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The Wisdom of Crowds in Markets

Crowd Behavior in Prediction, Betting, and Stock Markets

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Introduction

In 1932, Bernard Baruch, a wealthy financier who made his fortune on Wall Street in the early 20th century, contributed the foreword to a reprint of the 1852 edition of Charles Mackay's classic book on markets, *Memoirs of Extraordinary Popular Delusions and the Madness of Crowds*.

Invoking a dictum from Friedrich von Schiller, a German poet and philosopher, Baruch wrote: "Anyone taken as an individual, is tolerably sensible and reasonable—as a member of a crowd, he at once becomes a blockhead." He added, "Without due recognition of crowd-thinking (which often seems crowd-madness) our theories of economics leave much to be desired."[1]

About 40 years later, Eugene Fama, a professor of finance at the University of Chicago and a winner of the Nobel Prize in Economics, published "Efficient Capital Markets: A Review of Theory and Empirical Work." It is among the most famous papers ever written in finance. This might be considered the theory Baruch had in mind. Fama posited, "A market in which prices always 'fully reflect' available information is called 'efficient.'"[2]

Fama found that strategies investors commonly applied to try to outperform the market, including using past price patterns to project the future and doing fundamental analysis to distinguish between price and value, failed in their objective. In other words, there is no reliable way to take advantage of the blockheads.

Nearly all those who study markets carefully agree that they appear sensible for the most part, as theory would have it, but periodically go bonkers.[3] Having one framework to accommodate both realities is useful.

James Surowiecki wrote about such an approach in 2004.[4] Riffing on Mackay's madness of crowds, Surowiecki called his book, *The Wisdom of Crowds*. He showed that crowds can be remarkably accurate in reflecting objective values or outcomes. Indeed, the prices generated by collectives commonly converge on the proper theoretical price in experimental settings.[5] This thinking runs against the idea that individuals are reasonable and crowds mad.

But key to Surowiecki's case is that the wisdom of crowds depends on satisfying certain conditions. When those conditions are in effect, crowds are generally wise. When one or more of those conditions are violated, crowds can be mad.

This report specifies those conditions, identifies various types of problems, and examines how they apply to prediction markets, sports betting, parimutuel betting, and the stock market. The goal is to see how the conditions function in each market, and where they are the same or different for each.

These concepts are useful for investors for a few reasons. First, the wisdom (and madness) of crowds is a sound way to explain market behavior. Practitioners have had a sense of this for centuries and academics now take the idea seriously.[6] Second, prediction markets provide real-time probabilities for events that may be helpful to investors.

Finally, the conditions for collective intelligence apply within organizations as well, which has relevance for hiring and training employees as well as structuring meetings and making decisions. There remains a large gap between what research reveals as best practices and what most organizations actually do.

Conditions for Crowds to Be Wise

We discuss three conditions for crowds to be wise: diversity, aggregation, and incentives.

Diversity. In organizations, it is common to understand diversity as a reflection of social categories such as gender, age, ethnicity, and religion. Effective collective decision-making relies on cognitive diversity, which captures how group members differ in their information, knowledge, heuristics, representations, and mental models.

Scott E. Page, a professor of complex systems, political science, and economics at the University of Michigan, is one of the leading researchers on diversity.[7] As we will see in a moment, Page also shows the math of how and why cognitive diversity reduces collective error.

Here are the elements of cognitive diversity that Page features:

- *Information* consists of facts about the world. Friedrich Hayek, who received the Nobel Prize in Economics, made the point that information tends to be incomplete and local. It can also be contradictory.[8] Information is not just data but rather something an individual interprets as meaningful.

  Prices reflect all information in an efficient market. Yet having better information than others can be a source of advantage in all of the markets that we will discuss.

- *Knowledge* has to do with structural understanding and entails a theoretical or empirical comprehension of how things work. It is tied to critical thinking and can be specific to a domain. Relying on the output of generative artificial intelligence (GenAI) without the benefit of knowledge creates the risk of misunderstanding.

- *Heuristics* are rules of thumb, approaches, or techniques to solve problems and generate ideas. A diverse set of heuristics contributes to collective results because different heuristics work for different problems. You can learn heuristics in any order and they often apply across disciplines.

- *Representations* capture the perspectives and categorizations individuals use when they consider a subject. People with different points of view will take alternative approaches to solving a problem. For instance, ask a group of people to list the largest countries in the world. One might create a list based on land mass, another on population, and a third on gross domestic product. These different perspectives can produce insight.

- *Mental models* are frameworks that help individuals think about how the world works. They are based on understanding and experience. Mental models are internal representations of external realities that trade specifics for speed.[9]

  Categorizations are important because humans think in analogies.[10] Grouping companies based on industry or positioning is a case in point. Nordstrom and Dollar General are retailers, and Ferrari and Suzuki are automobile manufacturers. A classification based on brand would link Nordstrom and Ferrari as premium and Dollar General and Suzuki as low-cost. Different categorizations can allow collectives to better assess alternatives and outcomes.

Collective error tends to be small when individual members are cognitively diverse and their views are properly aggregated.

Diversity is the most likely condition to be violated in financial markets because investing is an inherently social activity. Prices can be a source of information as well as influence. As a result, the behavior of investors is correlated from time to time, leading to booms and busts. We discuss diversity breakdowns in each of the markets we consider.

Aggregation. Having diverse information helps uncover the truth only when it can be effectively aggregated. The various markets we will discuss use several aggregation methods. In each case, the output of the aggregation is a quantity that reflects the likelihood of a particular outcome. As such, aggregation is essential for price discovery, the process of finding an asset's fair price through the interaction of buyers and sellers on an exchange.

There is evidence that the chosen approach to aggregation affects accuracy.[11] Straightforward methods such as averaging the answers of a group of experts or models can improve forecasts.[12] Accuracy can be boosted further by using more complex techniques such as weighted averages or extremizing algorithms that push forecasts away from the simple average when there is evidence that the original forecasts are too conservative.[13]

Information aggregation is prominent in nature, where getting to a good answer can be the difference between life and death. For example, honeybees use waggle dances to communicate the direction, distance, and quality of food sources. ("On average, one second of the combined body-waggling/wing-buzzing represents some 1,000 meters [six-tenths of a mile] of flight.")[14] When scouts return to the hive with conflicting information, the colony's action depends on the intensity and duration of competing dances.

Ant colonies do something similar with pheromone trails as they forage. Paths of higher quality get reinforced faster, which allows the colony to converge on the shortest path to the food.[15] Flocks of birds and schools of fish have also evolved sophisticated means to share information.[16]

Incentives. On one level, the importance of incentives, rewards for being right and penalties for being wrong, is self-evident. In markets, we can measure incentives with money. If an individual's goal is to make money (or excess returns in equity markets), they should participate only if they believe they have an edge, or a well-founded view that is different than what is priced into the market.

As Scott Page writes, "Information markets create incentives for less confident people to stay out, and for confident people to bet more."[17] In other words, your bet size should reflect your confidence in your edge.

Fama suggested that an efficient market is one where the price captures all available information. Two economists, Sanford Grossman and Joseph Stiglitz (Stiglitz won the Nobel Prize), demonstrated that markets cannot be fully informationally efficient because there is a cost to collecting information and reflecting it in prices. As a result, there should be a proportionate benefit in the form of excess returns to incentivize participants.[18]

In a nutshell, the Grossman-Stiglitz paradox says that investors would have no incentive to collect information if markets were perfectly efficient, but informed traders are necessary for markets to be efficient. Lasse Pedersen, a professor of finance, suggests markets must be "efficiently inefficient." Skilled participants can earn excess returns by identifying and trading on inefficiencies, but their efforts make markets more efficient.

Gathering information is but one cost. Reflecting it in prices is another. Transaction costs and market impact, where the act of buying and selling moves the market and reduces expected return, can be meaningful. Edge has to be sufficient to overcome costs.

We will also look at the distribution of winners across markets. Prediction markets, sports betting markets, and parimutuel markets are all zero sum in the sense that the payoffs to winners and losers net to zero before expenses. We will see that a small number of participants make money in these markets.

The stock market is zero sum for relative results, which means that excess returns net to nil before costs. But it is a positive sum market overall because stocks tend to rise over time. The stock market's positive expected return reflects the rate that those who want to consume now must pay and the rate those willing to defer their consumption will earn. This means that while some stock market investors may have negative excess returns, they will still have positive expected returns on an absolute basis over the long term.

Problem Types

Understanding the type of problem you face is an important first step in determining how best to solve it. In some cases, a crowd may be more of a hindrance than a help.

Take the example of Ebbsfleet United, a soccer team that competes in the lower tiers of the English league system.[19] Starting in 2007, a group called MyFootballClub was organized to own and run the team. At one point, more than 20,000 fans had a voice in managing the club, including making decisions about players.

After a bit of early success, the experiment went south. The violation of the conditions for crowd wisdom explains why. The baseline knowledge of the fans was poor, in part because the club played in a low tier and the central forums for discussion led to correlated views. The voting structure was cumbersome. And while fans paid a modest £35 subscription fee, it was insufficient to act as a compelling incentive. The club was later sold at a fraction of the purchase price.[20]

We describe the first problem as finding a needle-in-a-haystack. In this case, an objective answer exists and some members within the collective know it. Appendix A shows how crowds can answer these questions. But technology, such as search engines or GenAI, does so more quickly.

The second type of problem is estimating a state. In this case, no one within the collective knows the answer, but it exists and is later revealed. To open his book, Surowiecki offers an example of this type through the story of Francis Galton, a polymath in the United Kingdom's Victorian era, and the weight of an ox.[21]

In December 1906, the West of England Fat Stock & Poultry Society held its annual show in Plymouth, England. The show included a competition to guess the dressed weight of an ox. Participants paid sixpence (about $5 today) for a ticket and wrote their estimate. Eight hundred tickets were sold, and Galton's sample was 787 because 13 of them were "defective or illegible."

After the awards were passed out, Galton borrowed the tickets to examine them. He was excited about the data because the "judgments were unbiased by passion and uninfluenced by oratory." Participants "included butchers and farmers, some of whom were highly expert in judging the weight of cattle" and others "probably guided by such information as they might pick up, and by their own fancies."

Note that the conditions for the wisdom of crowds were in place: diversity in the nature of the guesses, aggregation via Galton's calculations, and incentives, including a cost to participate and a prize for accuracy ("the sixpenny fee deterred practical joking" and "the hope of a prize . . . prompted each competitor to do his best.")

The average guess of the collective was 1,197 pounds, equal to the actual weight of the ox. (Galton incorrectly transcribed it in the article as 1,198, which is the number Surowiecki uses.)[22] Galton comes across as a bit surprised, writing, "This result is, I think, more creditable to the trustworthiness of a democratic judgment than might have been expected."

Scott Page offers what he calls the "diversity prediction theorem" as a way to explain results such as those of Galton.[23] It states:

Collective error = average individual error – prediction diversity

Translated into simpler terms, the theorem says the wisdom of crowds (collective error) comes from individual smarts (average individual error) and diversity (prediction diversity).

