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Prediction Markets as Sociotechnical Assemblages

Specialized Competition and the Financialization of Uncertainty

by

Helen Wu

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Faculty Advisor: Dr. Anthony Lee Zhang
Preceptor: Dr. Linnea Turco

Abstract

This thesis reconceptualizes prediction markets as sociotechnical assemblages rather than simple information aggregation mechanisms. Drawing on empirical analysis of 489 election contracts on Polymarket, I demonstrate how these markets operate through structured trader ecologies and hierarchical information flows that challenge conventional economic understandings. Contrary to efficiency-centered frameworks that treat prediction markets as neutral aggregators of distributed knowledge, I show how they function as distinctive social arrangements that distribute agency across human and non-human elements while creating multiple forms of value. The assemblage framework reveals how prediction markets achieve forecasting accuracy despite systematic inefficiencies, through specialized competition rather than democratic wisdom aggregation. This theoretical reframing contributes to economic sociology by illuminating new forms of economic coordination and digital sociality that emerge through blockchain-based financial platforms.

Keywords: prediction markets, sociotechnical assemblages, distributed agency, digital sociality, economic sociology, market microstructure, blockchain, financial forecasting

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1 INTRODUCTION

Who will be the next Pope? Which candidate will win the Australian Prime Minister election? How much will the Fed increase interest rates? Contemporary society increasingly subjects human expectations about the future to processes of financialization. Events once considered outside the domain of market valuation—from electoral outcomes to papal selections—are now priced and traded on decentralized prediction markets, where participants wager on uncertain futures through blockchain-based platforms. This transformation represents what Appadurai terms "the financialization of uncertainty"—the progressive extension of market logics into domains previously governed by alternative modes of social coordination and collective judgment.[1]

The emergence of blockchain-based decentralized prediction markets has dramatically expanded the scope and significance of this financialization process. On prediction markets, users purchase tokens representing either "Yes" or "No" for specific questions, with prices ranging from $0 to $1, functioning as implied probabilities. A contract trading at $0.75 for "*Will Candidate X win the election?*" suggests a 75% likelihood of that outcome occurring, according to the collective judgment of market participants. By the 2024 US Presidential Election, a single prediction market on Polymarket—the largest global prediction market—had generated over $3.68 billion in trading volume, engaging nearly 88,000 participants—a scale unimaginable in previous prediction market implementations. This expansion represents a significant evolution from earlier market implementations, transforming how individuals engage with future uncertainty.[2]

Conventional accounts frame these markets primarily as information aggregation mechanisms—digital extensions of Hayek's price system that efficiently transform distributed knowledge into accurate forecasts.[3] As Wolfers and Zitzewitz argue, prediction markets "seem to effectively aggregate dispersed information about likely future events," providing probability estimates superior to alternative forecasting methods.[4] Similarly, proponents of the "wisdom of crowds" thesis suggest these markets harness collective intelligence through aggregating diverse independent judgments.[5] In both frameworks, any observed inefficiencies or inaccuracies represent temporary technical problems to be resolved through increased participation, improved market design, or enhanced liquidity.

The central paradox this thesis explores is how prediction markets achieve forecasting accuracy despite their systemic inefficiencies and extreme participation inequality.

1. Arjun Appadurai, *Banking on Words: The Failure of Language in the Age of Derivative Finance* (Chicago: University of Chicago Press, 2016).

2. Michel Aglietta, *Money: 5,000 Years of Debt and Power* (La Vergne: Verso, 2018).

3. F. A. Hayek, "The Use of Knowledge in Society," *The American Economic Review* 35, no. 4 (1945): 519–530.

4. Justin Wolfers and Eric Zitzewitz, "Prediction Markets," *Journal of Economic Perspectives* 18, no. 2 (2004): 108.

5. James Surowiecki, *The Wisdom of Crowds* (Westminster: Knopf Doubleday Publishing Group, 2005).

I argue that prediction markets achieve accuracy not through democratic wisdom aggregation but through specialized competition among elite traders operating within a distinctive sociotechnical assemblage. While these markets often produce remarkably accurate forecasts of electoral outcomes, they do so not through democratic aggregation of independent judgments—as the wisdom of crowds model would suggest—but through specialized competition among a small subset of traders who exert disproportionate influence on price formation. Unlike elections where each voter has equal influence, market participants have radically unequal impact determined primarily by capital deployment rather than informational advantage. Yet despite this inequality, these markets often outperform traditional forecasting methods like polls or expert opinions.

Drawing on a dataset of 489 Polymarket election contracts comprising 9.59 million transactions from 491,423 unique traders, I demonstrate how these markets operate through structured competition rather than democratic aggregation. This thesis makes three principal contributions to economic sociology. First, it reconceptualizes prediction markets as complex assemblages rather than simple information aggregation mechanisms, revealing how these markets distribute agency across human and non-human actants. Second, it provides the first comprehensive microstructural analysis of decentralized prediction markets, demonstrating how these markets operate through structured trader ecologies and hierarchical information flows rather than democratic participation. Third, it identifies unique forms of digital sociality that emerge through the configuration of these markets, including pseudonymous identity formation, market-mediated communities, and performative relationships between prices and real-world events.

The analysis proceeds in four substantive sections. The first develops a theoretical framework for analyzing prediction markets, explaining how these arrangements distribute agency across human and non-human elements while creating multiple forms of value. This multidimensional value creation extends beyond simple epistemic functions to include what Belk terms "identity markers" within digital environments.[6] The second examines the microstructural properties of prediction markets, demonstrating how systematic inefficiencies reflect essential characteristics of these markets rather than temporary imperfections. The third analyzes the emergence of structured trader ecologies, revealing how different participant categories create interdependent relationships within market environments. The fourth explores how prediction markets enable new forms of digital sociality through pseudonymous participation, market-mediated communities, and performative effects.

By examining prediction markets as sociotechnical assemblages rather than simple information aggregation mechanisms, this thesis contributes to broader sociological understandings of how technological infrastructures transform economic coordination in contemporary society. It challenges efficiency-centered approaches that treat markets as

6. Russell W. Belk, "Extended Self in a Digital World," *Journal of Consumer Research* 40, no. 3 (2013): 477–500, https://doi.org/10.1086/671052.

neutral aggregation mechanisms, instead revealing how markets function as social arrangements through their unique microstructural properties.

Table 1. *Key Terminology*

Term	**Definition**
Prediction Market	A market where participants trade contracts that pay out based on the outcome of future events, with prices functioning as implied probabilities
Decentralized Prediction Market	Prediction markets operating on blockchain networks without centralized control or intermediaries
Binary Event Contract	Contract with two possible outcomes (e.g., "Yes"/"No"), where the winning outcome pays $1 per token and the losing outcome pays $0
Outcome Token	Digital asset representing a specific outcome that pays $1 if correct and $0 if incorrect
Blockchain	Distributed ledger technology that records transactions across multiple computers, ensuring transparency and tamper-resistance
Automated Market Maker	Algorithmic mechanism that provides continuous liquidity without requiring traditional market makers
Oracle	System that translates real-world information onto the blockchain to determine market outcomes
Smart Contract	Self-executing code on blockchain networks that automatically enforces agreement terms
Sociotechnical Assemblage	Heterogeneous arrangement of human and non-human elements that together constitute a distinctive form of coordination
Market Efficiency	The degree to which prices reflect all available information, typically measured through statistical tests

2 PREDICTION MARKETS AS SOCIOTECHNICAL ASSEMBLAGES

Neoclassical economic approaches to understanding prediction markets have predominantly centered on their capacity for information aggregation and efficient price formation. The Efficient Market Hypothesis posits that prediction market prices should incorporate all available information, making future price movements unpredictable based solely on past patterns. Similarly, the "wisdom of crowds" thesis suggests that diverse, independent judgments aggregated through market mechanisms should produce remarkably accurate forecasts. These frameworks encounter significant limitations when applied to decentralized prediction markets. First, they presume uniformly rational actors with equal market influence, contradicting empirical evidence of extreme concentration among a small participant subset. Second, they assume independence of judgment when actual participation demonstrates clear interdependence through cascading information flows. Third, they conceptualize markets as passive aggregation mechanisms rather than active social arrangements that transform the phenomena they claim to predict.

The theoretical framework I propose departs from these conventional understandings in three fundamental ways. First, rather than treating prediction markets as efficient information processors, I conceptualize them as hybrid arrangements that generate value through specialized competition among heterogeneous participant types. Second, instead of assuming that accuracy emerges from the wisdom of crowds, I demonstrate how it develops through structured information hierarchies dominated by a small subset of elite traders. Third, rather than focusing solely on the epistemic dimension of these markets, I examine how they simultaneously function as sites of financial speculation, cultural meaning-making, and identity formation.

2.1 From Information Aggregation to Specialized Competition

The specialized competition framework I develop explains how prediction markets achieve forecasting accuracy despite systematic inefficiencies. While classical accounts assume that market efficiency and forecasting accuracy necessarily coincide, my analysis reveals a more complex relationship. Prediction markets maintain accuracy not because they seamlessly incorporate all available information through efficient pricing mechanisms, but because a small subset of informed traders with specialized knowledge exert disproportionate influence on price formation. These markets generate epistemic value not through democratic aggregation of distributed knowledge but through competitive dynamics among specialized participants with different information access, analytical capabilities, and strategic approaches.

