}\}$: Hal Finney is named (yes) and else (no). This is a normal case where each share in J corresponds to an outcome in Ω but it is possible that the number of shares could exceed the number of outcomes.[16]

J is the index set of contract labels—the names of the tradeable shares. In this binary market we take $J = \{\mathsf{YES}, \mathsf{NO}\}$.

The labels get their meaning from the component payoff functions $R_j : \Omega \to \mathbb{R}_{\geq 0}$. In this example, a payoff of 1 is given for shares that correctly predict the outcome and 0 otherwise. This means $R_{\mathsf{YES}}(\mathsf{True}) = 1$, $R_{\mathsf{YES}}(\mathsf{False}) = 0$, $R_{\mathsf{NO}}(\mathsf{True}) = 0$, $R_{\mathsf{NO}}(\mathsf{False}) = 1$.

Recall Definition 1 of a prediction–market system $\mathcal{S} = (\mathcal{M}, \mathcal{N}, \mathsf{Res})$: $\mathcal{M}$ is the (countable) catalog of markets; $\mathcal{N}$ is the numeraire (unit of account used to price and settle claims); and $\mathsf{Res} = \{\mathrm{res}_M\}_{M \in \mathcal{M}}$ assigns to each market M a resolution register that is initially $\perp$ and flips exactly once to some $\omega_M \in \Omega_M$. When $\mathrm{res}_M \neq \perp$, we set $\omega_M := \mathrm{res}_M$ and each unit of label $j \in J$ settles for $R_j(\omega_M)$ units of $\mathcal{N}$.

The market tuple $M = (E, \Omega, J, R)$ specifies *what* to pay *given* an outcome (via R). The register res_M is the system's single source of truth for *which* outcome actually occurred: before resolution $\mathrm{res}_M = \perp$ (no settlement), after resolution $\mathrm{res}_M = \omega_M \in \Omega_M$ (settlement applies).

Polymarket instantiates $\mathcal{S}$ with $\mathcal{M}$ equal to its live and historical markets, $\mathcal{N}$ the USD–denominated stablecoin USDC, and Res implemented by its on–chain resolution process (e.g., UMA's optimistic oracle) that writes a single outcome to each res_M.

For the Hal–only binary market, the system maintains a resolution register $\mathrm{res}_{M_{\mathrm{Hal}}} \in \{\perp\} \cup \Omega$ with $\Omega = \{\mathsf{True}, \mathsf{False}\}$ (i.e., "yes/no" to the proposition). The register is initially $\perp$ and, after the platform's resolution process completes, the oracle writes a single value $\omega_{M_{\mathrm{Hal}}} \in \Omega$ to the register.

Set $\omega_{M_{\mathrm{Hal}}} = \mathsf{True}$ iff the documentary (per stated criteria) identifies *Hal Finney* as Satoshi; otherwise set $\omega_{M_{\mathrm{Hal}}} = \mathsf{False}$.

[16] For example, consider a market of where Newcastle United (NUFC) finishes in the 2024-35 English Premier League season. Since there are 20 teams, the outcome has 20 possible labels: positions 1 to 20. Shares could exist for each of the 20 positions. But the outcome could also settle shares for whether NUFC finishes in the top 5 (which is relevant to champions league admittance), or shares on finishing in the bottom 3 (which is relevant to relegation).

Shares are fully collateralized to \$1 in the numeraire $\mathcal{N}$ (USDC): a unit of YES pays 1 USDC at True and 0 USDC at False; a unit of NO pays 1 USDC at False and 0 USDC at True. Formally,

$$R_{\mathsf{YES}}(\mathsf{True}) = 1, \quad R_{\mathsf{YES}}(\mathsf{False}) = 0, \qquad R_{\mathsf{NO}}(\mathsf{True}) = 0, \quad R_{\mathsf{NO}}(\mathsf{False}) = 1.$$

In the aired documentary, *Peter Todd* was named; therefore

$$\mathrm{res}_{M_{\mathrm{Hal}}} = \omega_{M_{\mathrm{Hal}}} = \mathsf{False},$$

and each unit settles as

$$\mathsf{YES} \ \to \ 0 \text{ USDC}, \qquad \mathsf{NO} \ \to \ 1 \text{ USDC}.$$

This market is a winner–take–all (Arrow–Debreu) special case: there is a bijection $\iota : J \to \Omega$ and payoffs $R_j(\omega) = \mathbf{1}\{\omega = \iota(j)\}$. Hence, for each $\omega \in \Omega$, exactly one label pays 1 and all others pay 0. In the prediction–market system, the resolution register $\mathrm{res}_M \in \{\perp\} \cup \Omega$ is initially $\perp$ and flips exactly once to $\omega_M \in \Omega$; one unit of label $j \in J$ then settles for $R_j(\omega_M)$ units of the numeraire $\mathcal{N}$.

C.2 Pass 2: YNB Market

Families. Given an index set C, a *family of markets* indexed by C is a map $c \mapsto M_c$; we write $\{M_c\}_{c \in C}$. Each $c \in C$ names one market in the family.