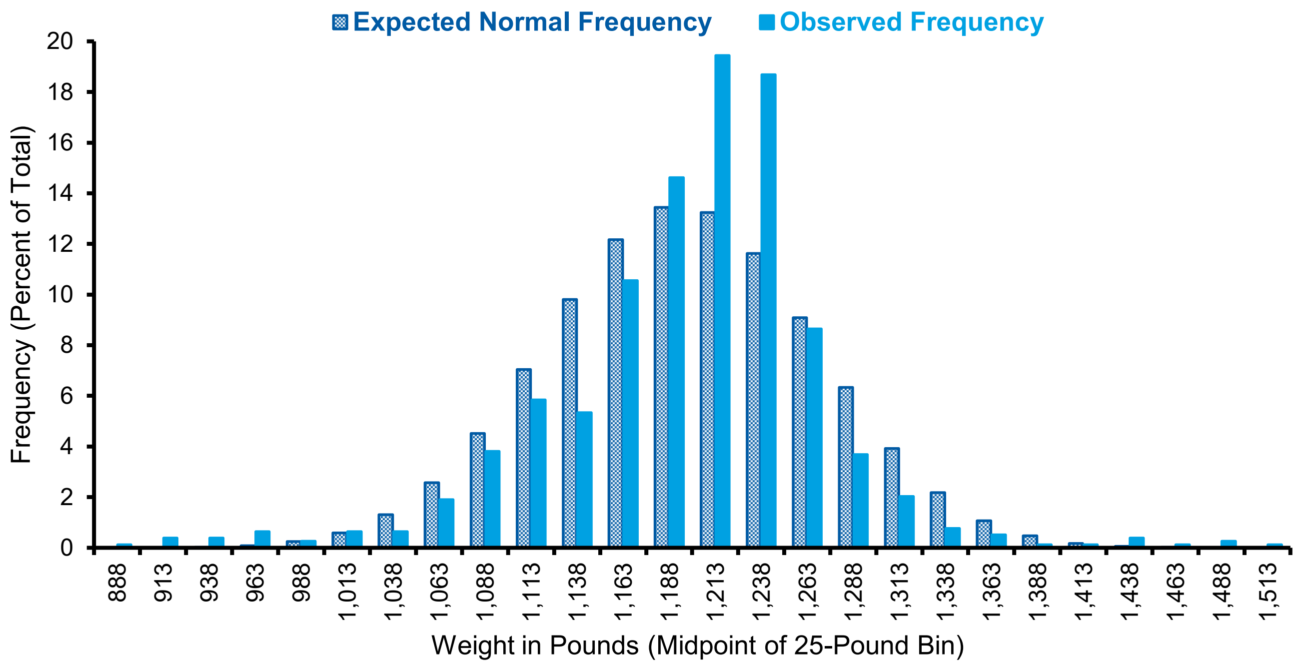
The theorem has two implications. The first is that a collective with any diversity will be more accurate than the average individual within the collective.

The second is that collective wisdom is a combination of both smarts and diversity. You can make the crowd smarter by reducing individual error or increasing diversity.

Appendix B applies the diversity prediction theorem to Galton's data. We use the full sample of 787 guesses.

One of the points that Galton made about the data is that it did not follow a normal distribution, where results take the shape of a bell with the top defined as the average and the width of the bell as the standard deviation. Exhibit 1 compares the Galton data to the expected normal distribution.

Exhibit 1: The Guesses of the Ox's Weight Do Not Follow a Normal Distribution



Source: Kenneth F. Wallis, "Revisiting Francis Galton's Forecasting Competition," Statistical Science*, Vol. 29, No. 3, August 2014, 420-424.*

Jack Treynor, an economist and luminary in the investment industry, wrote a paper using the problem of estimating a state as a way to illustrate a path to market efficiency. Rather than guessing the weight of an ox, Treynor had his students guess the number of beans in a jar. He had a result similar to that of Galton, albeit with a much smaller sample.[24]

Applying the lesson to financial markets, Treynor explained that the result "comes from the faulty opinions of a large number of investors who err independently. If their errors are wholly independent, the standard error in equilibrium price declines with roughly the square root of the number of investors." This originates from an equation derived by the renowned French mathematician, Abraham de Moivre.

The important implication is that small samples of a large and diverse population can produce meaningful deviations from true value because the draw might randomly have more high or low guesses.[25]

The third type of problem is a prediction about an outcome that is resolved in a timely manner. In this case, no one knows the answer in advance, but an event occurs that settles the score. Prediction markets, sports betting, and parimutuel betting are examples of ways to solve problems of prediction. We know the results after an election is held, a game is played, or a race is run.

The fourth type of problem is a prediction about an outcome that remains unresolved. The stock market is a case in point. The value of a company, which in theory should be equal to its market price, is based on the present value of future cash flows. But because no one knows what the future holds, there is no resolution unless a company is acquired or goes bankrupt.

A perpetual futures contract, a form of derivative that provides economic exposure to the price of an asset, is another example. The Commodity Futures Trading Commission (CFTC) recently approved a perpetual contract that references the spot price of bitcoin.[26]

We now turn to how the wisdom or madness of crowds applies to the four markets. In each case, we describe the market, offer a brief history, discuss its accuracy, specify the aggregation mechanism, consider diversity, and assess incentives, including the cost to play as well as the distribution of profits.

Betting markets share several characteristics with financial markets, including large numbers of participants, widespread access to information, and meaningful financial incentives. But they are different because there are outcomes that provide a way to measure efficiency.[27]

The Wisdom (or Madness) of Crowds by Market

Prediction markets. Prediction markets aggregate information and generate forecasts about future events. Participants buy or sell a contract that has a payoff that reflects the result. While there are various forms of contracts, most are binary.[28] For example, the contract for candidate A in an election pays $1.00 if she wins and $0 if she loses.

The contract price, which is updated continuously through trading, reflects the probability that a particular outcome occurs. The interpretation of a contract trading at $0.70 is that there is a 70 percent probability the event will occur. Those who believe the likelihood is higher will be inclined to buy, and those who believe it is lower will sell.

Brief history. Betting on outcomes has been around for a long time. For instance, there were quotes on betting odds for the pope of the Catholic Church in 1503 (Pius III was elected), and that type of wagering was already viewed as "an old practice."[29]

We trace three eras of modern prediction markets.

The first reflects betting on political outcomes in the U.S. from the 1880s to the 1920s. Paul Rhode and Koleman Strumpf, professors of economics, note that these markets were active and well followed. The 1916 presidential election had betting volume exceeding $300 million (in 2026 dollars), and prominent newspapers such as *The New York Times* provided price quotations on the candidates nearly every day.

Rhode and Strumpf show "that the market did a remarkable job forecasting elections," identifying the winning candidate in all but one presidential election from 1884 to 1940.[30]

Despite their accuracy, betting markets were always tarnished by their association with gambling. *The Literary Digest*, a weekly magazine, introduced a non-scientific poll that successfully called the presidential elections from 1916 to 1932. George Gallup created a scientific poll that famously called the 1936 election correctly while *The Literary Digest* got it wrong.

Over time, media coverage came to focus more heavily on polling results than on prediction markets. Rhode and Strumpf note that there were more articles about *The Literary Digest* polls than betting markets in *The Washington Post* in 1924 and in *The New York Times* in 1928. Coverage of the Gallup poll started in 1936 and exceeded that of both *The Literary Digest* poll and betting markets by 1940.[31]

The launch of the Iowa Electronic Markets (IEM) in April 1988 marked the beginning of the second era.[32] The market was the brainchild of three economists at the University of Iowa and operated under exemption from gambling laws in the state. While the market used real money, the economists capped the individual stakes at $500. The IEM is designed to predict the popular vote.

In the 1988 election, the IEM's closing prices were more accurate than the polls published by The Gallup Organization, Harris and Associates, CNN/USA Today, ABC/Washington Post, NBC/Wall Street Journal, and CBS/New York Times. The IEM has consistently been better than polls since then with the exception of 2024.[33]

While the IEM came out of academia, commercial prediction markets emerged in this era as well. The development of the internet facilitated these markets.

Intrade, which operated from 2001 to 2013, created contracts for elections, economic indicators, and geopolitical events. Hollywood Stock Exchange was founded in 1996 and has contracts on movie openings and entertainment awards. TradeSports, started by the founders of Intrade, operated sporadically from the early 2000s through 2015 and traded in sports and other events.

As in the prior era, these markets proved to be more accurate than common alternatives such as polls and expert forecasts.[34] But they faced regulatory scrutiny and, similar to the past, suffered from the stigma of gambling.

Another setback for prediction markets occurred when the Defense Advanced Research Projects Agency, a research and development agency within the U.S. Department of Defense, proposed what came to be called the Policy Analysis Market in 2001.[35] This market was intended to better assess geopolitical risk, a topic on the minds of analysts and policymakers in the wake of intelligence failures preceding the terrorist attacks on September 11, 2001. In the summer of 2003, the plan was roundly denounced by U.S. senators and subsequently scuttled.

The third era started about a decade ago and has benefited from ongoing technological advancements, such as blockchain platforms, and even more significantly from regulatory relief. Market leaders by trading volume include Polymarket, Kalshi, and ForecastEx.

The CFTC specifies which exchanges are designated contract markets (DCMs), which means they operate under the CFTC's regulatory oversight. Historically, the CFTC allowed platforms such as the IEM to operate under strict exemptions, including limiting individual investments. The CFTC also permitted the DCMs to self-certify contracts but retained the right to block those contracts it deemed inappropriate.

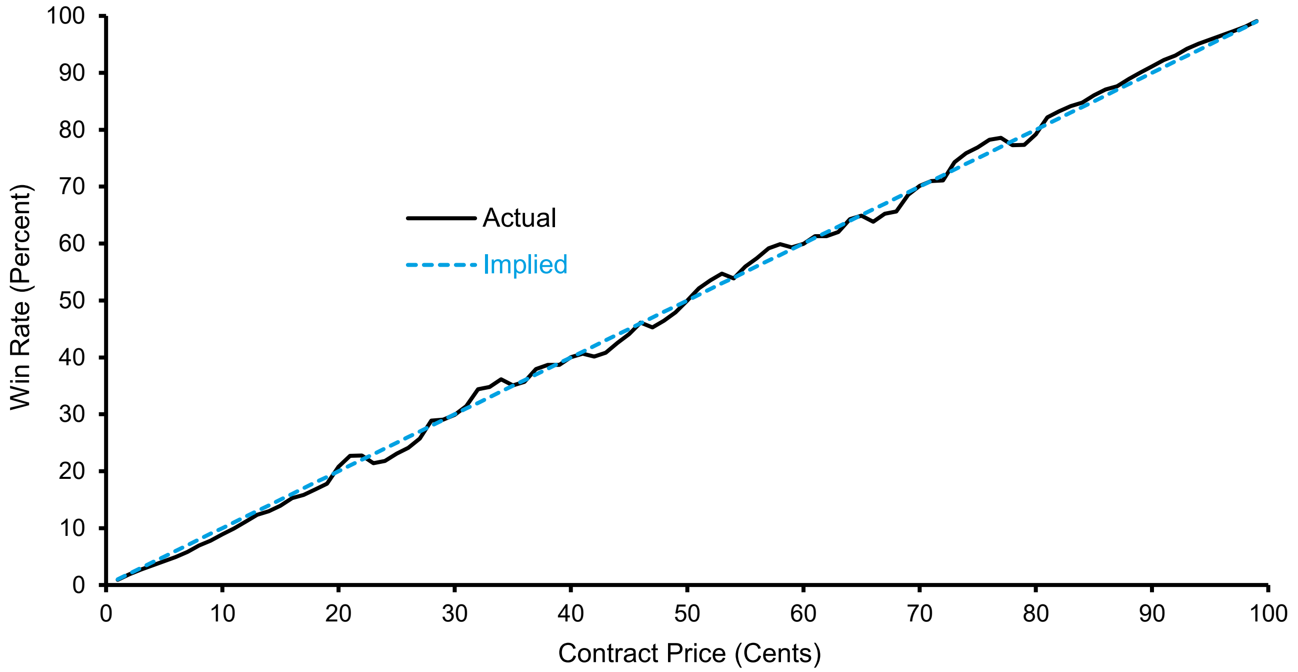
In 2023, the CFTC barred some contracts at Kalshi that were based on the outcome of elections for Congress. The CFTC considered them to be election gambling that was in violation of state laws. Kalshi sued the CFTC and won the case in U.S. District Court in the District of Columbia in September 2024.

Following that ruling and a change in administration, the CFTC has largely permitted the DCMs to self-certify contracts freely.[36] This allowed the DCMs to introduce sports contracts. These contracts compete with sports betting, which is regulated at the state, rather than federal, level. In fact, the CFTC has sued states that have tried to use their wagering laws to regulate prediction markets.[37] In the U.S. as of July 2026, 39 states and Washington, D.C. have legalized sports betting, with 30 of them and D.C. allowing betting on mobile devices or websites.