Figure 1 illustrates this sociotechnical assemblage approach to prediction markets, highlighting the individual components and their interactions:

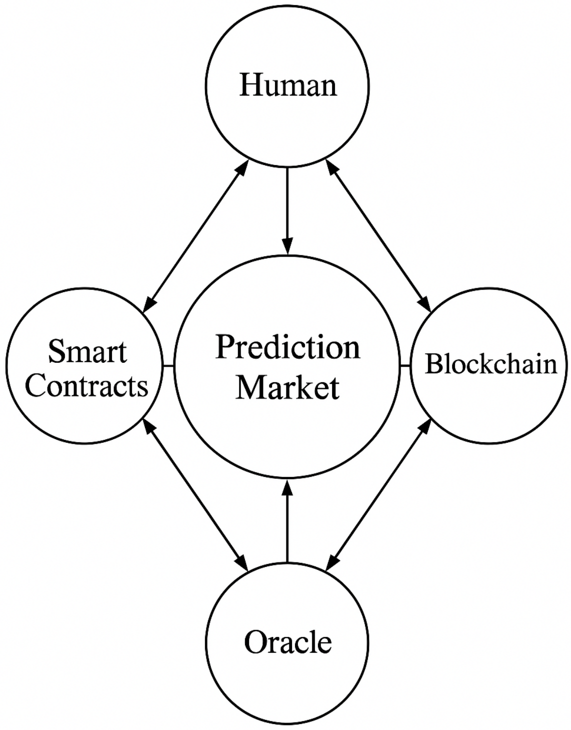

Figure 1. *Components of Prediction Markets as Sociotechnical Assemblages.*

Unlike models that reduce markets to either technical mechanisms or social constructions, this approach examines how diverse components—human traders, smart contracts, oracle systems, interfaces—function together to produce emergent properties that exceed their individual capacities. This perspective aligns with Callon and Muniesa's observation that market calculation emerges through "collective hybrids" rather than discrete individual decisions.[7] It also builds on MacKenzie's analysis of financial models as performative elements that actively shape market behaviors rather than merely describing them.[8]

This perspective resolves the apparent paradox of how prediction markets can produce accurate forecasts despite exhibiting clear evidence of inefficiency. Unlike efficient market models that assume random price movements, prediction markets systematically display particular inefficiency patterns—most notably mean reversion, where price overshoots are followed by corrections. These patterns reflect the competitive dynamics among different trader types rather than simple information processing failures. Elite traders exploit these patterns through sophisticated strategies that simultaneously contribute to price discovery while generating financial returns. The regular occurrence of exploitable inefficiencies

7. Michel Callon and Fabian Muniesa, "Peripheral Vision: Economic Markets as Calculative Collective Devices," *Organization Studies* 26, no. 8 (2005): 1236, https://doi.org/10.1177/0170840605056393.

8. Donald MacKenzie, *An Engine, Not a Camera: How Financial Models Shape Markets* (Cambridge, MA: MIT Press, 2006).

creates incentives for informed participation that ultimately enhances forecasting accuracy despite departures from technical efficiency. This perspective aligns with Martin's analysis of derivatives as social technologies that transform uncertainty into calculable risk while simultaneously creating new forms of social relations.[9]

2.2 Institutional Features of Prediction Markets

The historical evolution of prediction markets reflects their progressive expansion from controlled academic experiments to decentralized global networks. The 1988 Iowa Electronic Market (IEM), operated by University of Iowa professors, served as an early template for centralized prediction markets focused on electoral outcomes.[10] The IEM operated under regulatory approval from the Commodity Futures Trading Commission (CFTC) with strict participation limitations and position size constraints. Despite these restrictions, it demonstrated remarkable predictive accuracy, correctly forecasting the winner of every presidential election within its operational period and typically outperforming traditional polling methods in estimating vote shares.[11]

Similarly, corporate prediction markets adopted by firms like Google, Microsoft, and Ford successfully forecasted commercial outcomes such as product launches and earnings reports, albeit at limited scale and with participation restricted to employees.[12] These early implementations signaled the budding potential of prediction markets as forecasting tools but remained fairly limited in both scope and accessibility. Buckley suggests these early implementations demonstrated the potential of collective intelligence mechanisms while remaining constrained by traditional financial infrastructures.[13]

Contemporary prediction markets represent a technical innovation—a heterogeneous arrangement of human and non-human elements that together constitute a specific form of economic coordination. This assemblage integrates three key technological innovations that fundamentally transform how these markets function:

First, automated market makers (AMMs) replace traditional order books with algorithmic pricing mechanisms, creating price impact dynamics that differ fundamentally from traditional exchanges. By implementing continuous liquidity through mathematical formulas rather than human market makers, AMMs enable trading on virtually any

9. Randy Martin, *Knowledge Ltd: Toward a Social Logic of the Derivative* (Philadelphia ; Rome ; Tokyo: Temple University Press, 2015).

10. Russ Ray, "Prediction Markets and the Financial 'Wisdom of Crowds'," *Journal of Behavioral Finance* 7, no. 1 (2006): 2–4, https://doi.org/10.1207/s15427579jpfm0701_1.

11. Joyce E. Berg, Forrest D. Nelson, and Thomas A. Rietz, "Prediction Market Accuracy in the Long Run," *International Journal of Forecasting* 24, no. 2 (2008): 285–300, https://doi.org/10.1016/j.ijforecast.2008.03.007.

12. Bo Cowgill and Eric Zitzewitz, "Corporate Prediction Markets: Evidence from Google, Ford, and Firm X," *The Review of Economic Studies* 82, no. 4 (2015): 1309–1341, https://doi.org/10.1093/restud/rdv014.

13. Patrick Buckley, "Harnessing the Wisdom of Crowds: Decision Spaces for Prediction Markets," *Business Horizons* 59, no. 1 (2016): 85–94, https://doi.org/10.1016/j.bushor.2015.09.003.

Table 2. *Evolution of Prediction Market Platforms*

Market Name	**Start Date**	**Structure**	**Technical Architecture**	**Participation Constraints**
Iowa Electronic Markets (IEM)	1988	Centralized	University server, manual order matching	Academic affiliation, $500 position limit
Corporate PMs (Google, Ford)	2005-2013	Private	Intranet platforms, centralized databases	Employee-only participation
Augur	2018	Decentralized	Ethereum blockchain, fork-based resolution	Global access, high transaction costs
Polymarket	2020	Decentralized	Polygon L2, AMM liquidity, centralized oracles	Global pseudonymous access
Kalshi	2021	Regulated	CFTC-licensed, KYC compliant	US residence requirement, $25,000 position limit

outcome without requiring balanced participation or institutional intermediaries. This technological arrangement transforms how market participation occurs, creating specific opportunities for strategic positioning that would be impossible in traditional market structures.

Second, blockchain infrastructure enables pseudonymous participation, transparent transaction records, and tamper-resistant contract enforcement. This technological arrangement fundamentally reshapes market participation by eliminating traditional gatekeeping mechanisms, enabling unlimited position sizes, and creating permanent public records of all trading activity. Unlike traditional markets where institutional requirements limit participation, blockchain-based platforms enable genuinely global, permissionless access while simultaneously allowing reputation formation through pseudonymous identities.

Third, oracle systems translate real-world information onto blockchains, enabling automatic contract settlement without requiring trusted institutional intermediaries. This technological arrangement transforms how market outcomes are determined, creating new typologies of authority and adjudication that differ from traditional contract enforcement mechanisms. Unlike traditional markets where settlement depends on institutional discretion, oracle-based systems create predetermined resolution criteria that execute regardless of participant preferences or institutional priorities.

Together, these technological elements create not simply an improved version of traditional prediction markets but a qualitatively different arrangement consisting of economic coordination and social relationship. This arrangement distributes agency across human and non-human elements in ways that transform standard conceptions of market participation, enabling new forms of digital sociality that differ from both traditional financial markets and non-market social relations.

Table 3. *Comparative Features of Traditional vs. Decentralized Prediction Markets*

Feature	**Traditional Prediction Markets**	**Decentralized Prediction Markets**
Ownership Structure	Centralized (e.g., university, corporation)	Distributed across network participants
Participation Access	Typically restricted by geography, affiliation	Global, permissionless access
Market Creation	Controlled by platform operators	Permissionless (anyone can create markets)
Settlement Mechanism	Platform operators determine outcomes	Oracle systems translate external events
Transaction Transparency	Limited visibility into trading activity	Complete transparency through blockchain
Regulatory Status	Often operates under regulatory exemptions	Regulatory ambiguity in many jurisdictions

2.3 Distributed Agency and Digital Sociality

The sociotechnical character of prediction markets manifests primarily through the innovative ways these markets distribute agency across human and non-human actants. Traditional economic frameworks conceptualize market activity as the aggregation of autonomous individual decisions, with agentic power located primarily in human traders making rational choices based on private information and preferences. These complex distributions of agency allow technological components to actively shape market dynamics rather than merely facilitating human decisions.

In prediction markets, Automated Market Makers (AMMs) determine prices according to mathematical formulas rather than human judgment, creating characteristic price impact patterns different from traditional order book markets. Oracle systems exercise decisive authority in translating real-world events into market outcomes, functioning as what Latour might term "mediators" rather than passive conduits.[14] Smart contracts

14. Bruno Latour, *Reassembling the Social: An Introduction to Actor-Network-Theory* (Oxford: Oxford University Press, 2005).

enforce commitment mechanisms without requiring institutional intermediaries, creating new algorithmic social coordination outside of traditional social means. User interfaces structure participation possibilities through their design choices, making certain actions more accessible than others regardless of formal market rules.

This distributed agency fundamentally transforms how prediction markets generate forecasts. Rather than simple information aggregation through independent human judgments, forecast accuracy emerges through specialized competition among different participant types, each exploiting specific features of the market devices. High-frequency traders leverage the AMM's mathematical structure to capture small margins on numerous transactions. Information specialists exploit the blockchain's transparency to identify and follow influential traders. Retail participants provide capital that enables sophisticated traders to profit from information advantages, creating incentives for informed participation.

This specialized competition model explains how prediction markets achieve forecasting accuracy despite systematic inefficiencies.[15] The market's structure creates financial incentives for information revelation through profit opportunities, enabling sophisticated participants to exert disproportionate influence on price formation based on their information or analytical advantages. The regular occurrence of exploitable inefficiencies—rather than being a defect—actually contributes to market accuracy by ensuring continuous participation by information-driven traders seeking profit opportunities.

Beyond distributed agency, prediction markets create new forms of digital sociality that differ from both traditional financial markets and non-market social relations. The pseudonymous nature of blockchain participation transforms identity formation by enabling experimentation with different trading strategies, interaction styles, and social positions without established identity constraints. This creates what might be termed "crypto-identities"—reputation constructions that develop through trading histories and comment contributions rather than through traditional institutional affiliations or credentials.

Trading activity itself functions as communication, with transactions serving as social signals alongside their financial function. Parallel comment sections enable discussions that create feedback loops between trading behaviors and social interpretations. Market-mediated communities extend beyond platforms into both digital forums and physical gatherings organized around prediction market participation. These particular social arrangements transform how participants relate to each other through market mechanisms, creating what Knorr Cetina and Bruegger term "post-social relations" where markets themselves become objects of attachment beyond traditional social bonds.[16]

15. Andrei Shleifer and Robert W. Vishny, "The Limits of Arbitrage," *The Journal of Finance* 52, no. 1 (1997): 35–55; Karin Knorr Cetina and Urs Bruegger, "Global Microstructures: The Virtual Societies of Financial Markets," *American Journal of Sociology* 107, no. 4 (2002): 905–950.