Instantiation for the HBO event. Let C be the set of candidates (e.g., {Szabo, Sassaman, Back, . . . , Other/Multipl
Polymarket lists a family $\{M_c\}_{c \in C}$, one binary market per candidate:

$M_c = (E_c, \Omega_c, J_c, R^{(c)}), \quad E_c =$ "The documentary identifies c as Satoshi", $\Omega_c = \{\mathsf{True}, \mathsf{False}\}$, $J_c = \{\mathsf{YES}, \mathsf{NO}$

with indicator payoffs

$$R^{(c)}_{\mathsf{YES}}(\mathsf{True}) = 1, \ R^{(c)}_{\mathsf{YES}}(\mathsf{False}) = 0, \qquad R^{(c)}_{\mathsf{NO}}(\mathsf{True}) = 0, \ R^{(c)}_{\mathsf{NO}}(\mathsf{False}) = 1.$$

System-level mapping to Polymarket. Polymarket instantiates the prediction–market system $\mathcal{S} = (\mathcal{M}, \mathcal{N}, \mathsf{Res})$ as follows:

- $\mathcal{M}$ contains all candidate markets $\{M_c\}_{c \in C}$ under the HBO event (plus all other site markets).
- $\mathcal{N}$ is USDC (USD–denominated stablecoin). Each unit share settles to 0 or 1 USDC according to $R^{(c)}$.
- $\mathsf{Res} = \{\mathrm{res}_M\}_{M \in \mathcal{M}}$ gives each M_c a register $\mathrm{res}_{M_c} \in \{\perp\} \cup \Omega_c$, initially $\perp$, that flips exactly once to $\omega_{M_c} \in \Omega_c$ when the platform's oracle process (e.g., UMA's optimistic oracle) writes the outcome on-chain.

Settlement in our notation is $R^{(c)}_j(\omega_{M_c})$ USDC for each unit of label $j \in J_c$.

What resolved in the HBO case. The documentary focused on *Peter Todd*, which Polymarket grouped under Other/Multiple. Hence

$$\omega_{M_{\text{Other/Multiple}}} = \text{True} \quad \text{and} \quad \omega_{M_c} = \text{False} \ \text{ for all named } c \neq \text{Other/Multiple}.$$

Equivalently: Other/Multiple: YES paid 1 USDC; every named candidate's NO paid 1 USDC; the corresponding YES paid 0 USDC.

Relation to Arrow–Debreu (single book) vs. Polymarket (bundle). A single winner–take–all (Arrow–Debreu) market would model the event as one market $M^\star = (E^\star, \Omega^\star, J^\star, R^\star)$ with $\Omega^\star = C$ and $J^\star$ in bijection with $\Omega^\star$, so exactly one label pays 1 at resolution. Polymarket instead uses a *bundle of binaries* $\{M_c\}_{c\in C}$ (one YES/NO pair per candidate). This is a different microstructure: prices live in separate order books, and each market M_c resolves independently via its own register res_{M_c}.

Negative risk (Polymarket's cross-market linkage). When the parent event is configured as *negative risk*, Polymarket enables a conversion that links prices across the family: informally, a NO on candidate i is convertible into the basket of YES on all $j \neq i$. At the price level this couples the binaries so that, up to frictions,

$$\text{price}(\text{NO}_i) \ \approx \ \sum_{j\neq i} \text{price}(\text{YES}_j) \quad \Longrightarrow \quad \sum_{j\in C} \text{price}(\text{YES}_j) \ \approx \ 1,$$

making the bundle trade *as if* it were a single Arrow–Debreu book while remaining, in our abstraction, a family $\{M_c\}$ with distinct $(E_c, \Omega_c, J_c, R^{(c)})$ and registers res_{M_c}.

D Leverage

Edge, capital, and "leverage" in binary prediction shares. Let a YES share pay \$1 if the event occurs and \$0 otherwise. If the market price is $v \in (0, 1)$ and your subjective probability is p^*, then the expected profit per share is

$$\mathbb{E}[\pi] = p^* - v.$$

Although the dollar edge per share may look small (e.g., $p^* = 0.60$ vs. $v = 0.48$ gives $\mathbb{E}[\pi] = 0.12$), the capital at risk is only the purchase cost v. The expected *return on capital* for that trade is

$$\text{ROC}_{\text{EV}} = \frac{p^* - v}{v} = \frac{0.12}{0.48} \approx 25\%,$$

which is large. If price moves toward your view before resolution, you can also exit early and realize gains without tying up capital to maturity.

Sizing the position with Kelly (from first principles). Suppose you invest a fraction f of current wealth W into the share at price v. You buy fW/v shares. If the event occurs (probability p^*), post-settlement wealth is

$$W^+ = W - fW + \frac{fW}{v} = W\big[1 + f\,(v^{-1} - 1)\big],$$

and if it does not occur (probability $1 - p^*$), wealth is $W^- = W(1 - f)$. Kelly sizing chooses f to maximize expected log-wealth:

$$\max_{0 \le f < 1} \; p^* \ln\big(1 + f(v^{-1} - 1)\big) + (1 - p^*) \ln(1 - f).$$

Differentiating and setting the derivative to zero yields the closed-form optimal fraction

$$f^* \;=\; \frac{p^* - v}{1 - v}.$$

Equivalently, writing the "net odds" on a \$1 stake as $b = (1 - v)/v$, the familiar Kelly form is $f^* = (b\,p^* - (1 - p^*))/b$. For the running example ($p^* = 0.60$, $v = 0.48$), $f^* = (0.60 - 0.48)/0.52 \approx 0.231$, i.e., about 23% of bankroll on the YES side.[17]

Practical notes. Kelly is optimal for log-utility over *repeated, independent* favorable bets with known p^*. In markets, p^* is estimated, bets are correlated, capital is finite, and fees and liquidity matter. Practitioners therefore use fractional Kelly (e.g., $f = \lambda f^*$ with $\lambda \in [0, 1]$, often $\lambda = \frac{1}{2}$) to reduce drawdowns and model-error risk. Time to resolution also matters: tying up v until maturity lowers annualized return unless you recycle capital via interim exits.

[17] For shorting a YES share priced at v (i.e., taking NO), replace v by $1 - v$ and p^* by $1 - p^*$ in the formula, or derive symmetrically.