Prediction markets and sports betting markets now largely overlap as the result of these developments. Estimates suggest that sports contracts were 80 percent of Kalshi's volume and about 40 percent of Polymarket's volume from July 2024 to April 2026.[38]

Accuracy. One of the main attractions of prediction markets is that they are more accurate than other popular sources of information, including polls and the opinions of single experts. Exhibit 2 shows the contract price on the horizontal axis and the win rate on the vertical axis for more than 72 million trades on Kalshi.[39]

Exhibit 2: Actual Win Rate versus Contract Price on Kalshi



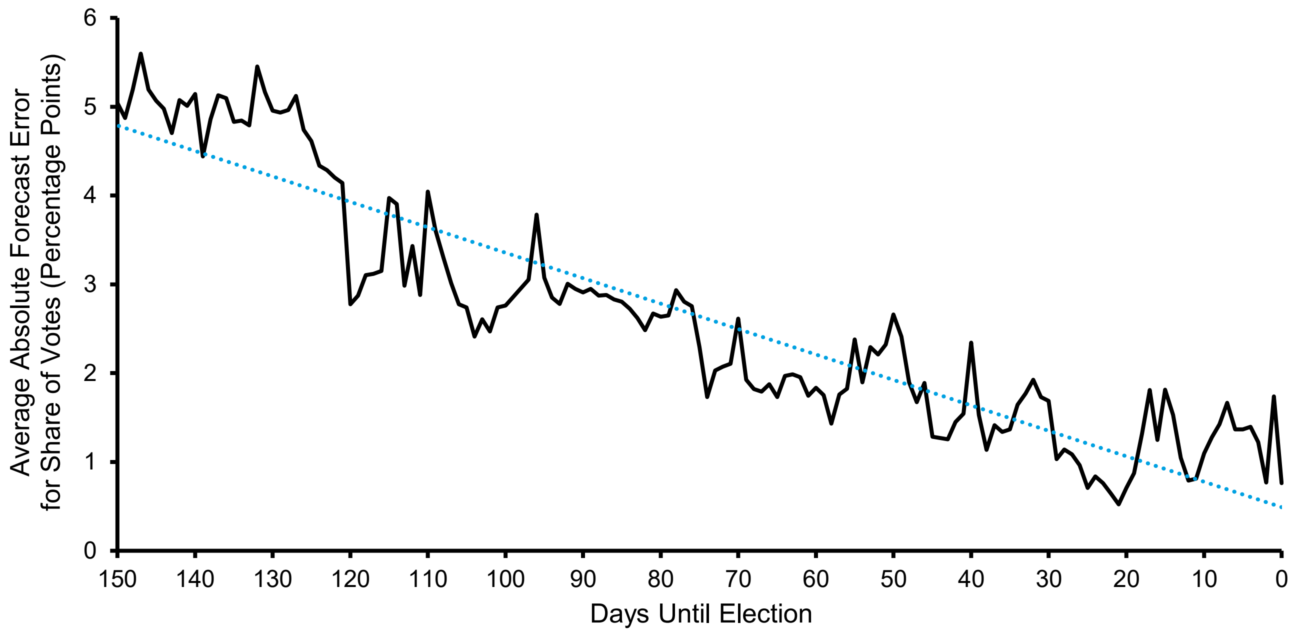
Source: Counterpoint Global based on Jonathan Becker, "The Microstructure of Wealth Transfer in Prediction Markets," Independent Research*, January 18, 2026.*

In a market that is perfectly calibrated, the contract prices and win rates would fall on the 45-degree line from 0 to 100 on both axes. This is marked with the dashed line labeled "Implied" in the exhibit. The actual results do not deviate much from what an efficient market suggests.

If you look closely, you will observe that the actual line is slightly above the implied line for high contract prices and slightly below the line for low prices. This is the "favorite-longshot bias," which is underestimating the winning rate for favorites, or high-probability bets, and overestimating the winning rate for long shots, or low-probability bets.[40] As we will see, the favorite-longshot bias is a well-known phenomenon in betting markets. The larger question is why it exists.

Most researchers conclude that prediction markets are more accurate than polls.[41] For example, exhibit 3 shows data from the IEM for U.S. presidential elections in 1988, 1992, 1996, and 2000. The horizontal axis is days until the election, and the vertical axis is the average absolute forecast error. One week prior to the election the IEM predicted vote shares with an average absolute error of 1.5 percentage points while the final Gallup poll, for the same elections, had an average absolute error of 2.1 percentage points.[42]

Exhibit 3: Information Revelation Through Time on Iowa Electronic Markets



Source: Counterpoint Global based on Iowa Electronic Markets and Kenneth J. Arrow, Robert Forsythe, Michael Gorham, Robert Hahn, Robin Hanson, John O. Ledyard, Saul Levmore, Robert Litan, Paul Milgrom, Forrest D. Nelson, George R. Neumann, Marco Ottaviani, Thomas C. Schelling, Robert J. Shiller, Vernon L. Smith, Erik Snowberg, Cass R. Sunstein, Paul C. Tetlock, Philip E. Tetlock, Hal R. Varian, Justin Wolfers, and Eric Zitzewitz, "The Promise of Prediction Markets," Science, *Vol. 320, No. 5878, May 16, 2008, 877-878.*
Note: Dotted blue line is a fitted trend line.

It is important to bear in mind that markets and polls are not measuring the same thing. A market aggregates bets on who will win, while polls summarize how respondents intend to vote. Further, participants in prediction markets can use information from the polls, while participants in polls may not care about the market's assessment.

Joe Nocera, a journalist, tells the story of how Théo, an anonymous French trader, made $85 million on Polymarket betting that Donald Trump would win the U.S. presidential election in 2024.[43] Most polls found the race to be even, but Théo commissioned a special poll in key swing states based on social circle polling.[44] This poll does not ask participants who they intend to vote for, but rather who they think their neighbors will vote for.

Those polls showed much more support for Trump than the standard ones did. As a result, Théo increased his wagers on Trump winning the Electoral College, the popular vote, and swing states in the Midwest. He more than doubled his money when Trump won all three.

However, the case for the superiority of prediction markets over polls or pundits is not totally clear-cut. Adjustments to raw polls, such as sophisticated aggregation methods, can match or exceed the predictions of markets.[45] How questions are asked can also affect accuracy.[46] Further, "superforecasters," individuals who demonstrate the ability to consistently make accurate predictions, outperformed prediction markets when working in teams and when their forecasts were aggregated using statistical algorithms.[47]

Overall, prediction markets provide useful information for those forecasting outcomes in politics, sports, economics, and corporate performance. The Forecasting Research Institute, a nonprofit that does large studies of forecasting accuracy, projects that large language models will reach parity with superforecasters at some point in 2027.[48]

Aggregation mechanism. Most prediction markets use a continuous double auction (CDA) mechanism. Here, buyers and sellers submit orders to an electronic book that is updated constantly to reflect all existing bids and offers. Transactions occur when there is an overlap in the price that each party seeks. This mechanism is most effective when there are enough buyers and sellers to generate frequent transactions.

Robin Hanson, a professor of economics, developed the logarithmic market scoring rule (LMSR), which works well when there are few buyers and sellers.[49] This approach replaces the order book with an automated market maker that always quotes a price and absorbs any trade. The sponsor bears the cost of losses. LMSR is used in thin or experimental markets because it provides liquidity even when the pool of buyers and sellers is small.

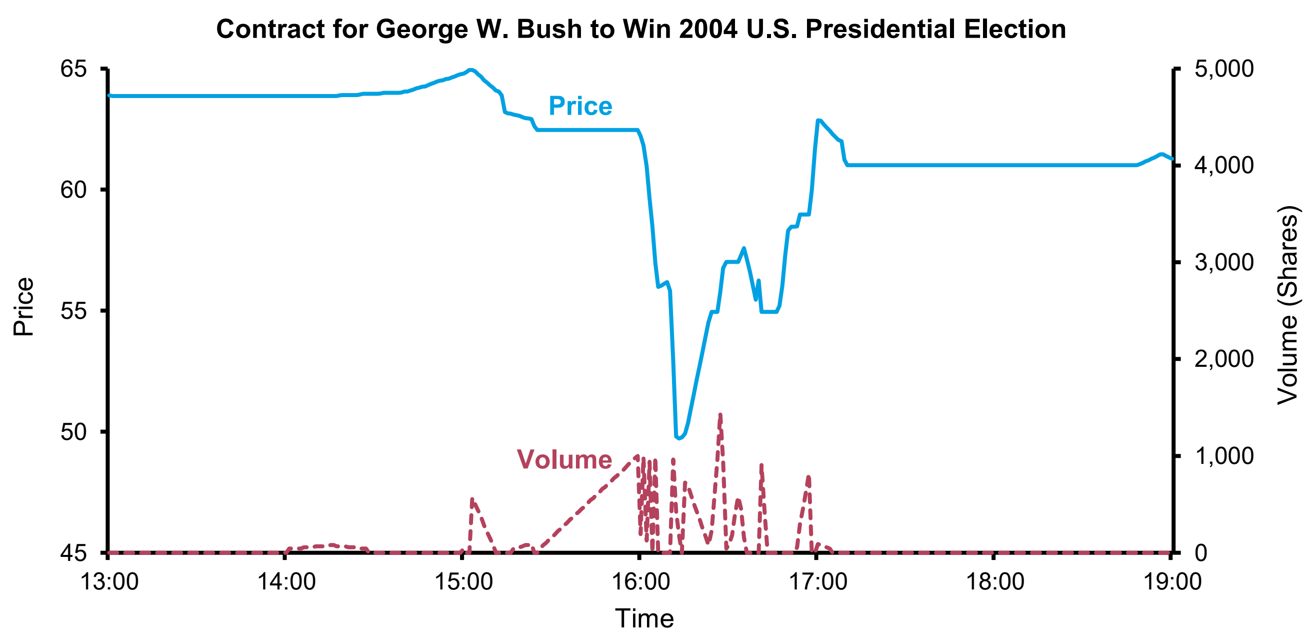
With either a CDA or LMSR mechanism, price changes reflect the actions of a buyer or seller who either has new information or a belief that the current price fails to correctly capture the probability of the outcome. The CDA is a tried and true method for information aggregation in active markets.

Diversity (and breakdowns). Diversity breakdowns occur when participants have correlated beliefs, leading to extreme optimism or pessimism. These types of beliefs are less likely in prediction markets because the outcome is observed at a predetermined time.

Still, participants can attempt to manipulate prediction markets. Rhode and Strumpf examined three markets: election betting markets from 1880 to 1944, TradeSports bets against George W. Bush for the 2004 U.S. presidential election, and a field experiment of manipulation of the IEM based on the 2000 U.S. presidential election.[50]

In all cases, the manipulation initially moved the market, but prices returned to normal shortly thereafter. Exhibit 4 shows an example of the speculative attack on the Bush contract on September 13, 2004. The episode briefly lowered the contract price by about 13 points, on heavy volume, but the price recovered quickly.

Exhibit 4: Temporary Impact of Attempted Price Manipulation of a TradeSports Contract



Source: Counterpoint Global based on Paul W. Rhode and Koleman Strumpf, "Manipulating Political Stock Markets: A Field Experiment and a Century of Observational Data," Working Paper*, February 2006.*
Note: Greenwich Mean Time.

Robin Hanson, along with some colleagues, tested the effect of manipulation in an experimental setting. They provided some participants with incentives to manipulate the market, which they did. However, those efforts did not lead to inaccurate prices as the crowd treated the order flow of the manipulators as noise.[51] A follow-up paper used a model to suggest that manipulation can increase accuracy because it provides an incentive to trade for potential participants with information.

Two economists, David Rothschild and Rajiv Sethi, carefully examined transaction data on the prediction market, Intrade, prior to the 2012 U.S. presidential election.[52] They found one trader accounted for one-third of all of the money spent on Mitt Romney in the two weeks before the election and about one-quarter for the two years preceding the election.