16. Knorr Cetina and Bruegger, "Global Microstructures: The Virtual Societies of Financial Markets,"

2.4 Theoretical Positioning

This assemblage framework builds on several theoretical traditions while offering a new perspective on prediction markets specifically. From economic sociology, it draws on conceptions of markets as social constructions embedded in cultural systems while emphasizing the active role of technological elements in shaping social arrangements.[17] From science and technology studies, it incorporates insights about the distribution of agency across human and non-human actants while focusing specifically on market environments rather than technical systems generally.[18] From platform studies, it engages with analyses of how digital infrastructures shape interaction possibilities while examining the typical characteristics of decentralized rather than centralized platforms.[19]

The microstructural approach towards prediction markets offers an alternative to both efficiency-centered approaches that treat prediction markets primarily as information aggregation mechanisms and cultural analyses that emphasize social meaning without attending to technological specificity. Instead, it examines how prediction markets function as sociotechnical devices that create novel forms of economic coordination and social relationship through their unique configurations of human and non-human elements.

In particular, I pair a quantitative analysis of market dynamics with a sociological interpretation of trader ecologies, information hierarchies, and forms of digital relations that characterize these markets in practice. Rather than treating empirical deviations from efficiency as temporary anomalies, the assemblage framework enables me to examine these patterns as essential characteristics of how prediction markets function as social arrangements. The subsequent sections demonstrate how this theoretical framework illuminates the unique properties of prediction markets through systematic empirical analysis.

907.

17. Viviana A. Zelizer, *The Social Meaning of Money* (New York: Basic Books, 1994).
18. Latour, *Reassembling the Social: An Introduction to Actor-Network-Theory*.
19. Tarleton Gillespie, “The Politics of 'Platforms',” *New Media & Society* 12, no. 3 (2010): 347–364.

3 MICROSTRUCTURAL PROPERTIES: THE ANATOMY OF MARKET INEFFICIENCY

Having established prediction markets as sociotechnical assemblages, I now examine how this framework explains their systematic deviation from efficient market behavior—a key component of my specialized competition model that challenges wisdom-of-crowds narratives. This section examines how prediction markets systematically deviate from the efficient behavior expected by economic theory. By documenting persistent inefficiency patterns across hundreds of markets, I demonstrate that these deviations reflect fundamental characteristics of the sociotechnical assemblage rather than temporary imperfections or developmental stages. These findings challenge the traditional understanding of prediction markets as efficient information aggregation mechanisms, instead revealing how accuracy emerges through specialized competition despite systematic inefficiencies.

3.1 Beyond Random Walks: Systematic Inefficiency in Prediction Markets

The 2024 US Presidential Election market on Polymarket represents the most developed prediction market in history—with unprecedented volume ($3.68 billion), extraordinary participation (87,843 traders), and continuous liquidity throughout its 296-day lifecycle. According to economic theory, this market should display nearly perfect efficiency with prices following a random walk pattern. My analysis reveals a starkly different reality.[20]

From my dataset of 489 Polymarket election contracts, I selected six representative case studies spanning diverse electoral contexts, market sizes, and geographical locations to examine different prediction environments:

The price movements in this market demonstrate systematic reversals—where significant price changes in one direction tend to be followed by subsequent movements in the opposite direction. Statistical analysis confirms this pattern with high statistical significance. After controlling for fundamental information changes, the market shows clear mean reversion rather than the random walks predicted by efficient market theory. Such deviations align with Whelan's findings on price formation in commercial prediction markets, where behavioral factors consistently influence pricing dynamics.[21] Mean reversion—the tendency for prices to bounce back after moving too far in one direc-

20. The testing framework examined whether prices follow patterns consistent with weak-form EMH using: (1) random walk tests; (2) return stationarity tests; (3) autocorrelation analysis; (4) runs tests; and (5) autoregressive modeling. Markets were classified by composite scores, with none achieving "Highly Efficient" classification.

21. Karl Whelan, "On Prices and Returns in Commercial Prediction Markets," *Quantitative Finance* 23, no. 11 (2023): 1699–1712, https://doi.org/10.1080/14697688.2023.2257756.

Table 4. *Selected Case Study Markets*

Market	**Volume (USD)**	**Traders**	**Duration**	**Outcome**
2024 US Presidential Election	$3.68 billion	87,843	296 days	Correct prediction (Trump win)
2025 German Parliamentary Election	$134.62 million	37,449	62 days	Correct prediction (CDU/CSU win)
2024 Pennsylvania Senate Election	$5.48 million	2,666	217 days	Incorrect prediction (Casey win)
2025 Croatia Presidential Election	$3.14 million	6,742	47 days	Correct prediction (Milanović win)
2024 San Francisco Mayoral Election	$7.13 million	1,874	43 days	Correct prediction (Farrell win)
2024 UK Parliamentary Election	$4.24 million	5,302	82 days	Correct prediction (Labour win)

tion—directly contradicts the efficient market principle that past price movements cannot predict future changes. These patterns persist throughout the market's lifecycle despite extraordinary volume and participation, indicating a structural characteristic rather than a temporary imperfection.

This inefficiency pattern appears consistently across all markets examined, regardless of size, geographical context, or electoral type. From the German Parliamentary election to smaller contests like the Croatia Presidential race, every market demonstrates statistically significant deviations from efficiency. Moreover, these inefficiencies follow remarkably similar patterns across diverse contexts, with negative autocorrelation in returns appearing as the most consistent inefficiency signature.

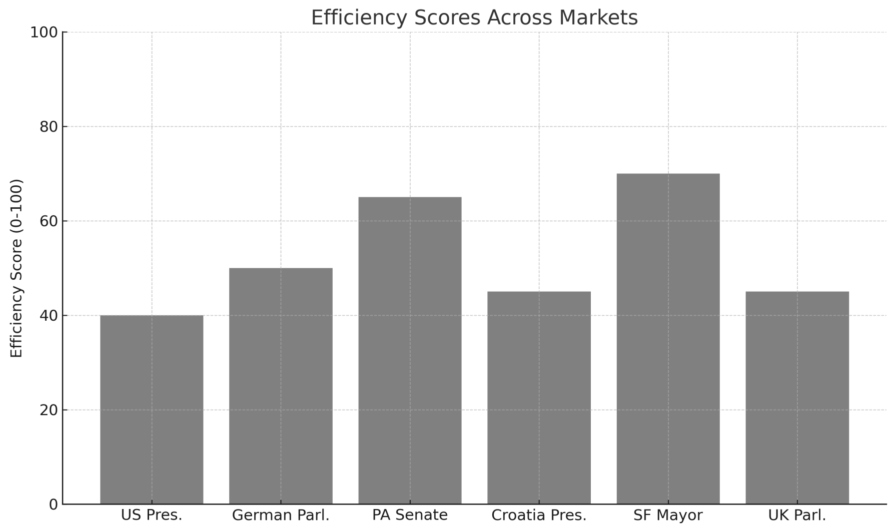

Figure 2. *Efficiency Scores Across Selected Prediction Markets.*

What makes these findings particularly significant is their challenge to the fundamental premise of prediction markets as efficient information aggregation mechanisms. According to Hayek's (1945) influential conception, markets function primarily to coordinate dispersed knowledge, with prices serving as signals that efficiently incorporate all available information. The inefficiency documented here reveals a more complex reality: prediction markets operate not simply as information aggregation mechanisms but as social arrangements that generate accurate forecasts through specialized competition despite persistent inefficiencies.

This observation is profound: despite overall accuracy and large trade volumes, prediction markets overwhelmingly exhibit inefficiencies. Far from being an anomaly, prediction markets consistently fail to aggregate beliefs by incorporating information advantages into prices. Instead, these market failures enable sophisticated traders with superior information and analytical capabilities to deploy capital. The imperfect and often porous nature of the markets suggests that the fundamental claims of prediction market proponents may be incorrect—while the markets are accurate, they do not aggregate the wisdom of crowds but rather allow for structured competition among a few specialized participants.

3.2 The Pennsylvania Senate Election: Anatomy of a Market Failure

When and how do prediction markets fail? To understand how prediction markets operate as novel social platforms, it is instructive to examine instances where they fail. The Pennsylvania Senate Election market provides a compelling case study of how the specific market configuration can produce dramatic forecast errors despite substantial participation and volume.

On November 5, 2024, as vote tallies accumulated in Pennsylvania's closely watched Senate race, a remarkable disconnect emerged between electoral reality and market expectations. Despite Republican Dave McCormick's growing lead in the vote count, Polymarket's prediction contract maintained high confidence in Democratic incumbent Bob Casey's reelection, closing at 0.78 (implying a 78% probability of Democratic victory) just hours before McCormick was declared the winner. This dramatic prediction failure—in a market with substantial volume ($5.48 million) and participation (2,666 traders)—reveals how market conditions can produce collective misjudgment.

Three key patterns characterize this market failure, each reflecting how the sociotechnical architecture shapes market outcomes:

First, the market exhibited extreme concentration of trading activity, with a Gini coefficient of 0.961. Just 21 traders—less than 1% of all participants—contributed over half of all trading volume. This extraordinary concentration created a market structure dominated by a tiny elite whose trading decisions fundamentally shaped collective outcomes. Unlike traditional financial markets where regulatory constraints limit concentration, the decentralized nature of Polymarket enables this extreme inequality as a defining feature of the market structure.

Second, the market displayed a pronounced divergence in trading strategies between participant categories. The small group of sophisticated traders maintained balanced strategic approaches, while retail participants (the vast majority) showed a strong tendency to trade against recent price movements. This contrarian tendency among retail traders—which appeared in over 60% of their trades—created a persistent bias toward Casey that sophisticated traders failed to fully counteract.

Third, the market suffered from compressed temporal participation, with trading activity heavily concentrated in the final days despite a 217-day duration. This temporal compression meant that early warning signs of a potential McCormick victory received insufficient attention, while late-stage participation was heavily influenced by pre-existing price levels rather than fresh information analysis.

Analysis of the market's comment section reveals a further dimension of the market within the reciprocal relationship between trading activity and discursive sense-making. As one participant noted shortly before market resolution: "Bob Casey is way underpriced in this. Multiple organizations haven't called yet. McCormick is leading by 36.5k. There are roughly 100k votes left to count." This commentary—attempting to rationalize a position increasingly disconnected from electoral reality—demonstrates how the market functions not simply as a price formation mechanism but as a site of collective meaning-making where participants develop narratives to justify trading decisions.