The trader bet heavily on Romney, and against Barack Obama, on election day in an apparent effort to put a floor under the price of Romney's contract and a ceiling over that of Obama's contract. Meanwhile, a large gap opened between Intrade and another market, Betfair.

The economists considered several possible motives for the trading and concluded that political manipulation was plausible, though impossible to prove conclusively. Eventually, the trader's bids and offers were pulled and the prices on Intrade and Betfair converged rapidly. Rothschild and Sethi estimate the trader lost about $7 million.

Overall, the research suggests that manipulation can move prices temporarily but the effect eventually wanes. Diversity breakdowns are difficult to sustain because the contracts are settled in a timely fashion. But to the degree that policymakers and managers rely on prediction markets as accurate sources of information, manipulation can lessen trust in markets and hence reduce their utility.[53]

Incentives. The incentives are straightforward in prediction markets. Because the contracts are almost always winner-take-all, you make money if you are right and lose money if you are wrong. One study showed that a prediction market based on play money can be just as accurate as one using real money. In this case, the incentive may be reputational versus simply monetary.[54]

Arbitrage is a cornerstone of efficient markets. This entails simultaneously buying a cheap contract and selling an expensive one with the same payoff. The result is a risk-free profit. In reality, arbitrage is costly. In general, lower costs of arbitrage are associated with more efficient prices.

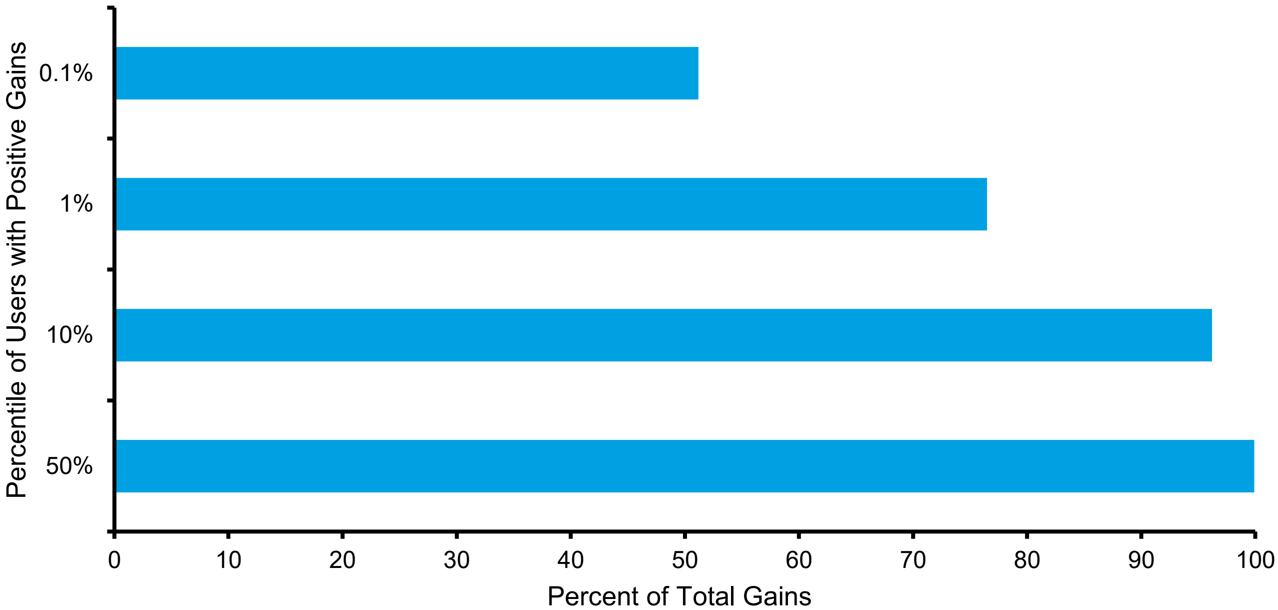
One study of Intrade suggests that arbitrageurs may be as few as 1 percent of the traders but responsible for 15 to 20 percent of the trading volume.[55]

These markets can also be used as a means to hedge. During the 2026 National Basketball Association finals, a bar owner in New York City offered a free tab up to $100 if the New York Knicks won for patrons who got there before the game started. Through Kalshi, he bet $5,000 on the Knicks at a price of $0.37 and received a payout of about $13,500, enough to cover the bar tabs.[56]

In general, the costs of transacting in prediction markets include commissions as well as fees for transactions and withdrawals. Exchanges and platforms vary in their mix of costs. Overall, however, prediction markets tend to have total costs similar to or lower than other wagering markets.

The profits in prediction markets tend to accrue to a small percentage of participants. One study that included nearly 600 million trades on Polymarket from November 2022 through March 2026 showed that among users with gains, the top 1 percent captured 77 percent of the profits and the top 10 percent gathered 96 percent (see exhibit 5). Of the 2.4 million users overall, 69 percent lost money.[57]

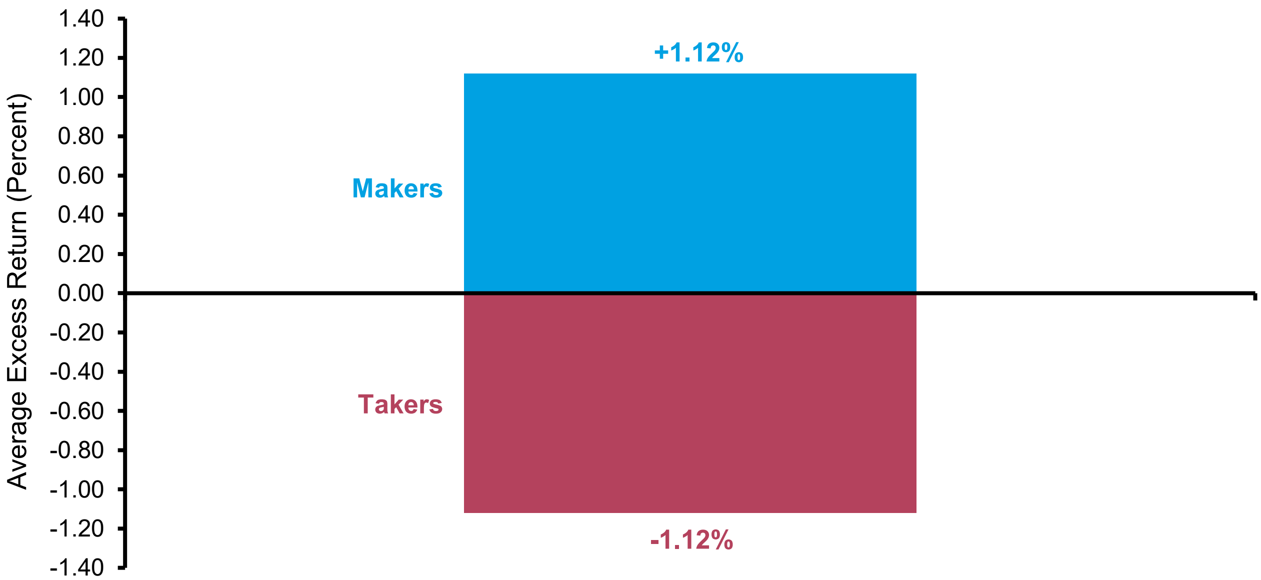
Exhibit 5: Concentration of Gains on Polymarket



Source: Counterpoint Global based on Pat Akey, Vincent Grégoire, Nicolas Harvie, and Charles Martineau, "Who Wins and Who Loses In Prediction Markets? Evidence from Polymarket," Working Paper*, June 12, 2026.*

Further, traders can be categorized as "makers," those who provide liquidity by placing orders in the order book, and "takers," who use liquidity by trading with orders in the book. Exhibit 6 shows that the average excess return is positive 112 basis points for the makers, and negative 112 basis points for the takers, for millions of trades on Kalshi.[58]

Exhibit 6: Average Excess Returns of Makers versus Takers on Kalshi



Source: Counterpoint Global based on Jonathan Becker, "The Microstructure of Wealth Transfer in Prediction Markets," Independent Research*, January 18, 2026.*

The cash payoffs and relatively low costs, combined with regulatory leeway, have made prediction markets attractive for participants. This explains the rapid growth of these markets. Further, since these markets deal with contracts, there is no issue with limiting participants, as there can be in sports betting.

Still, the profits remain highly concentrated among a few bettors, and a large majority lose money when they wager. Further, the tax treatment of wins and losses is not clearly specified.

Following Kalshi's victory in the courts in late 2024 and the CFTC's laissez-faire stance, prediction markets have expanded rapidly into our next area of discussion, sports betting.

Sports betting. Sports bets are wagers on the outcome of a sporting event. These bets are commonly made through a "bookmaker," a person or organization that keeps track of bets, bet sizes, and odds. The term refers to the fact that a person literally used to make a book to compile these data.

There are a couple of popular forms of sports bets. The first is a "moneyline" contract, which is a bet with fixed odds on the winner. American moneyline odds are stated with positive and negative numbers and commonly use a base of $100.

Favorites to win have a negative sign, and the number tells you how much you must bet to win $100. For example, at -200 odds you have to bet $200 to win a $100 profit.

Underdogs have a positive sign, and the number indicates how much you will win with a $100 bet. For instance, at +175 odds, a $100 bet earns a $175 profit.

Moneyline odds are common in the U.S., but the same odds can be expressed as decimal or fractional. (For example, -200 is equivalent to 1.5 decimal odds and 1/2 fractional odds.) Each approach allows you to derive the implied probability of winning. The implied probability for -200 is 66.7 percent, calculated as 200 ÷ (200 + 100) = 0.667.

Importantly, the bookmaker charges vigorish, a fee or commission to handle the bet. Moneyline contracts are most prevalent for events that have low scores such as soccer, baseball, and ice hockey.

The second form is a point spread contract (also called "line" or "handicap"), which is a bet on the margin of victory in a game. Charles McNeil, a bookmaker and former math teacher, devised this contract in the 1940s. A bet on a team listed as a 4-point favorite pays off only if the team wins by more than 4 points. If the team wins by exactly 4 points, the bet is considered a "push," and the wager is returned to the bettor.

A bookmaker who sets the point spread so that betting volume is equal for both sides has little or no exposure to the outcome and collects the vigorish. Spread bets can also be translated into probabilities and tend to be more common with sports that have more scoring or larger win margins such as American football and basketball.[59]

Bookmakers often set point totals, a third form of wager, to allow bets on whether the final score will be over or under that amount.

Parlay bets, single wagers that combine two or more individual bets ("legs"), have grown sharply in recent years. Each leg must win for a parlay bet to pay off. As a result, the probability of winning is low but the payoff is high. These types of bets tend to be profitable for sportsbooks.

Soccer is the most popular sport in the world and the one that draws the most betting. American football is the most-bet-on sport in the U.S. Other sports with substantial wagering include basketball, tennis, and baseball. In the U.S., betting on the professional and college levels is common in football and basketball.

Brief history. Wagering on athletic contests is about as old as organized sport itself. For example, there are reports of betting on the outcomes of the Ancient Olympic Games (776 BCE to 394 CE).[60] Betting was informal, with two parties agreeing on terms and transferring money directly without an intermediary.

Betting became more formalized during Victorian Britain as professional bookmaking grew around horse racing. It should be noted that gambling was generally frowned upon and often illegal.[61]

Further, sports betting has a long history of being associated with scandal. One of the U.S.'s first professional leagues was for baseball. Called the National League, it was launched in 1876. Just one season later, players on one of the teams, the Louisville Grays, were caught fixing games for money, and the club folded in 1878. The "Black Sox Scandal" is among the most famous episodes. Eight players on the Chicago White Sox baseball team were accused of scheming with gamblers to throw the 1919 World Series in exchange for money.

Sports betting continued but was largely illicit. To recover from the Great Depression, Nevada legalized gambling in 1931 and sports betting in 1949.

As with prediction markets, sports betting is intertwined with law. The Professional and Amateur Sports Protection Act (PASPA), passed by Congress in 1992, barred states from authorizing or licensing sports betting operations outside of Nevada and a handful of sports lotteries.

Leaders of the state of New Jersey, which believed it was losing potential revenue from sports gambling, challenged PASPA in the courts. After initial setbacks, the case went to the Supreme Court, which ruled against PASPA in 2018. The ruling was based on the "anti-commandeering doctrine" that says the federal government cannot tell the states what to do.

Sports betting then became an issue for each state to decide, and it has become legal in some form in all but 11 states as of 2026. It remains illegal in California and Texas, which make up about 20 percent of the population in the U.S. Sports betting is mostly regulated by state gaming commissions.

FanDuel, founded in 2009, and DraftKings, founded in 2012, started as platforms for daily fantasy sports (DFS). DFS is a short-term version of traditional fantasy sports and has operated with legal ambiguity for much of its existence.

Following the Supreme Court ruling in 2018, both FanDuel and DraftKings entered the market for sports betting. As of the end of the first quarter of 2026, FanDuel had a 44 percent share, and DraftKings a 34 percent share, of the gross gaming revenue of the U.S. sportsbook market.[62]

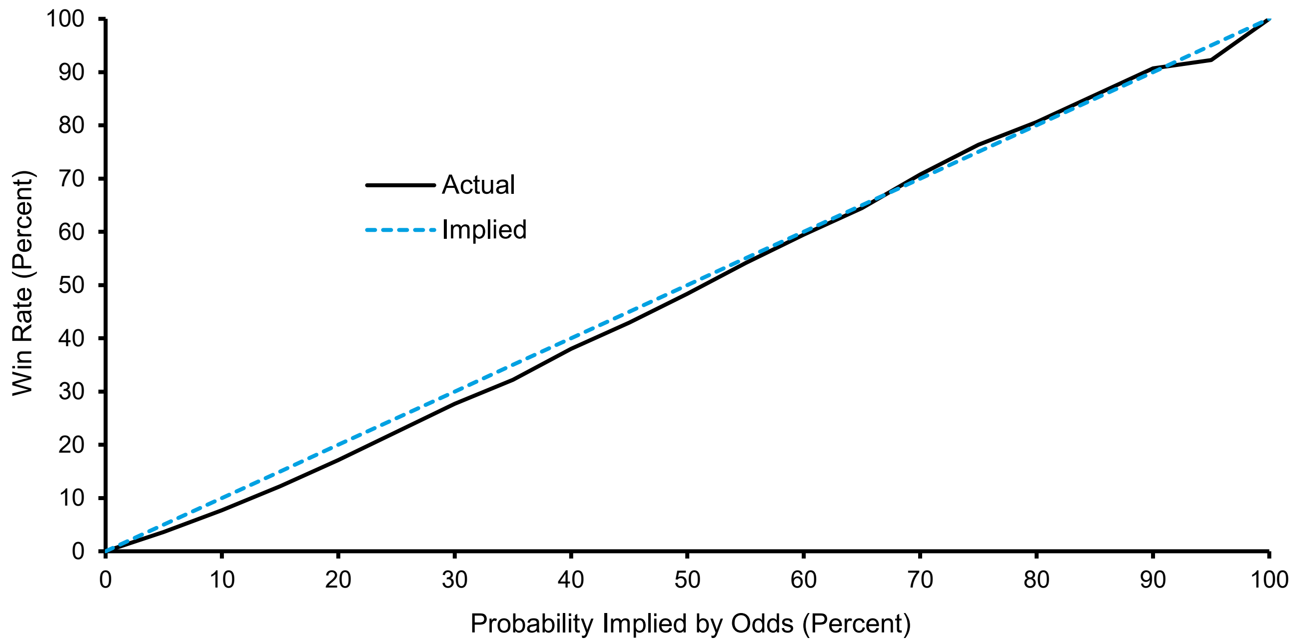
As noted above, prediction markets such as Polymarket and Kalshi started with contracts related to politics, weather, and economics but moved quickly into sports contracts following the court ruling in 2024.

The American Gaming Association estimates that states have forgone nearly $1.2 billion in potential gaming tax revenue from the start of 2025 through the middle of 2026, as betting on sports has moved to prediction markets, which are generally not subject to the state gaming taxes imposed on licensed sportsbooks.[63]

Accuracy. Economists like to study sports betting markets because they are the equivalent to a laboratory for examining market efficiency. The short answer is that they are mostly efficient, especially after consideration of the vigorish that is required to participate.

Exhibit 7 shows the probability implied by the betting odds on the horizontal axis and the win rate on the vertical axis for a dataset of roughly 400,000 soccer matches from more than 6,000 leagues. The results for a market that is perfectly efficient would fall on the 45-degree line from 0 to 100 percent. This market is close to efficient.

Exhibit 7: Probability Implied by Odds and Win Rate for Soccer Matches



Source: Counterpoint Global based on Cuamckuu, "Domain-driven-soccer-probs," GitHub*, https://github.com/cuamckuu/domain-driven-soccer-probs, Last modified November 1, 2025 and Artur Karimov, Aleksandr Koshkin, Dmitrii Kaplun, and Denis Butusov, "Domain-Driven Identification of Football Probabilities,"* Mathematics*, Vol. 13, No. 24, Article 3976, 2025.*

As with the prediction markets, there is evidence for the favorite-longshot bias in bets on sports, but the evidence for the bias varies by game and form.[64] For instance, the bias is visible for fixed-odds outcome markets in soccer, college football, college basketball, and tennis but weak, mixed, or absent for the National Football League, National Basketball Association, and the National Hockey League.[65]

The bias can show up in a moneyline contract but not in the point spread contract for the same game.[66] The reason is that with a moneyline contract, the underdog has a low probability of winning but a high payoff if it does. With a point spread contract, the payoffs are much closer to 50-50 because the underdog can lose but still cover the spread.

Overall, sports betting markets appear largely efficient in that it is difficult to systematically find mispricings that are sufficient to cover the cost of wagering. That said, bookmakers are wary of smart bettors and consistently limit the amount they can bet.

Aggregation mechanism. Bookmakers, rather than bettors, set prices in fixed-odds sportsbook markets. A common assumption is that bookmakers seek to set odds and point spreads as needed so that the money or liability on each side is equal.[67] In that case, the bookmaker bears little to no directional risk and is simply paid the vigorish for making the market.

In 2004, Steven Levitt, a professor of economics, published a paper suggesting that sportsbooks do not merely balance bets. Instead, he found evidence that they set point spreads to exploit bettor biases and increase expected profits. He also observed that point spreads changed only modestly and relatively infrequently once posted.[68]

Subsequent research largely supports the view that sportsbooks often operate with imbalanced books, though the evidence that this pricing consistently increases profits is more mixed.[69]

Most online sportsbooks now use algorithms, overseen by bookmakers, to establish and revise odds. Some sportsbooks allow proven winners to bet a small amount early on to glean information from their action.[70]

Moneyline prices often move more frequently than point spreads prior to the start of a game because new information usually has a bigger impact on the odds of a team winning outright than it does on the handicap.[71] Bookmakers can also reflect additional news by moving the point spread itself or by changing the price associated with a given spread.

Diversity (and breakdowns). Among the markets we are considering, diversity breakdowns are less likely in sports betting for two reasons. First, the bookmakers set the odds and prices, and they can change them to reflect the pattern of bets. For the other markets, the actions of the bettors dictate the odds and prices.

Second, the outcome is independent of the implied probabilities. The goal of manipulating a political prediction market is to change the posted probabilities for a particular candidate with the intent of swaying the views of prospective voters. In sports, the teams play the game and are not influenced by the odds (absent any nefarious activity).

Further, the profit potential is insufficient to overcome the vigorish even for those markets that exhibit a pattern such as the favorite-longshot bias.

Incentives. Similar to the other markets discussed, participants who bet on sports can earn money if they win. But many sports bettors also cite nonmonetary benefits. For example, in one survey, 92 percent of participants said that betting is “fun and exciting,” and 89 percent reported that it makes them more interested in watching the games live.[72]

The vigorish for sportsbooks varies by sport, market, and type of wager, but for many standard straight bets it commonly falls around 4 to 5 percent and is built into the price.[73]

For example, in Game 5 of the National Basketball Association finals in 2026, the San Antonio Spurs were 5.5-point favorites over the New York Knicks. In spread bets, it is common to have to risk $110 to win $100. A sportsbook that takes $110 on each side of this type of bet receives $220 and pays $210 to the winner. The result is a profit of $10 or a little more than 4.5 percent of the amount wagered, or “handle.”

The so-called “One Big Beautiful Bill Act,” a federal tax and spending statute that went into law in the U.S. in July 2025, includes a provision that is onerous for sports bettors.

Specifically, all gains are taxable, but only 90 percent of losses can be deducted against gains for tax years after December 31, 2025. For example, a bettor with $10,000 of winnings and $10,000 of losses in a year is required to pay taxes on $1,000 ($1,000 = $10,000 – [$10,000 × 0.90]).[74]

Estimates suggest only about three to five percent of sports bettors make money over the long run.[75] This reflects the vigorish and the difficulty of turning an informational edge into large profits in relatively efficient betting markets.

In addition, many sportsbooks limit the wager sizes or restrict the accounts of bettors they identify as skillful, commonly called “sharps.” Because sharps often struggle to place enough bets to get a satisfactory return on their investment, they hire “runners” or “beards” (as in a beard conceals one’s identity) to bet on their behalf and share the profits with them.[76]

Notwithstanding the small percentage of winners, the survey found that 39 percent of bettors claim that they win more than they lose, and 28 percent said they break even. That self-assessment contrasts sharply with estimates that 95 percent or more of sports bettors are unprofitable over the long run.[77]

Parimutuel betting. In a parimutuel betting system, the money from all of the bets of the same type (e.g., on which horse will win the race) is put into a pool. The operator then subtracts a commission, or “takeout,” to cover items such as track expenses, purses, and applicable taxes. In the U.S., the takeout rate is commonly set by state regulators. The net pool is used to pay winnings. Parimutuel is a French word that translates as “mutual wager.”

The amount bet on each horse determines the payout odds and reflects the market’s implied view of that horse’s chances. In contrast to other markets, the odds are not set by a bookmaker or by buyers and sellers agreeing to transact at a price.

A straight bet is a wager on a specific horse to finish first, second, or third. Win pools are generally the largest of these. An exotic bet can cover either the extended order of finish in a particular race (e.g., first-second, first-second-third) or the winners of consecutive future races. As with parlays, exotic bets tend to have low probabilities of success but high payoffs.[78]

Parimutuel betting is used primarily for horse races, but it is also the system for other competitions such as greyhound racing and jai alai. It is a relatively new mechanism for aggregating information when compared to bookmaking and double auction markets.

Brief history. Horse racing has been around since antiquity, but the modern era of regulated racing can be traced to Charles II, King of England. He instituted The Articles of the Newmarket Town Plate in 1665, and the race has been run consistently since 1666, interrupted only briefly during World War II and COVID-19. Betting in the early modern period was generally informal or done through bookmakers.

The parimutuel system was introduced in France by Joseph Oller, an entrepreneur, in 1867. The system was controversial from the start. The French authorities declared parimutuel betting illegal in the mid-1870s and Oller, along with other parimutuel operators, was sued and found guilty in 1874. But because of scandals involving bookmaking, the government allowed parimutuel betting in 1887. The French government banned bookmaking altogether in 1890 and legalized parimutuel betting by legislation in 1891.[79]

The Jerome Park Racetrack, in what was then Westchester County, New York, and now the Bronx, was a thoroughbred horse racing facility that operated from 1866 to 1894. It established parimutuel betting in the U.S. in 1872. By 1877, parimutuel pools “made their appearance upon every racetrack.”[80]

The legality of the parimutuel system was called into question in most countries at some point. Allegations that pool operators were unreliable or dishonest did not help. In New York City, pools on the 1876 U.S. presidential election between Samuel Tilden and Rutherford Hayes were particularly contentious. John Morrissey, a pool operator, was suspected of manipulating the market in favor of Tilden. Hayes ultimately won the presidency after a contested electoral process.