The Pennsylvania case illuminates how prediction markets operate as diverse assemblages rather than simple information aggregation mechanisms. The market's failure emerged through collective misjudgment that cannot be understood through efficiency-centered frameworks. This perspective challenges the traditional viewpoint that treat such failures as temporary anomalies, instead revealing how market behavior emerges from the specific characteristics of the microstructure itself.

3.3 Efficient Price Formation or Social Architecture?

If prediction markets exhibit systematic inefficiencies and occasionally fail dramatically, how do they nonetheless achieve impressive forecasting performance across most electoral contexts? I propose a specialized competition framework to resolve this apparent paradox.

Markets generate accurate forecasts not through perfect efficiency but through structured competition among different participant types with complementary functions within the market ecology. High-frequency traders provide continuous liquidity and exploit short-term inefficiencies, creating rapid price adjustments to new information. Active traders contribute information-driven positioning based on analytical capabilities and specialized knowledge. Retail traders, while individually exhibiting strong behavioral biases, collectively provide capital that enables sophisticated participants to profit from information advantages, creating incentives for informed participation.

This ecological arrangement creates a market structure where sophisticated participants can profit from systematically exploiting the behavioral tendencies of retail traders. Rather than perfect efficiency where no profitable trading strategies exist, prediction markets maintain a dynamic equilibrium where consistent inefficiencies create profit opportunities that attract institutional traders whose participation enhances price discovery. The persistence of exploitable patterns—rather than their elimination—actually contributes to market accuracy by ensuring continuous participation by information-driven traders.

The Pennsylvania Senate case represents a situation where this dynamic equilibrium temporarily broke down. The combination of trader concentration, retail trader bias, and compressed temporal participation created conditions where expert traders either failed to identify the mispricing or lacked sufficient incentive to correct it. While such failures occur occasionally, the specialized competition framework explains why they remain relatively rare: the financial incentives for exploiting mispricings generally ensure that significant information advantages are eventually incorporated into prices, even if the process occurs through competitive dynamics rather than perfect efficiency.

This perspective fundamentally reframes how we understand prediction market accuracy. Rather than assuming that accuracy emerges automatically from crowd wisdom, it reveals how accuracy depends on specific structural properties of the market assemblage that enable specialized competition among heterogeneous participant types. Markets that maintain these properties—balanced trader ecologies, sufficient liquidity, appropriate incentive structures—tend to produce accurate forecasts despite systematic inefficiencies. When these properties break down, as in the Pennsylvania Senate case, market failures become more likely. These structural characteristics reflect what Guyer terms the "disjunctive temporalities" of platform-based financial arrangements, where technical systems mediate heterogeneous economic practices.[22]

The empirical evidence of market inefficiency challenges conventional understandings of prediction markets as primarily information aggregation mechanisms. These inefficiency patterns reveal how prediction markets function as social arrangements. The non-random price behaviors reflect distributed agency, where automated market makers, blockchain infrastructures, and heterogeneous human participants interact to create systematic trading patterns that generate accurate forecasts through specialized competition rather than perfect efficiency.

22. Jane I. Guyer, *Legacies, Logics, Logistics: Essays in the Anthropology of the Platform Economy* (Chicago: The University of Chicago Press, 2016).

4 TRADER ECOLOGIES: STRUCTURED RELATIONSHIPS IN PREDICTION MARKETS

The evidence of systematic market inefficiency presented above raises a critical question: If prediction markets don't function through efficient information aggregation, how do they operate? This section examines the structured trader ecologies that form the backbone of the specialized competition framework. By identifying distinct participant types with characteristic behavioral patterns, I demonstrate how specialized competition among these different trader categories generates accurate forecasts despite extreme participation inequality. These findings challenge the wisdom of crowds narrative, instead revealing how accuracy emerges through hierarchical information flows and strategic interaction among trader types with complementary functions in the market ecology.

4.1 Beyond Homogeneous Rationality: Structured Participant Ecologies

When a trader known simply as "Théo" began placing massive bets on Trump's victory in the 2024 Presidential Election through his pseudonymous accounts, other traders took notice. By the election's conclusion, this single pseudonymous trader had accumulated approximately $85 million in profit and achieved almost mythic status in prediction market communities.[23] But was Théo an anomaly, or did his influence reveal something fundamental about how these markets actually function?

Conventional wisdom portrays prediction markets as democratic aggregators of dispersed knowledge—digital town squares where diverse participants contribute equally to collective intelligence. My analysis reveals a starkly different reality: prediction market participants occupy ecological niches characterized by specific behavioral patterns, temporal rhythms, and strategic approaches that remain remarkably consistent across diverse market contexts. Rather than independent agents, they function as interdependent components within a structured social system.

Using machine learning clustering techniques applied to behavioral metrics calculated from transaction data, I identified three distinct trader types with characteristic patterns that appear consistently across different electoral contexts.[24]

23. Alexander Osipovich, "Exclusive | Trump Whale Scores $85 Million Windfall on Election," *Wall Street Journal*, November 2024, https://www.wsj.com/finance/trump-whale-scored-85-million-windfall-on-election-7c2cd906.

24. Unsupervised learning techniques identified behavioral patterns through k-means clustering of multidimensional trader features. Silhouette analysis consistently identified three trader categories across markets. This data-driven approach revealed ecological structures based on actual market behavior rather than self-reported intentions.

Table 5. *Trader Type Characteristics*

Trader Type	Population	Volume	Behavioral Signature	Strategic Tendency
High-Frequency Traders	19.7%	64.0%	Early entry, continuous participation	Balanced/Market-making
Active Traders	37.1%	23.7%	Selective timing, moderate frequency	Information-driven
Retail Traders	43.1%	12.3%	Late entry, episodic participation	Contrarian bias

High-Frequency Traders (HFTs) function as the market's infrastructure providers, characterized by early market entry, continuous participation, and extraordinary trading volume relative to their population size. In the US Presidential market, these participants—accounting for just 19.7% of traders but contributing 64.0% of total volume—maintained balanced strategy distributions and neutral sentiment profiles reminiscent of professional market-makers in traditional financial markets. Their trading patterns showed sophisticated optimization for capturing small margins on numerous transactions while maintaining neutral directional exposure, establishing the market's fundamental liquidity conditions.

Active Traders occupied an intermediate position, characterized by moderate trading frequency, strategic market timing, and selective participation during significant information events. These traders—representing 37.1% of participants and 23.7% of volume in the US Presidential market—demonstrated information-driven positioning rather than pure liquidity provision or momentum following. Their trading approach showed strategic deployment of capital when they perceived informational advantages rather than continuous participation, functioning as the market's primary information specialists.

Retail Traders constituted the majority of participants (43.1% in the US Presidential market) while contributing disproportionately little volume (12.3%). Their behavioral signature included later market entry, episodic participation, smaller position sizes, and pronounced contrarian bias. Unlike professional traders who optimize strategies based on market microstructure, retail participants often traded based on personal beliefs, emotional responses to events, or simple heuristics. Their consistent contrarian tendency—appearing in nearly 50% of retail trader transactions across markets—suggests a systematic behavioral pattern shaped by the prediction market's unique structure.

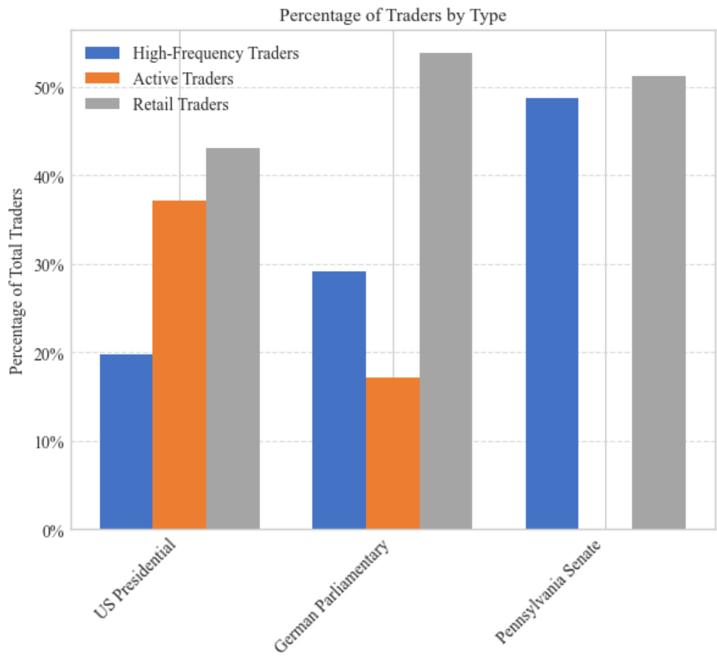

Figure 3. *Trader Type Distribution Across Selected Markets.*

This ecological stratification appeared consistently across diverse electoral contexts, from the US Presidential Election to smaller regional races like the Croatia Presidential contest. While the relative proportions varied by market size and context, the fundamental structure—characterized by specialized niches with behavioral patterns—remained remarkably stable. This consistency suggests these ecological patterns reflect fundamental characteristics of the sociotechnical assemblage rather than contextual peculiarities.

The structured ecology fundamentally challenges the wisdom of crowds model that underpins historical understandings of prediction markets. Rather than equal participation by independent actors, these markets operate through interdependent relationships among specialized participant types who fulfill complementary functions within the market ecosystem. Each trader category occupies a niche shaped by the specific affordances, creating a structured market ecology that generates accurate forecasts through specialized competition rather than democratic aggregation of independent judgments.

4.2 Extreme Concentration: Elite Dominance in “Democratic” Markets

Prediction markets are often portrayed as democratizing platforms that enable diverse participants to contribute equally to collective intelligence regardless of status or resources. The empirical reality reveals a starkly different picture: these markets operate through extreme concentration of activity among a tiny elite whose trading decisions fundamentally shape collective outcomes. This concentration emerges directly from the sociotechnical configuration of blockchain-based prediction markets, which enables unlimited position sizes, pseudonymous participation, and algorithmic pricing without regulatory constraints.

The 2024 US Presidential Election market—with its unprecedented scale and participation—vividly illustrates this concentration. Despite involving nearly 88,000 traders, the market displayed extraordinary inequality in participation, with a Gini coefficient of 0.943 (where 1.0 represents complete inequality). Just 87 traders—representing 0.1% of all participants—contributed nearly half (47.9%) of the market's total volume. The top 1% of traders (878 accounts) accounted for more than two-thirds (69.2%) of all activity, while the remaining 99% collectively contributed less than a third of total volume.