Morrissey ended up canceling the pools and returning the stakes to the bettors, less his commission. This encouraged efforts to ban pool betting in New York. Other states followed, and the parimutuel system faded.

Horse racing continued to gain popularity in the U.S. in the late 1800s, and betting was done largely through bookmakers. Progressives of the time, who sought social and political reforms to improve society, were against gambling in general and bookmaking in particular. As a result of their influence, the number of racetracks in the U.S. fell sharply from 314 in 1897 to 43 in 1908.[81]

In 1908, Churchill Downs, a racetrack in Kentucky and host of the Kentucky Derby, received a racing license and reintroduced parimutuel betting to great success.[82] From there, parimutuel betting on horse racing again spread throughout the U.S.

Several other factors helped the expansion of parimutuel betting. One was the solution to the problem of the substantial calculation to reflect the odds. George Julius, an engineer born in England, invented the “automatic totalizator,” or what is now known as the “tote board.” This allowed bettors to see the odds in near real time. The first tote board was installed in New Zealand, Julius’s adopted home, in 1913 and came to the U.S. in 1932.[83]

Another factor was the general rise in interest in professional sports, including horse racing, following World War I. Finally, states needed revenue during the Great Depression, and taxes on racing wagers were a way to raise funds without direct taxation.

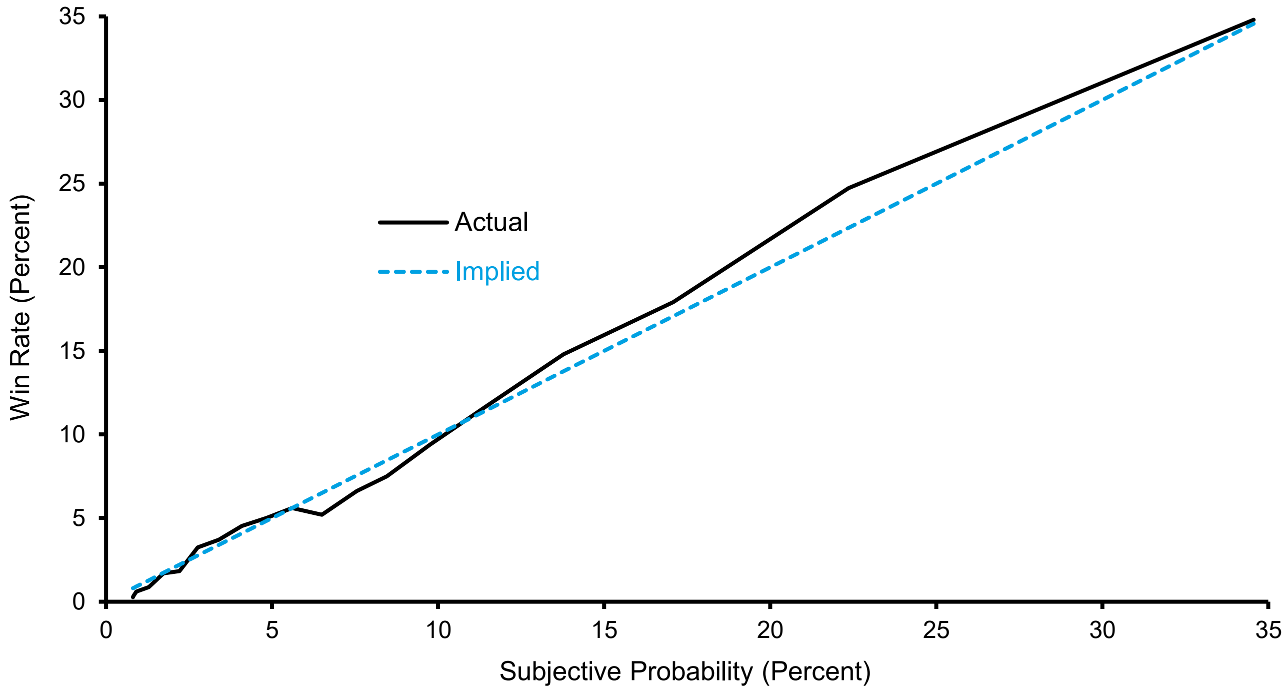
Horse racing is regulated primarily by state racing commissions or state gaming commissions. The Federal Trade Commission is the main federal agency that oversees the Horseracing Integrity and Safety Authority, an organization that oversees Thoroughbred horse racing in the United States.

Today, betting on horse racing is vastly smaller than the broader market for sports, especially in the U.S. The largest markets for horse racing, measured as the total amount of money wagered, include Japan, Hong Kong, and the U.S.

Accuracy. The efficiency of markets for horse-racing wagers has been studied extensively, and entire volumes have been devoted to the topic.[84] The literature generally finds that these markets are highly, but not perfectly, efficient. However, the potential profit opportunities are insufficient to cover the takeout for most wagers to win consistently. Specifically, the pools for win bets are more efficient than those for place and show (a place wager pays if the horse finishes first or second and a show wager pays if it finishes first, second, or third).[85]

Exhibit 8 shows the probability implied by the betting odds on the horizontal axis and the win rate on the vertical axis for a dataset of roughly 30,000 horses running in 2,400 races. The results for a market that is perfectly efficient would fall on the 45-degree line from 0 to 35 percent. This market is close to efficient.

Exhibit 8: Probability Implied by Odds and Win Rate for Horseracing



Source: Counterpoint Global based on Constancedongg, "Horse-Racing," GitHub*, https://github.com/constancedongg/Horse-Racing, Last modified July 6, 2019.*

Consistent with other wagering markets, horse racing results generally display a favorite-longshot bias. Why this bias exists and persists remains the subject of ongoing research. The two main explanations are that bettors are willing to accept lower expected returns for the chance of a large payoff, or that they midjudge the probabilities of different outcomes. Two economists, Erik Snowberg and Justin Wolfers, used a novel approach to show that misperceptions of probability likely drive the bias.[86]

Aggregation mechanism. A parimutuel system is a different mechanism for aggregating information than a continuous double auction or a bookmaker.

Exhibit 9 is a very simple example of how it works. This is a pool of $10,000 of wagers on which of five horses will win a race. The amount wagered on a horse determines its implied probability of winning. Here, $4,000 of the $10,000 in bets are on Horse A, making its implied probability of winning 40 percent.

Exhibit 9: Simple Example of Implied Probability of Winning in a Parimutuel System

Horse	Bet	Winning Chance
A	$4,000	40.0%
B	3,000	30.0
C	2,000	20.0
D	750	7.5
E	250	2.5

Source: Counterpoint Global.

However, the economics of wagering are more difficult in a parimutuel market because of the takeout, which can be 15-20 percent of the pool. If we assume a 20 percent takeout rate, the initial $10,000 shrinks to a payout of $8,000. With a standard bet size of $2, if Horse A wins it does not pay $5 ($10,000 ÷ 2,000 bets), but rather $4 ($8,000 ÷ 2,000 bets).

This means that if you think that Horse A has a 40 percent chance of winning and you wager accordingly, the expected payout is $1.60 ($1.60 = .40 × $4), which is less than the $2 bet. Horse A has to have a probability of winning that is 50 percent for the bet to have an expected value of zero ($2.00 = 0.50 × $4) and greater than 50 percent for it to be positive.

Horseracing is unusual in that some tracks accommodate both bookmaking and parimutuel betting. One study of such a market found that the bookmakers posted relatively efficient prices from the beginning of the betting window and aggregated information effectively. Parimutuel prices, in contrast, were less informative initially but improved as the betting progressed. And the accuracy of the final prices depended in part on the size of the pools.[87]

Inefficiencies exist in both markets, but the profit opportunities are generally insufficient to cover the costs of betting for all but a small subset of bettors.

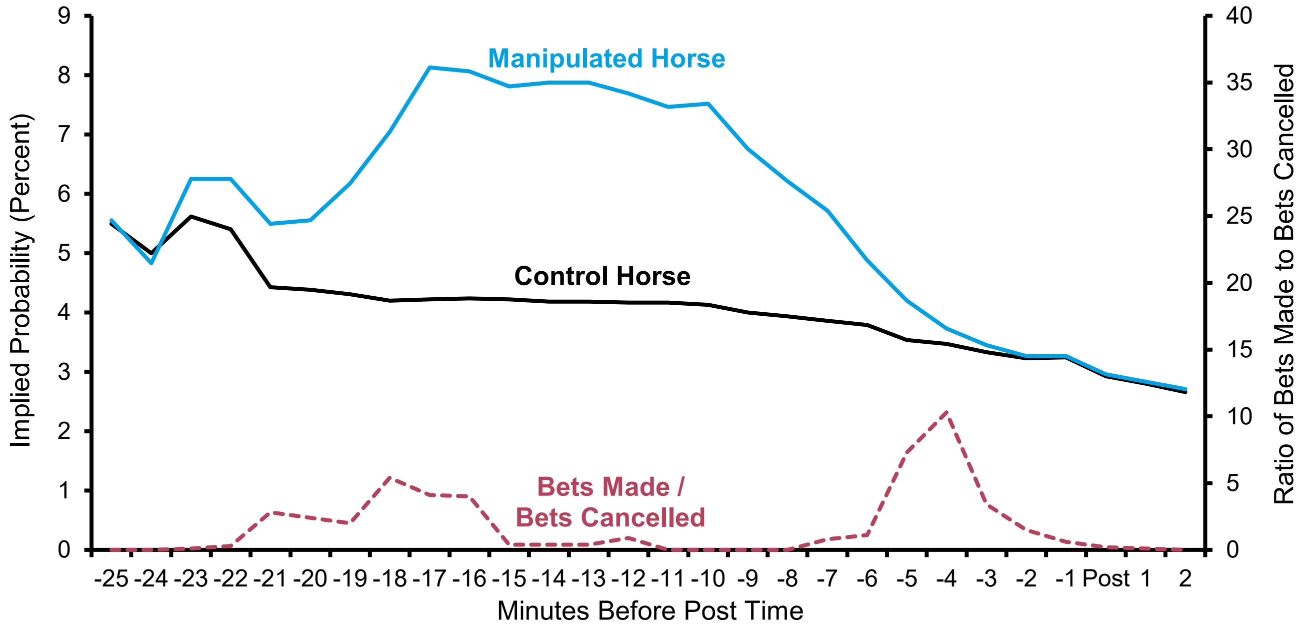
Diversity (and breakdowns). On the one hand, betting pools, collections of wagerers, set the odds and implied probabilities. This introduces the possibility of correlated behavior among the bettors. On the other hand, races are won and bets are settled. Groups who bet in a way that pushes implied probabilities to extremes will lose money on average.

Colin Camerer, an economist, ran an experiment to see if he could manipulate a market for horse racing.[88] He defined market manipulation as “trading against one’s information or preferences” in order “to create price movements that will lure other investors and ultimately allow later profit.” He wanted to know if he could encourage a breakdown of diversity.

He selected horses from particular races that had similar odds so that he could compare the results of the manipulation to a control condition. Further, he was able to cancel his bets, which allowed him to observe the net effect of his intervention.

He found that his bets initially moved the odds on the target horses, but that the effect was temporary. He concluded that the reactions of bettors who inferred information from manipulation were mostly canceled out by the responses of those who were unaffected by the false signal.

Exhibit 10: Temporary Impact of Manipulation of a Market for Horse Racing



Source: Counterpoint Global based on Colin F. Camerer, "Can Asset Markets Be Manipulated? A Field Experiment With Racetrack Betting," Journal of Political Economy*, Vol. 106, No. 3, June 1998, 457-481.*
Note: Post time is when the race begins and betting is closed.

Most research on efficiency compares final odds to outcomes. Recent work shows that the informed bettors often act shortly before betting windows are closed and attenuate (but do not eliminate) the favorite-longshot bias.[89]

Steven Crist, an author and well-known handicapper, has noted that "the best friend that horseplayers have are the big race days."[90] The reason is that a wave of uninformed participants place bets that create a large gap between the implied and likely probability of winning. This opens an opportunity for informed handicappers to make profitable bets.

Horses in a position to win the Triple Crown are a prime example. Capturing the Triple Crown is an impressive feat, as a horse must win the Kentucky Derby, the Preakness Stakes, and the Belmont Stakes on three tracks over just five weeks. Horses that win the first two legs generate a lot of enthusiasm from the public, and betting pools generally surge on the day the Belmont Stakes, the last leg, is run.

Exhibit 11 lists the 24 horses that were in a position to win the Triple Crown from 1950 to 2026. The third column shows that the average implied probability of the horse winning was 61 percent, and the fourth column reveals that only 21 percent of the horses that tried actually succeeded.

This is a case of the limits to arbitrage in the parimutuel market. Professional bettors have insufficient capital to offset the wave of bets on the Triple Crown contender. But they do stand to benefit from these lopsided circumstances. Crist remarked that he made about 25 percent of a year's salary betting against Smarty Jones in 2004.[91]

Exhibit 11: Implied Win Probability and Success Rate for Triple Crown Contenders, 1950-2026

Year	Horse	Implied Probability	Won Belmont / Triple Crown?	Odds (Fractional)
1958	Tim Tam	87.0%	No	3-20
1961	Carry Back	71.4%	No	2-5
1964	Northern Dancer	55.6%	No	4-5
1966	Kauai King	62.5%	No	3-5
1968	Forward Pass	50.0%	No	1-1
1969	Majestic Prince	43.5%	No	13-10
1971	Canonero II	58.8%	No	7-10
1973	Secretariat	90.9%	Yes	1-10
1977	Seattle Slew	71.4%	Yes	2-5
1978	Affirmed	62.5%	Yes	3-5
1979	Spectacular Bid	83.3%	No	1-5
1981	Pleasant Colony	55.6%	No	4-5
1987	Alysheba	55.6%	No	4-5
1989	Sunday Silence	55.6%	No	4-5
1997	Silver Charm	50.0%	No	1-1
1998	Real Quiet	55.6%	No	4-5
1999	Charismatic	40.0%	No	3-2
2002	War Emblem	44.4%	No	5-4
2003	Funny Cide	50.0%	No	1-1
2004	Smarty Jones	74.1%	No	7-20
2008	Big Brown	80.0%	No	1-4
2014	California Chrome	54.1%	No	17-20
2015	American Pharoah	57.1%	Yes	3-4
2018	Justify	55.6%	Yes	4-5
	Average	**61.0%**		
	Success rate		**20.8%**	

Source: Counterpoint Global and Wikipedia.

Any market that has a known outcome within a specified period will not be as vulnerable to diversity breakdowns as those that are perpetual and indeterminate, such as the stock market.

Incentives. As with the other markets we reviewed, the main incentive to participate in parimutuel betting is to win. Also consistent with other markets, bettors say they wager because it is exciting and fun.[92]

Betting is an activity with a negative expected payout in the aggregate because of the cost to participate. That cost is the takeout in parimutuel markets, which can range from 15 to 24 percent based on the pool.

For example, in the state of New York, the takeout rate is 16 percent for win, place, and show bets and 24 percent for some exotics such as a trifecta (predicting the correct order of the first, second, and third-place finishers in a race).[93]

Importantly, big bettors commonly get a rebate, which is effectively a discount on the takeout. These rebates can cut the takeout rate in half or less.

The percentage of parimutuel bettors who are profitable in the long run is comparable to that of sports bettors, around three to five percent. Also consistent with other markets, a small percentage of sophisticated bettors do very well.[94]

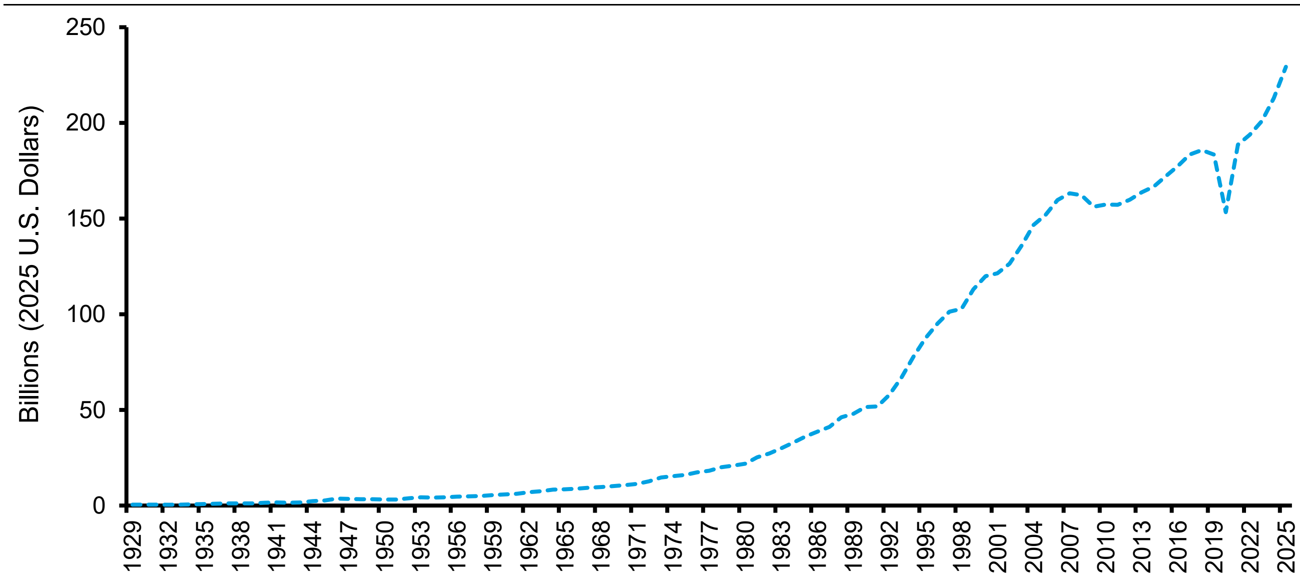
The tax treatment for parimutuel wagers is the same as for sports betting: gains are taxable but only 90 percent of losses are deductible. This further increases the cost and makes profitable wagering more difficult.

Stock market. A stock market is an exchange where buyers and sellers trade shares of publicly listed companies. Each share represents partial ownership of a company.

In this way, the stock market is very different from a betting market. Owning a diversified portfolio of stocks has a positive expected return because the values of businesses tend to grow over time. The stock market created $91 trillion in wealth in the 100 years ended in 2025.[95]

Betting markets have a negative expected return because the loser pays the winner and the intermediary takes a cut. Gamblers in the U.S. cumulatively lost $3.9 trillion nominally, and $5.8 trillion in 2025 U.S. dollars, from 1929 to 2025 (see exhibit 12). These losses do not include those from prediction markets.

Exhibit 12: Annual Losses from Gambling in the U.S., 1929 to 2025



Source: Counterpoint Global; U.S. Bureau of Economic Analysis, Personal consumption expenditures: Services: Gambling [DGAMRC1A027NBEA], retrieved from FRED, Federal Reserve Bank of St. Louis; U.S. Bureau of Economic Analysis, Gross domestic product (implicit price deflator) [A191RD3A086NBEA], retrieved from FRED, Federal Reserve Bank of St. Louis.

This is not to say that the stock market does not have an element of speculation. Investors and speculators have forever coexisted in markets, and the behavior of many market participants is a blend of the two. But it is useful to recognize that these are distinct activities.

Investors own partial stakes in businesses and focus on the present value of the cash the businesses can distribute to their shareholders. Speculators buy stocks in anticipation that they will go up without reference to their value.

The other way in which stocks differ from wagers is that there are no settled outcomes.[96] Stock prices are based on expectations that are at the whims of collective beliefs. As a result, testing market efficiency is inherently challenging.

Brief history. A precursor to the modern stock market was launched in Amsterdam in 1602 when the Dutch East India Company went public and helped establish the Amsterdam Stock Exchange. Here, however, we will focus on the development of U.S. markets.

Before 1792, securities trading in New York was relatively informal, taking place through auctions, coffeehouses, street trading, and broker networks. On May 17, 1792, two dozen brokers signed the Buttonwood Agreement, which stipulated that the brokers would "give preference to each other" at a commission of no less than one-quarter of one percent. The name derives from the legend that the deal was sealed under a buttonwood tree, the American sycamore, near 68 Wall Street in Lower Manhattan.

That informal call market was eventually replaced by a more formal organization. Brokers adopted a constitution creating the New York Stock & Exchange Board, the forerunner of today's NYSE, in March of 1817.

In the early years, brokers gathered twice a day in a room at 40 Wall Street to trade a list of about 30 stocks and bonds. The president of the board called each security from a podium, and brokers shouted bids and offers from assigned chairs. This is why exchange memberships were known as "seats." This format is a call system or call market.

By the mid-1800s, trading volume grew large enough to strain the call system. During the Civil War era, a competing group called the Open Board of Stock Brokers used a more modern system of continuous trading. Each stock was assigned a specific location, or "post," where brokers, and later specialists, matched a steady flow of bids and offers.

This became the model of a continuous double auction market. Specialists were expected to maintain limit-order books, make markets in assigned securities, and help provide liquidity and orderly trading. Electronic systems replaced much of the manual process over time, but the core mechanism of matching buy and sell orders in an auction market remains.

Following the stock market crash in 1929, Congress created the Securities and Exchange Commission (SEC), an agency of the federal government that enforces laws related to stock market manipulation. The Financial Industry Regulatory Authority, under the SEC's oversight, regulates brokerage firms, and the SEC regulates national securities exchanges and clearing agencies.

Accuracy. In the stock market, efficiency reflects how accurately the price captures all of the known information about the present value of future cash flows for a company. Accuracy does not apply in the same way as it does for other markets because while there is a price, the value is generally not revealed. There is no easy way to compare expectations to results.

As a consequence, a model that predicts asset price returns becomes the proxy for outcomes. That reality introduces what is known in finance as the "joint hypothesis problem."[97]

The first hypothesis is that there is a framework that forecasts asset price returns accurately. The capital asset pricing model (CAPM), which depicts the connection between risk and reward, is popular with executives and investors. Lots of other approaches exist as well.[98]

The second hypothesis is that the market is efficient. The problem is that you can consider an outcome anomalous only if your model is accurate. As a result, inaccuracy may be because of a faulty model, an inefficient market, or some combination of the two.

Our report, "Who Is On the Other Side?," provides a detailed analysis of market efficiency, so we will not delve into the topic here.[99] But there are a few points worth highlighting.

In their consideration of the efficiency of the stock market, Nicholas Barberis, a professor of finance, and Richard Thaler, an economist and recipient of the Nobel Prize, distinguish between "prices are right" and "no free lunch."[100]

Prices are right means that price is an unbiased estimate of value, or correct on average. This is what the calibration charts seek to measure, with the probability implied by the betting odds on the horizontal axis and the win rate on the vertical axis.

No free lunch states that there are no investment strategies that consistently produce excess returns.

If prices are right, it stands to reason that there is no free lunch. But the reverse need not be true. There can be no free lunch even when prices are wrong if the cost and risk of correcting a mispricing are sufficiently high. This is precisely what we see with the favorite-longshot bias in sports betting. The opportunity it presents is more than offset by the cost to take advantage of it.

Stock markets are both efficient and inefficient. There is research showing that the market accurately reflects incremental information and does a solid job of anticipating the future.[101]

But there is also research showing that the market can do a poor job of ingesting information, leading to gaps between price and value.[102] We will consider how this happens when we look at diversity.

Academics did research that captures this tension well.[103] They studied 13,800 U.S. public firms that started trading between 1975 and 2019, calculated the present value of future earnings, the basis for fair value, and compared it to the stock price at which the company first listed. They call this the ratio of "remaining lifetime earnings to price," or RLTEP. Their methodology accommodated firms that were acquired or delisted.

They found an average ratio of lifetime earnings to stock price of 0.9 for the full sample. In other words, price was within 10 percent of value for the stocks that started trading during this time. This would seem to indicate a reasonably efficient market.