This extreme stratification appeared consistently across all markets examined, regardless of size, electoral context, or geographical location. The German Parliamentary election market displayed even more extreme concentration (Gini coefficient 0.980), with just 51 traders (0.14% of participants) generating over half of trading volume. Even smaller regional markets like the Croatia Presidential race showed similar patterns (Gini coefficient 0.938), though with slightly less concentration (1.80% of traders contributed 50% of volume).

Table 6. *Trader Concentration Across Electoral Markets*

Market	**Gini Coefficient**	**% Traders for 50% Volume**	**% Traders for 90% Volume**
US Presidential	0.943	0.10% (87 traders)	5.00% (4,392 traders)
German Parliamentary	0.980	0.14% (51 traders)	2.24% (840 traders)
Pennsylvania Senate	0.961	0.79% (21 traders)	5.10% (136 traders)
Croatia Presidential	0.938	1.80% (122 traders)	10.86% (733 traders)

Note: Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality). Values above 0.9 indicate extreme concentration of trading activity.

These findings reveal a profound irony: blockchain technology, often celebrated for its democratizing potential, actually enables more extreme concentration than traditional markets by removing regulatory safeguards like position limits and identity verification requirements. Rather than creating genuinely democratic participation, these markets establish new forms of elite dominance through their distinctive technological configuration. Unlike democratic processes where each participant has equal formal influence (one person, one vote), prediction markets operate through radical inequality where a small participant subset exercises disproportionate influence over collective outcomes.

The concentration documented here challenges the democratic narrative surrounding prediction markets, revealing tensions between the theoretical promise of decentralized technologies and their practical implementation. While blockchain infrastructure theoretically enables permissionless participation, the actual patterns of engagement reveal how technological openness can coincide with extreme social stratification. The absence of position limits, identity verification requirements, or capital constraints—features often portrayed as democratizing—actually enables the concentration of influence among a small participant subset with disproportionate resources or expertise. Unlike traditional polls, in prediction markets, traders 'vote' with their wallets—those with outsized capital influence market expectations far more than the average retail trader.

Contrary to the wisdom of crowds narrative, this elite dominance does not necessarily undermine forecasting accuracy—elite traders often possess superior information or analytical capabilities—but it fundamentally challenges democratic narratives about prediction markets as egalitarian knowledge aggregation mechanisms. Rather than wisdom emerging from the aggregation of diverse independent judgments, market prices primarily reflect the positioning of a small trader elite whose decisions ripple through the market ecosystem through cascade effects. This reality stands in stark contrast to the idea that portrays prediction markets as harnessing the collective intelligence of diverse independent participants. Perhaps these market predictions outperform traditional polling mechanisms because of—and not in spite—of the unequal trader concentration across markets.

4.3 Information Hierarchies and Knowledge Flows

The concentration of trading activity is further reinforced by distinct patterns of information flow through the market ecology. Rather than democratic aggregation of distributed knowledge, prediction markets operate through information hierarchies where knowledge cascades from elite traders to broader participant circles through structured patterns. These hierarchical information flows transform how prediction markets create epistemic value, generating forecasts through structured competition rather than wisdom of crowds. This hierarchical structure resembles what Coleman termed "social capital"—the capacity to leverage one's position within networks to achieve desired outcomes.[25] The key distinction is that within prediction markets, this social capital operates through pseudonymous digital identities rather than traditional status markers, creating what might be termed "virtual information capital."

By examining the temporal sequencing of trading activity following significant position changes by influential traders, I mapped these information cascades with remarkable precision. Across all markets analyzed, a consistent pattern emerged: High-Frequency Traders responded most rapidly to whale activity (average follow time 4.81 minutes in the US Presidential market), followed by Active Traders (11.97 minutes), and finally

25. James S. Coleman, "Social Capital in the Creation of Human Capital," *American Journal of Sociology* 94 (1988): S95–S120.

Retail Traders (7.74 minutes). This structured sequence—with each trader category demonstrating characteristic response timing to elite signals—reveals prediction markets as hierarchical information systems rather than forums for independent judgment aggregation.

This cascade pattern varied systematically by market context, revealing how information hierarchies adapt to different environments. In the German Parliamentary election, High-Frequency Traders exhibited extremely rapid responses to whale activity (1.67 minutes average), while Retail Traders showed substantial delays (18.19 minutes). By contrast, the Croatia Presidential Election displayed more compressed response timing across trader categories (6.00, 8.12, and 9.46 minutes respectively), suggesting a less stratified information environment. These contextual variations reflect how cascade patterns adapt to different information landscapes.

Table 7. *Price Impact Patterns Across Markets*

Market	**Whale Impact**	**Non-Whale Impact**	**Impact Ratio**
US Presidential	−0.0024	+0.0019	−1.285
German Parliamentary	+0.0030	−0.0033	−0.919
Pennsylvania Senate	+0.0090	−0.0030	−2.690
Croatia Presidential	+0.0310	−0.0056	−5.550

Note: Whale Impact and Non-Whale Impact represent the average price change following trades by each trader category. Impact Ratio is calculated as Whale Impact divided by Non-Whale Impact.

The differential price impacts that various trader categories exert provide further evidence of these hierarchies. By tracing price movements following specific trader actions, I discovered that "whale traders" (the top 1% by volume) demonstrate dramatically different market influence than other participants. In the 2024 Presidential Election market, whale traders exhibited negative price impact (−0.0024), while all other traders showed positive impact (+0.0019). This counterintuitive pattern—where elite traders' activities correlate with price movements opposite to their trading direction—suggests sophisticated contrarian positioning that fundamentally differs from how retail participants engage with the market.

These influence patterns varied systematically by market context. While Presidential Election whale traders demonstrated sophisticated contrarian positioning, smaller regional market whales showed straightforward positive impacts ranging from +0.0030 (German Parliamentary) to +0.0310 (Croatia Presidential). These striking differences suggest that elite traders employ context-specific strategies, controlling information flow differently when operating in different prediction environments.

Table 8. *Response Times to Whale Trading Activity (minutes)*

Market	**High-Frequency Response**	**Active Trader Response**	**Retail Trader Response**
US Presidential	4.81	11.97	7.74
German Parliamentary	1.67	9.24	18.19
Pennsylvania Senate	7.83	11.45	13.66
Croatia Presidential	6.00	8.12	9.46

Note: Response time is measured as the average time elapsed between a whale trade and a following trade by the specified trader category.

What emerges is not a democratic wisdom-of-crowds mechanism where each participant contributes equally to knowledge creation, but a structured information hierarchy where signals originate with a small elite group and propagate through the broader market ecology.[26] The blockchain transparency that enables participants to observe specific trader behaviors rather than just aggregate price movements creates more direct forms of observational learning than possible in traditional markets. The AMM pricing mechanism creates price impact patterns that differ from traditional order book markets, enabling specific forms of market influence through its mathematical structure.

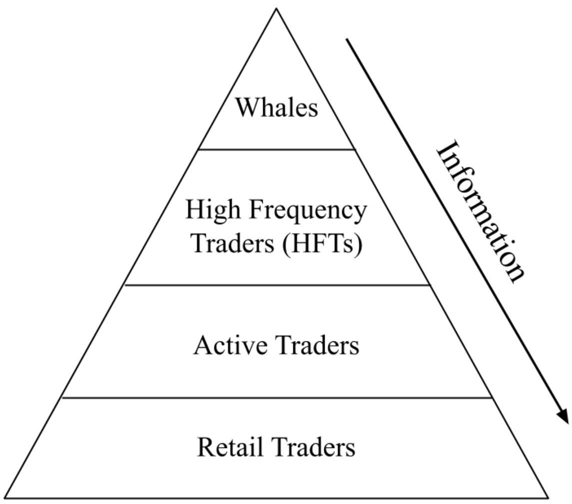

Figure 4. *Hierarchical Information Flow in Prediction Markets.*

These cascade patterns align with what DeLong et al. termed "positive-feedback trad-

26. This hierarchical structure has parallels in other market systems but operates through mechanisms unique to blockchain-based platforms. Cascade patterns remained remarkably consistent across all analyzed markets despite contextual differences.

ing," where some market participants systematically follow the trades of others rather than trading based on independent information.[27] However, unlike their model where feedback traders follow price trends, the evidence here suggests direct observational learning where specific participant actions trigger subsequent aligned behavior by others.

These hierarchical information flows fundamentally transform how prediction markets create epistemic value. Rather than generating forecasts through the averaging of independent judgments, these markets operate through structured competition among specialized participants with different information access, analytical capabilities, and strategic approaches. Elite traders with superior information or analytical capabilities establish price trends that cascade through the market ecosystem, while other participants respond to these signals with varying levels of acceptance or resistance based on their own information sets and strategic positioning. This competitive dynamic can produce remarkably accurate forecasts despite—or perhaps because of—its hierarchical structure, as it enables sophisticated participants to exert disproportionate influence on price formation while creating financial incentives for information revelation through profit opportunities.

The structured participant ecology, extreme concentration, and hierarchical information flows documented in this section reveal prediction markets as social arrangements that generate accurate forecasts through specialized competition rather than democratic wisdom aggregation. Unlike conventional accounts that emphasize the wisdom of crowds through diverse independent judgments, my analysis demonstrates how prediction markets function through structured trader ecologies with participant niches, concentration among a small elite, and hierarchical information flows that transform how collective judgment forms through these markets.

27. J. Bradford DeLong et al., "Noise Trader Risk in Financial Markets," *Journal of Political Economy* 98, no. 4 (1990): 703–738.

5 DIGITAL SOCIALITY: NEW FORMS OF MARKET-MEDIATED INTERACTION

This section examines how prediction markets function as sites for digital sociality. Beyond their epistemic and financial dimensions, these markets enable novel social arrangements through pseudonymous participation, market-mediated communities, and performative relationships between prices and real-world events. These social dimensions transform how participants develop identities, form communities, and create meaning through market participation, revealing prediction markets as a decentralized technology that create multiple forms of value beyond simple information aggregation.

5.1 Pseudonymous Identity Formation: The Construction of Market-Based Reputations

Prediction markets enable novel identity formation through pseudonymous participation that transforms how status and reputation develop in digital environments. Unlike traditional financial markets where identity depends on institutional affiliation or credentials, these markets enable identity construction primarily through trading histories and pseudonymous personas visible on the blockchain. This arrangement creates what might be termed "algorithmic identities" that develop through market performance rather than traditional status markers.

The French trader known as "Théo" exemplifies this pseudonymous identity formation. Operating through accounts including "RepTrump," "Jenzigo," and "mikatrade77," Théo reportedly made approximately $85 million in profit during the 2024 US Presidential election and received mainstream coverage from the Wall Street Journal. When asked about this newfound notoriety, Théo remarked: "To be frank, I'm a bit tired of the whole thing—I'd like to fade back into my normal daily life."[28] This pattern of digital identity experimentation aligns with what Yee, Bailenson, and Ducheneaut term the 'Proteus effect,' whereby an individual's behavior and self-perception are transformed by the characteristics of their digital representation.[29]

Similarly, during the 2024 US Presidential Election campaign, traders operated under digital identities like "DJTHolder," "polywannacracker," "Treadmilled," and "Sponge-Gatorade-Zyn." Fedorenko, Berthon, and Rabinovich describe such pseudonymous identity performance as a form of "crowded identity," where participants curate digital personas specifically for platform environments.[30] These pseudonyms developed substantial

28. Osipovich, "Exclusive | Trump Whale Scores $85 Million Windfall on Election."

29. Nick Yee, Jeremy N. Bailenson, and Nicolas Ducheneaut, "The Proteus Effect," *Communication Research* 36, no. 2 (2009): 285–312, https://doi.org/10.1177/0093650208330254.

30. Ivan Fedorenko, Pierre Berthon, and Tamara Rabinovich, "Crowded Identity: Managing Crowdsourcing Initiatives to Maximize Value for Participants through Identity Creation," Crowdsourcing,

reputation capital within market communities, with their trading activities closely monitored by other participants seeking market signals. This reputation formation occurs without traditional institutional validation or certification requirements, creating market-based status hierarchies that operate independently of social position.

This pseudonymous identity formation transforms how status and reputation develop in market environments. Rather than relying on traditional credentials or institutional positions, market participants establish digital personas through consistent trading patterns, comment contributions, and profit performance. These digital identities can accumulate substantial social capital within prediction market communities despite complete anonymity regarding actual identities. The blockchain's transparency creates a permanent record of trading history that functions as reputation capital, enabling participants to build status through market performance rather than external credentials.

This form of identity formation differs substantially from both traditional financial markets and non-market social relationships. Unlike institutional financial markets where identity depends on formal credentials and organizational position, prediction markets enable identity construction through pseudonymous market participation that can operate independently of traditional status markers. Unlike social media platforms where identity performance occurs primarily through content creation, prediction markets enable identity formation through financial positioning on future events.

5.2 Market-Mediated Communities and Discourse

Beyond individual identity formation, prediction markets enable community development through their unique configuration. Each Polymarket event includes a digital comment section that allows traders to engage in complex social discourse about market events, creating interpretive communities that extend beyond simple price formation. These communities develop distinctive norms, specialized vocabularies, and status hierarchies that reflect the specific characteristics of the market itself.

Analysis of these comment sections reveals several patterns of market-mediated sociality. First, trading positions shape commenting behavior, with participants often justifying or rationalizing their market positions through commentary. In markets like "Who will be the next Pope?", participants engage in heated debates regarding outcomes and ethics, with sophisticated participants displaying specialized knowledge as a form of status performance. User @thetadecay noted, "can we add a warning for Catholics on this market? Gambling on papal elections is explicitly punishable by excommunication ," while another user offered detailed analysis of papal candidates, demonstrating specialized knowledge that functioned as status performance within the community.

Second, comments reflect distinct interpretive conflict, where participants develop competing narratives about market events and price movements. During the Pennsyl-

Business Horizons 60, no. 2 (2017): 155–165, https://doi.org/10.1016/j.bushor.2016.10.002.

vania Senate election, commenters engaged in intense debate about the significance of voting patterns, with some interpreting early returns as favorable for Casey while others emphasized the importance of uncounted rural districts. These interpretive conflicts reveal prediction markets not simply as price formation mechanisms but as sites of collective meaning-making where participants develop shared understandings of complex events through discursive interaction.

Third, these market-mediated communities extend beyond digital spaces into physical gatherings organized around prediction market participation. The Forecasting Meetup Network hosts monthly gatherings for "prediction markets traders, political gamblers, and forecasting hobbyists" across major cities, creating physical manifestations of digital communities formed through market participation. In a recursive demonstration of market identity, participants can even bet on attendee numbers for these gatherings through meta-markets on platforms like Manifold, creating nested layers of identity formation through the market mechanism itself.

These community structures emerge directly from the sociotechnical configuration of prediction markets.The phenomenon resembles what Cetina terms "synthetic situations"—digitally mediated social arrangements creating new interaction possibilities.[31] The combination of parallel comment sections that enable interpretive discourse alongside trading, blockchain transparency for trading histories, and pseudonymous participation together create these market-mediated communities as emergent properties of the assemblage itself. Unlike traditional financial communities that depend on institutional affiliation, these communities develop through the specific technological mechanisms of prediction market platforms, enabling characteristic digital connections that differ from both traditional market communities and non-market social arrangements.

5.3 Performative Dimensions: Markets as Reality Creators

Prediction markets do not merely forecast future events but potentially influence them through collective belief formation and performative effects. This performative dimension transforms markets from passive measurement tools into active participants in the social construction of reality through their recursive relationship with the events they claim to predict. This performative dimension extends beyond simple boundary work between representation and reality, creating what MacKenzie and Munster term "platform seeing"—new regimes of visualization that emerge through digital mediation.[32] Drawing on performativity theory from economic sociology, my analysis reveals how prediction markets function as "market devices" that actively reconstitute social reality rather than

31. Karin Knorr Cetina, "The Synthetic Situation: Interactionism for a Global World," *Symbolic Interaction* 32, no. 1 (2009): 61–87, https://doi.org/10.1525/si.2009.32.1.61.

32. Adrian MacKenzie and Anna Munster, "Platform Seeing: Image Ensembles and Their Invisualities," *Theory, Culture & Society* 36, no. 5 (2019): 3–22, https://doi.org/10.1177/0263276419847508.

merely describing it.[33]

Evidence of this performativity appears in social media discussions about prediction market prices. X user @joeyManarinoUS attached a screenshot of Polymarket market odds and tweeted on April 23, 2025: "The fact that Polymarket has Parolin at 29% is a disaster for the Church. Parolin would be Francis on steroids and everyone needs to understand that. Parolin is literally the man that Francis chose to be the Vatican Secretary of State." This response demonstrates how prediction prices are interpreted not merely as forecasts but as signals that potentially influence discourse about the events they claim to predict.

For electoral outcomes specifically, prediction market prices increasingly function as focal points in public discourse about election prospects, potentially influencing campaign strategies, donor decisions, and voter behavior through their perceived authority as probability estimates. Media coverage often treats these prices as objective indicators rather than socially constructed judgments, amplifying their potential influence on the events they purport to merely predict. This recursive relationship between market prices and real-world events creates complex feedback loops that challenge simple conceptions of prediction markets as neutral measurement tools.

As O'Dwyer writes: "Money links the present to the future. And so the value would not only measure the likelihood of whether such a thing might happen—it would be a measure of the collective will of the market to make it happen. The token could call such a future into being."[34] This perspective emphasizes how markets create complex feedback loops between prices and real-world events, challenging simple conceptions of directionality between markets and outcomes. Rather than simply predicting events, markets potentially participate in their creation through these performative effects.

This performative dimension transforms how we understand prediction markets as combinatorial forms of innovation. Beyond their epistemic function as forecasting tools or their financial function as speculative venues, these markets operate as sites of reality construction where collective beliefs form through market participation and potentially influence the events they claim to predict. This performative aspect transforms how participants relate to uncertain futures through market mechanisms.

5.4 The Extended Digital Self in Prediction Markets

Perhaps the most distinctive aspect of prediction market sociality involves what can be termed the "extended digital self"—a form of identity that develops through the projection of beliefs and expectations onto market structures. Through participation in prediction markets, individuals engage in a process of self-externalization, where their

33. Michel Callon, "Introduction: The Embeddedness of Economic Markets in Economics," *The Sociological Review* 46, no. S1 (1998): 1–57.

34. Rachel O'Dwyer, *Tokens: The Future of Money in the Age of the Platform* (London New York: Verso, 2023), 156.

judgments about uncertain futures become concrete financial positions visible to others. This process transforms how participants relate to both future events and their own beliefs, creating novel forms of identity expression that differ fundamentally from traditional polling or social media participation.

This externalization process manifests in several ways. First, prediction markets clearly delineate the boundary space between environment and agent. The natural world, by becoming something tradeable and priced, becomes 'outside' of the agent itself—creating dis-entanglement from reality by assuming that it exists on a separate layer. This separation enables people to trade on outcomes they may not personally desire but expect to occur, creating a separation between personal preference and market expectations.

Second, the continuous monitoring of prices creates a shared simulation of reality accessible to anyone anywhere as a type of universal 'language' of the commons. A user from Japan will observe the same election prediction as another user from Australia, then form their own reactions based on the same set of information flows. This form of digital sociality distinguishes prediction markets from prior forms of distributed communication channels that remain largely localized due to language barriers, distribution constraints, and time-lags.

Finally, prediction markets enable the separation of personal preference from probabilistic judgment, allowing participants to trade on outcomes they may not personally desire but expect to occur. This separation creates cognitive distancing that differs from both traditional market participation and non-market social expression. Unlike traditional financial markets, prediction market traders imbue a significant part of their identity into the market—requiring participants to "put their money where their mouth is" in ways that transform how beliefs are expressed and validated. This commitment mechanism differs fundamentally from other forms of opinion expression like polling or social media posting, creating what might be termed "financialized belief expression."

This ontological liquidity means that markets are non-objective in the sense that their network composition (prices, participants, depth) constantly changes rather than remaining static. Participants engage with a continuously evolving system that represents collective belief formation in real time. The distinctive social patterns documented in this chapter—comment section dynamics, pseudonymous identity formation, market-mediated communities, and performative dimensions—reveal these markets as sites where new forms of social relation emerge through technologically mediated interaction.

The extended digital self in prediction markets operates through a fundamental transformation in how participants relate to their own beliefs and expectations. Unlike polls where opinions are expressed without financial consequences, or traditional financial markets where positions reflect investment strategies rather than explicit probability judgments, prediction markets create a new form of commitment where participants financially back their beliefs about future events. This arrangement creates what might be termed "identity risk"—where being wrong not only carries financial penalties but also threatens the participant's reputation and self-conception as a knowledgeable forecaster.

This analysis of digital sociality in prediction markets demonstrates how they reshape social relationships beyond simple information aggregation. The pseudonymous identity formation, market-mediated communities, performative effects, and extended digital self documented in this section reveal prediction markets as complex social arrangements that transform how participants relate to uncertain futures, to each other, and to their own beliefs and expectations. Understanding these social dimensions is essential for comprehending how prediction markets function beyond their simple epistemic or financial aspects.

6 CONCLUSION: REIMAGINING MARKETS BEYOND EFFICIENCY

This thesis has reconceptualized prediction markets as sociotechnical assemblages that achieve accuracy through specialized competition rather than democratic wisdom aggregation. My analysis of 489 Polymarket election contracts reveals three fundamental insights: first, these markets maintain remarkable forecasting accuracy despite systematic inefficiencies that contradict efficient market theory; second, they operate through extreme concentration of trading activity among a tiny elite rather than broad popular participation; and third, they create distinctive forms of digital sociality that transform how participants construct identities and form communities. These findings challenge both efficiency-centered economic approaches and democratic wisdom-of-crowds narratives, instead revealing how prediction markets function as distinctive social arrangements that distribute agency across human and non-human elements while creating multiple forms of value. The extreme concentration documented here aligns with Pistor's analysis of how digital platforms simultaneously democratize access while enabling unprecedented concentration of influence.[35]

The theoretical implications of this research extend beyond prediction markets to broader transformations in how technological systems mediate economic coordination and social life. By reconceptualizing markets as cultural, social, and economic assemblages that distribute agency across human and non-human elements, this framework contributes to economic sociology, platform studies, science and technology studies, and discussions of financialization. As McAfee and Brynjolfsson argue, the reconfiguration of economic coordination through digital platforms represents a fundamental shift in how collective judgment forms in contemporary society.[36] Future research should extend this analysis to other prediction domains beyond elections, conduct comparative studies across different platforms with idiosyncratic technological characteristics, and combine transaction analysis with qualitative methods to access participant intentions and motivations directly. As blockchain-based platforms enable financial trading on previously non-financialized events, understanding how these markets function as social arrangements becomes increasingly important for comprehending the changing relationship between economic coordination, knowledge production, and identity formation in contemporary society.

The framework developed in this thesis reveals prediction markets not as neutral information aggregation mechanisms but as specialized competition arrangements that generate multiple forms of value through their particular sociotechnical configuration. This

35. Katharina Pistor, "Rule by Data: The End of Markets?," *Law and Contemporary Problems*, 2020, 101–124.

36. Andrew McAfee and Erik Brynjolfsson, *Machine, Platform, Crowd: Harnessing Our Digital Future*, First edition (New York: W.W. Norton & Company, 2017),

perspective challenges both traditional economic approaches that emphasize efficiency and democratic narratives that emphasize wisdom of crowds, instead illuminating how market accuracy emerges from the structured interaction of heterogeneous participants within a specific technological environment. By examining prediction markets through this lens, we gain insight into not just these specific platforms but broader transformations in how economic coordination and social relationships evolve through technological mediation in the digital age.

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A METHODOLOGICAL DETAILS

A.1 Market Efficiency Testing Methodology

To assess the weak-form efficiency of prediction markets, I implemented a comprehensive statistical testing framework following and contemporary prediction market literature.[37] The methodology employs five distinct econometric approaches:

Random Walk Test The Augmented Dickey-Fuller (ADF) test examines whether price series follow a random walk process. For each market i, I test the null hypothesis that the price series contains a unit root:

$$H_0 : \text{Price series of market } i \text{ has a unit root}$$

Efficient markets exhibit non-stationarity in price levels (p-value > 0.05), indicating prices follow a random walk without systematic predictable patterns. The test statistic is computed using the regression equation:

$$\Delta p_t = \alpha + \beta p_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta p_{t-j} + \epsilon_t$$

where p_t represents the price at time t, and k is the lag order determined by the Akaike Information Criterion.

Return Stationarity Test The ADF test is applied to logarithmic returns to evaluate return stationarity. For efficient markets, returns should exhibit stationarity (p-value < 0.05), indicating a consistent underlying distribution. The test is applied to the log-return series $r_t = \ln(p_t/p_{t-1})$ using the same ADF methodology as the price series.

Autocorrelation Analysis The autocorrelation function (ACF) for log returns is computed across multiple lags to detect serial correlation. For a market with sample size n, I establish significance thresholds at $\pm 1.96/\sqrt{n}$. Efficient markets should demonstrate no significant autocorrelation in returns, as significant values would indicate predictable patterns. The autocorrelation at lag k is calculated as:

$$\rho_k = \frac{\sum_{t=k+1}^{n}(r_t - \bar{r})(r_{t-k} - \bar{r})}{\sum_{t=1}^{n}(r_t - \bar{r})^2}$$

Runs Test for Randomness The non-parametric runs test evaluates the randomness of return sequences independent of distributional assumptions. The test computes the number of "runs"—consecutive sequences of returns with the same sign—and compares it to the expected number under the random walk hypothesis. For a series with n_+

37. Eugene F. Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance* 25, no. 2 (1970): 383–417.

positive and n_- negative returns, the expected number of runs is:

$$E(R) = \frac{2n_+n_-}{n_+ + n_-} + 1$$

with standard deviation:

$$\sigma_R = \sqrt{\frac{2n_+n_-(2n_+n_- - n_+ - n_-)}{(n_+ + n_-)^2(n_+ + n_- - 1)}}$$

The standardized test statistic follows a normal distribution, with p-values ≥ 0.05 indicating random sequencing consistent with efficiency.

Autoregressive Model Test An AR(1) model is fit to return series to assess return predictability:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \epsilon_t$$

Efficient markets should exhibit statistically insignificant AR coefficients (p-value $\geq$ 0.05), indicating returns cannot be predicted from past values.

Composite Efficiency Score I construct a composite efficiency score through weighted aggregation of individual test results:

$$\text{Efficiency Score}_i = \frac{\sum_{j=1}^{5} w_j \cdot S_j}{\sum_{j=1}^{5} w_j} \times 100$$

where w_j represents test-specific weights (Random Walk: 25; Return Stationarity: 25; Autocorrelation: 20; Runs Test: 15; AR Model: 15), and S_j indicates the score for test j.

Markets are classified into four efficiency categories based on their composite scores:

- Highly Efficient [80,100]
- Moderately Efficient [60,80)
- Slightly Inefficient [40,60)
- Highly Inefficient [0,40)

A.2 Trader Classification Methodology

The trader classification approach employs unsupervised learning techniques to identify distinct behavioral patterns without imposing predefined categories. The implementation follows a systematic process:

Feature engineering: For each trader i, I computed a feature vector $\mathbf{x}_i$ comprising:

$$f_{freq,i} = \frac{\text{num\_trades}_i}{\text{active\_days}_i}$$

$$f_{vol,i} = \text{total\_trading\_volume}_i$$
$$f_{avg,i} = \frac{\text{total\_trading\_volume}_i}{\text{num\_trades}_i}$$
$$f_{dir,i} = \frac{\text{buys}_i - \text{sells}_i}{\text{buys}_i + \text{sells}_i}$$
$$f_{price,i} = \text{corr}(\text{trade\_direction}_i, \Delta\text{price})$$
$$f_{temp,i} = \frac{\text{late\_stage\_trades}_i}{\text{total\_trades}_i}$$

Dimensionality management: Features with high skewness were transformed using:

$$X_{log} = \log(1 + X)$$

Feature normalization: Standard scaling was applied:

$$X_{scaled} = \frac{X - \mu_X}{\sigma_X}$$

Clustering implementation: K-means clustering was applied to minimize:

$$\min_C \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in C_i} |\mathbf{x}_j - \boldsymbol{\mu}_i|^2$$

where C_i is the ith cluster, $\mathbf{x}_j$ is the feature vector for trader j, and $\boldsymbol{\mu}_i$ is the centroid of cluster i.

Optimal cluster selection: The number of clusters k was selected by maximizing the silhouette score:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

where $a(i)$ is the mean intra-cluster distance and $b(i)$ is the mean nearest-cluster distance for point i.

Trader strategy classification: For each trader, a strategy score was computed:

$$\text{Strategy}_i = \frac{\sum_{t \in T_i} \text{sgn}(\text{dir}_t) \cdot \text{sgn}(\Delta p_{t-1})}{|T_i|}$$

where T_i is the set of trades by trader i, dir_t is the direction of trade t (1 for buy, -1 for sell), and Δp_{t-1} is the price change prior to trade t.

A.3 Price Impact and Network Effect Analysis

The price impact measurement framework quantifies how different trader categories influence market prices:

Price Impact Calculation

For each trade i by trader type j, the immediate price change ΔP_i was calculated as:

$$\Delta P_i = P_{i+1} - P_i$$

To account for trade direction, adjusted price impacts $\Delta P_i'$ were computed:

$$\Delta P_i' = \begin{cases} \Delta P_i & \text{if trade is buy} \\ -\Delta P_i & \text{if trade is sell} \end{cases}$$

The weighted average price impact for trader type j was calculated as:

$$\overline{\Delta P}_j = \frac{\sum_{i \in j} V_i \Delta P_i'}{\sum_{i \in j} V_i}$$

where V_i is the volume of trade i.

The impact ratio between trader types A and B was computed as:

$$R_{impact} = \frac{\overline{\Delta P}_A}{\overline{\Delta P}_B}$$

Network Cascade Analysis

For whale identification, traders were classified based on volume percentile:

$$\text{Whale}_i = \begin{cases} 1 & \text{if volumeRank}_i \leq 0.01 \cdot N \\ 0 & \text{otherwise} \end{cases}$$

where N is the total number of traders.

For each whale trade w at time t_w, subsequent trades within a 60-minute window were analyzed:

$$F_w = \{i \mid t_i - t_w \leq 60 \text{ min} \wedge \text{dir}_i = \text{dir}_w\}$$

The follow ratio for trader type j was calculated as:

$$\text{Follow}_j = \frac{|\{i \in F_w \mid \text{type}_i = j\}|}{|\{i \mid t_i - t_w \leq 60 \text{ min} \wedge \text{type}_i = j\}|}$$

The average follow time for trader type j was computed as:

$$\text{AvgFollowTime}_j = \frac{\sum_{i \in F_w, \text{type}_i = j} (t_i - t_w)}{|\{i \in F_w \mid \text{type}_i = j\}|}$$

B MICROSTRUCTURAL ANALYSIS RESULTS

The following figures visualize key findings regarding differential price impacts and response times across trader categories:

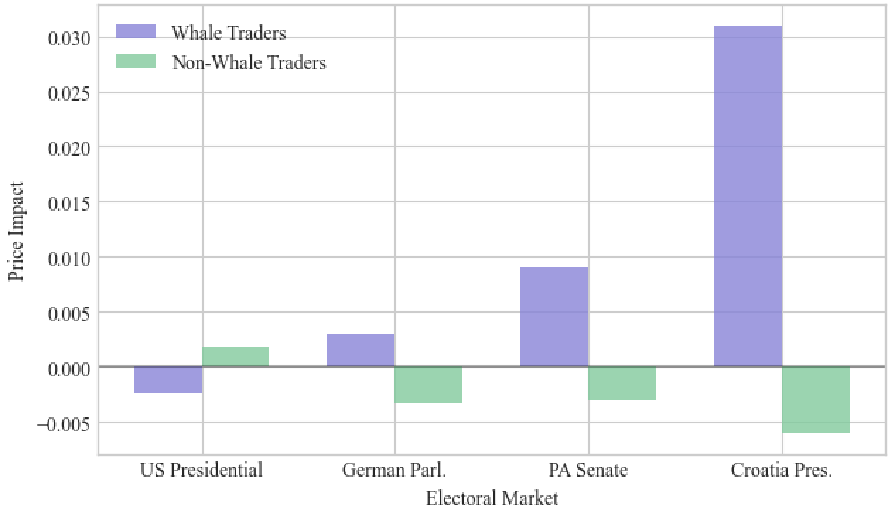

Figure 5. *Price Impact Across Markets. Positive values indicate prices follow trader direction; negative values indicate prices move in opposite direction.*

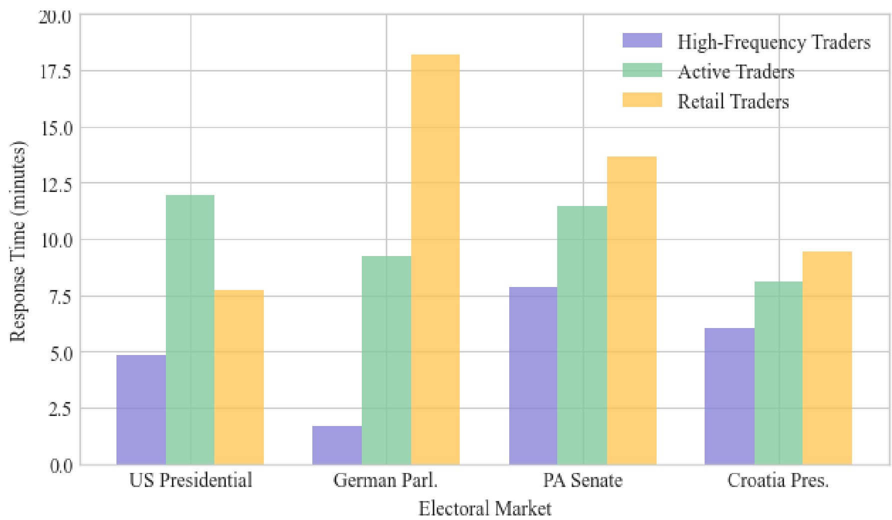

Figure 6. *Average Response Time to Whale Trader Activity.*

These visualizations support the findings discussed in Section III regarding hierarchical information flows and differential price impacts across trader categories. Figure 5 demonstrates how whale traders exhibit distinctive price impact patterns compared to non-whale participants, while Figure 6 illustrates the systematic response timing differences that characterize the trader ecology.

C CORE MARKET ANALYSES

Table 9. *US Presidential Election Market Characteristics*

Market	ID	Volume (USD)	Traders	Price	Result
Donald Trump	253591	1.53 billion	62,065	0.555	Yes
Kamala Harris	253597	1.04 billion	72,183	0.399	No
Other Republican	253642	241.66 million	22,339	0.001	No
Michelle Obama	253609	153.38 million	18,963	0.001	No
RFK Jr.	253595	141.61 million	19,391	0.001	No
Other Democrat	253641	116.56 million	18,519	0.001	No
Nikki Haley	253593	107.53 million	15,736	0.001	No
Hillary Clinton	253610	93.31 million	9,795	0.001	No
Joe Biden	253592	72.18 million	6,729	0.001	No
Gavin Newsom	253594	54.16 million	5,305	0.001	No

Table 10. *Key US Presidential Market Metrics*

Metric	Value
Market Duration	296 days
Trading Frequency	15,631 trades/day
Average Trade Size	$784
Trader-to-Trade Ratio	21.6 trades per trader
Two-Way Traders Ratio	0.64
Price Range (Trump)	0.715
Price Volatility (Trump)	0.289
Gini Coefficient	0.943
Market Efficiency Score (Trump)	40.0

Note: Two-Way Traders Ratio represents the proportion of traders who both bought and sold positions. Market Efficiency Score ranges from 0 (highly inefficient) to 100 (perfectly efficient).

Table 11. *US Presidential Market Efficiency Classifications*

Efficiency Classification	**Markets**	**Percent**	**Examples**
Highly Efficient (80-100)	0	0.0%	–
Moderately Efficient (60-80)	0	0.0%	–
Slightly Inefficient (40-60)	4	23.5%	Trump, Harris, Kennedy, Biden
Highly Inefficient (0-40)	13	76.5%	All other candidates

Table 12. *Trader Concentration in 2024 US Presidential Election Market*

Trader Category	**% of Traders**	**Number**	**% of Volume**
Top 0.1%	0.1%	87	47.9%
Top 1.0%	1.0%	878	69.2%
Top 5.0%	5.0%	4,392	84.7%
Top 10.0%	10.0%	8,784	91.1%

Table 13. *Trader Type Distribution in US Presidential Markets*

Trader Type	**%**	**Count**	**% Volume**	**Strategy Score**
Retail Traders	43.1%	37,860	12.3%	-0.392
Active Traders	37.1%	32,590	23.7%	-0.282
High-Frequency Traders	19.7%	17,305	64.0%	-0.331

Note: Strategy Score values range from -1 (fully contrarian) to +1 (fully momentum), with 0 representing neutral positioning.

Table 14. *Pennsylvania Senate Election Market Characteristics*

Market	**ID**	**Volume (USD)**	**Traders**	**Price**	**Result**
Republican (McCormick)	500109	2,564,649	1,326	0.22	Yes
Democrat (Casey)	500108	2,306,432	481	0.78	No
Other candidate	500110	613,378	1,085	0.002	No

Table 15. *Key Pennsylvania Senate Market Metrics*

Metric	**Value**
Total Volume	5.48 million USD
Market Duration	217 days
Trading Frequency	68.3 trades/day
Average Trade Size	$659
Trader-to-Trade Ratio	5.4
Two-Way Traders Ratio	0.36
Price Range (Democrat)	0.47
Price Volatility (Democrat)	0.189
Final Week Momentum (Democrat)	+0.15
Prediction Error (Brier Score)	0.608
Gini Coefficient	0.961

D COMPARATIVE ANALYSIS

Table 16. *Comparative Market Microstructure Metrics Across Electoral Contexts*

Metric	**US Pres.**	**German Parl.**	**PA Senate**	**Croatia Pres.**	**SF Mayor**	**UK Parl.**
Volume (USD millions)	3,680	134.62	5.48	3.14	7.13	4.24
Unique Traders	87,843	37,449	2,666	6,742	1,874	5,302
Market Duration (days)	296	62	217	47	43.6	82
Trading Frequency	15,631	9,827	68.3	116.4	212.8	117.5
Gini coefficient	0.943	0.980	0.961	0.938	0.951	0.964
Traders for 50% vol.	0.10%	0.14%	0.79%	1.80%	1.23%	0.89%
Traders for 90% vol.	5.00%	2.24%	5.10%	10.86%	8.42%	6.87%
Whale impact	−0.0024	+0.0030	+0.0230	+0.0310	+0.0186	+0.0040
Non-whale impact	+0.0019	−0.0033	−0.0080	−0.0060	−0.0025	−0.0029
Impact ratio	−1.285	−0.919	−2.860	−5.550	−7.440	−1.366
Closing price (winner)	0.555	0.967	0.220	0.940	0.610	0.875
Brier Score	0.19	0.001	0.608	0.01	0.14	0.02
Efficiency Score	40.0	50.0	65.0	45.0	70.0	45.0
% Contrarian (HFT)	45.9%	32.9%	34.9%	54.8%	40.2%	41.5%
% Contrarian (Retail)	49.6%	60.0%	63.9%	53.2%	58.7%	56.9%
Avg. follow time (min)	4.81-11.97	1.67-18.19	7.83-13.66	6.00-9.46	5.45-12.80	6.14-8.40

Table 17. *Market Distribution by Election Type and Region*

Election Type	**Count**	**Region**	**Count**
Presidential	197	United States	368
Senate	49	United Kingdom	21
Presidential Primary	48	Germany	15
Parliamentary	42	Ireland	14
Vice Presidential	41	Brazil	12
Prime Minister	24	Canada	10
Presidential Popular Vote	18	Belarus	7
Mayoral	16	France	6
Presidential Tipping Point	14	Romania	5
Balance of Power	9	Venezuela	5
Presidential Speech	8	Croatia	5
Governor	7	Moldova	4
Provincial	7	Mexico	4
Electoral College	6	Greenland	4
Presidential Administration	4	Taiwan	3

Table 18. *Prediction Accuracy by Election Type*

Event Election Type	**Accuracy**	**Count**	**Accuracy (%)**
Presidential	0.969	194	96.90%
Presidential Primary	1.000	48	100.00%
Senate	0.933	45	93.30%
Parliamentary	0.929	42	92.90%
Vice Presidential	1.000	41	100.00%
Prime Minister	0.958	24	95.80%
Presidential Popular Vote	0.889	18	88.90%
Mayoral	0.813	16	81.20%
Presidential Tipping Point	0.929	14	92.90%
Balance of Power	0.889	9	88.90%
Provincial	0.714	7	71.40%
Presidential Speech	1.000	7	100.00%
Electoral College	0.833	6	83.30%
Governor	1.000	6	100.00%