However, the *median* ratio of lifetime earnings to stock price was just 0.2, which means that the value was 20 percent or less of the initial price for one-half of the firms. This would seem to suggest a mostly inefficient market.

Aggregation mechanism. Most stock markets use a continuous double auction, which matches buyer and seller orders in a standard order book. Prediction markets generally use the same mechanism.

Friedrich Hayek and Vernon Smith were awarded Nobel Prizes in economics for showing that markets do a very good job at synthesizing distributed information to discover accurate prices.[104]

One relevant thread of research goes so far as to show that agents with zero intelligence, but some budget constraints, produce results similar to humans in a laboratory setting.[105] The implication is that the mechanism may be as important, or more important, than the smarts of investors in finding a proper price. The seminal paper on the topic summarizes the findings as follows: "Allocative efficiency of a double auction derives largely from its structure, independent of traders' motivation, intelligence, or learning."[106]

Diversity (and breakdowns). Of the markets we have reviewed, the stock market is the most likely to flip from the wisdom to the madness of crowds. Cognitive diversity is the condition of wisdom that is most prone to be violated. Adapting Rudyard Kipling's poem "If—," George J. W. Goodman, writing as Adam Smith in *The Money Game*, quipped: "If you can keep your head when all about you are losing theirs, maybe you haven't heard the news."[107]

A diversity breakdown occurs when investors share the same beliefs.[108] This can happen when all investors hold the same view, which is not likely, or when a subset of investors that hold a different view either cannot, or choose not to, participate in the market. For instance, research shows that a wide dispersion of analyst views does not translate into an accurate price if pessimistic beliefs are constrained or censored.[109]

This occurs because the question of what the right price should be has no definitive answer. While fundamental results based on cash flow determine a company's value in the long run, sentiment can dominate in the here and now. This is especially true if investors are focused on the short run.

Humans are inherently social, and most have a desire to conform to the beliefs of the crowd. This makes sense since being part of the group has conferred an advantage throughout most of human history. Neuroscientists have even studied the neurobiological basis for conformity.[110]

Investors say they feel the pull to conform. The CFA Institute surveyed more than 700 investors and learned that "being influenced by peers to follow trends" was the bias that had the largest impact on their decision making.[111]

The time horizon of investors can play a central role in diversity breakdowns. In theory, investors estimate the present value of future cash flows to determine the price they should pay for the stock of a company. Even investors who trade frequently effectively make short-term bets on long-term outcomes.

Researchers sought to test this idea through an experiment.[112] They created long-horizon sessions where investors held an investment to maturity and received a dividend payment. They also ran short-horizon sessions where investors could sell before maturity and were paid based on future market prices rather than the dividend itself.

The results were very different. Prices tended to converge toward fundamental value in the long-horizon markets. But bubbles often formed in the short-horizon markets. The investors in these sessions did not appear to work backward from dividends but rather extrapolated recent price trends.

Narratives can also play a part in belief formation and diversity breakdowns. A narrative is a causal or justificatory explanation of what happened or what is happening.[113] Robert Shiller, an economist and winner of the Nobel Prize, defines "narrative economics" as the study of how narratives spread, change, and influence economic outcomes. He uses an epidemiological model to explain the process of dissemination.

The "novel narrative hypothesis," developed by a professor of finance named Nicholas Mangee, suggests that investors create narratives to explain what is going on to resolve the uncertainty associated with novelty. These, in turn, affect investor sentiment and expectations.[114]

Measuring diversity breakdowns is difficult. The goal is to understand whether cognitive diversity has collapsed and investors are pursuing the same decision rules. Indicators such as common holdings and sentiment can be useful. The combination of strong sentiment, major stock moves, and extreme valuations is common at extremes.

One aspect of diversity breakdowns that is very difficult to capture is that their effect on outcomes tends to be non-linear. This is true in natural and physical systems as well as social systems.[115] That means a small incremental loss in diversity can lead to a large price move.[116]

Stock markets veer between the wisdom and madness of crowds precisely because of a lack of an anchor or specific outcome. This reflects human nature and has persisted despite major advances in information access, technology, and human capital.

Incentives. The incentive for investing in the stock market is to make money. The expected return of the market is effectively what those willing to defer their consumption will earn, as well as the cost, or opportunity cost, to those who want to consume today. Unlike all of the other markets we reviewed, the stock market offers participants a positive expectation. This does not mean that all investors make money all of the time, but it does mean that markets rise over time.

Investing is zero sum only in a relative sense. If the stock market is up 10 percent in a year, for example, the portfolios of some investors will do better than the market and those of others will do worse. But overall wealth will rise.

Participating in the U.S. stock market is much cheaper than the other markets under consideration. Parimutuel markets are generally the most expensive, and prediction markets and sports betting markets are in the middle.

While a small fraction of participants have made money in the betting markets, nearly all investors in U.S. stocks have over the long term. The future may differ from the past, but the U.S. stock market has been very attractive.[117]

The Role of Regulation

This report focuses on the various ways that information is assimilated into markets: essentially when, why, and how the wisdom of crowds works.

But assessing these markets in 2026 demands some discussion of the regulatory environment. As of now, each of these markets has a different main regulator (see exhibit 13). The challenge is that the products they offer are starting to overlap, calling into question regulatory boundaries. (This analysis is limited to the U.S. But naturally there are regulators in other markets as well, each with their own guidelines and objectives.[118])

Exhibit 13: Regulatory Topics for Prediction, Sports Betting, Parimutuel, and Stock Markets

Market	Main U.S. Regulators	What They Regulate	Main Overlap
Prediction Markets / Event Contracts	Commodity Futures Trading Commission (CFTC) for event contracts listed on CFTC-regulated designated contract markets (DCMs). National Futures Association may apply to derivatives intermediaries. Kalshi and Polymarket US are currently DCMs as designated by the CFTC.	Event contracts are derivatives tied to a specified event, occurrence, or value. CFTC rules and the Commodity Exchange Act give the CFTC authority to review and prohibit event contracts tied to activities such as terrorism, assassination, war, gaming, or conduct unlawful under federal or state law.	Largest overlap is with sports betting, including game outcomes, proposition bets, spreads, championships, or combinations that are similar to parlays. Platforms and the CFTC have argued that federal oversight preempts state jurisdiction. Several states are challenging this interpretation.
Sports Betting	Mostly state gaming commissions, lotteries, casino control boards, and state attorneys general. Tribal gaming involves tribal regulators and the National Indian Gaming Commission. Agreements between the state and tribes are reviewed by the Bureau of Indian Affairs, which operates under the U.S. Department of the Interior.	Licensing of sportsbooks, permitted bet types and wagering menus, geolocation, age limits, advertising, taxes, responsible-gambling rules, integrity monitoring, and illegal-operator enforcement. Federal overlays include payment restrictions under the Unlawful Internet Gambling Enforcement Act and enforcement for federal gambling and criminal law.	Overlaps with prediction markets when an event contract regulated by the CFTC is functionally a sports wager. Also overlaps with parimutuel regulation where the same state agency regulates sports wagering and horse racing.
Parimutuel Betting	Primarily state racing or gaming commissions. For Thoroughbred racing, Horseracing Integrity and Safety Authority operates under Federal Trade Commission oversight for racetrack safety, anti-doping, and medication rules. States may retain parimutuel and other racing authority.	Pooled wagering: bettors wager with each other through a pool, not against a bookmaker. The Interstate Horseracing Act defines parimutuel wagering, interstate off-track wagers, consent requirements, and takeout rules for interstate off-track wagering.	Overlaps with sports betting at the state-agency level. Structurally different from sportsbook odds because the operator extracts a pool takeout rather than act as bookmaker. Less direct CFTC overlap, except where platforms emphasize peer-to-peer market structure.
Stock Market / Securities Markets	The Securities and Exchange Commission (SEC) is the primary federal securities regulator. The Financial Industry Regulatory Authority regulates broker-dealers under SEC oversight. National securities exchanges and clearing agencies are SEC-regulated Self-Regulatory Organizations. State securities regulators also enforce state securities laws.	Issuers, public-company disclosures, broker-dealers, exchanges, securities trading, clearing, market manipulation, insider trading, investor protection, and security-based swap markets.	Overlaps with the CFTC for hybrid derivatives: SEC regulates security-based swaps, CFTC regulates swaps, and both jointly regulate mixed swaps; security futures are also jointly regulated.

Source: Counterpoint Global.

The most prominent example is the prediction markets, regulated by the Commodity Futures Trading Commission (CFTC), offering contracts in sports betting, overseen primarily by state gaming commissions. Further complicating the picture is that in states and territories where sports betting is legal, the governments collect taxes. So those states have lost regulatory control and revenues.

This hodgepodge of regulatory oversight in the U.S. has led to legal wrangling. For example, CME Group, a publicly-traded provider of derivatives markets that includes the Chicago Mercantile Exchange, sued the CFTC and its chairman in June 2026. At issue was the CFTC's decision, shared in May 2026, to allow prediction markets to list perpetual futures.

CME Group argued that the contracts were swaps, not futures, so the CFTC used the wrong legal process when it allowed them to be listed. A swap is a derivative in which two parties exchange an asset or cash flows, and a futures contract is an agreement to buy or sell a standardized asset at a set price on a specific date.

Further, the regulatory environment is subject to sudden change. For instance, the U.S. President selects a candidate to become the chair of the CFTC. A Senate subcommittee vets the nominee, and upon successful completion of the process the individual must be approved by the Senate with a majority vote.

The nominated chair of the CFTC is commonly an individual who is one of the five CFTC commissioners. To maintain independence, the commission can have no more than three people from the same political party. The president can therefore promote a candidate that aligns with his or her views.

Summary

Markets are mechanisms that facilitate transactions between buyers and sellers. Some buyers and sellers seek edge, an opportunity for an excess return that is based on sound analysis. Edge often relies on information that is either improperly reflected in prices or not yet known to the market. Through this process, prices aggregate information.

Stock market lore is filled with examples of markets veering to extremes. This planted the seed of the idea that crowds, which are collectives of investors, go mad from time to time.

James Surowiecki wrote a book called *The Wisdom of Crowds* to point out that collectives are often astonishingly accurate. His vital insight is that wisdom is accompanied by specific conditions. We summarize them as cognitive diversity, aggregation, and incentives.

Cognitive diversity means there are participants with varied views, rules for action, and information. As a result, the collective captures the richness of available knowledge. Importantly, the diversity prediction theorem, popularized by Scott Page, shows the math of how diversity reduces collective error.

Aggregation captures the mechanism to reflect information. This is what markets do, and examining the various approaches by which they operate is a key feature of this report.

Incentives are rewards for being right and penalties for being wrong. In markets, incentives can be quantified by monetary gains and losses, although there are non-monetary benefits and costs as well.

After noting that crowds are not the best way to solve all problems, we discussed the types of problems crowds can address. The first is comparable to finding a needle-in-a-haystack, where an answer exists and is known to some in the crowd. The second is estimating a state, the case where no one in the crowd knows the answer but there is one that is disclosed eventually.

Next were prediction problems. These come in two varieties: one where the result is revealed and the other where it is not. The accuracy of predictions is straightforward to measure in the first case but more difficult in the second.

The report reviewed the wisdom of crowds in the context of prediction markets, sports betting markets, parimutuel betting markets, and the stock market. In each case, we described the market, provided a very brief history, examined its accuracy, looked at the mechanism it uses to aggregate information, checked for whether and how diversity breakdowns occur, and considered the role of incentives.

There is a vital distinction between the three betting markets and the stock market. The betting markets are zero-sum propositions, before costs. For every winner there is a loser of the same size, and the provider of the market charges a toll. In roughly the last century, gambling losses in the U.S. were $5.8 trillion, including adjustments to make the total equivalent to 2025 dollars.

The stock market allows investors to own partial stakes in businesses, and the values overall tend to grow over time. *Relative* results in the stock market sum to zero before costs because some investors earn higher returns than those of the market and others have those that are correspondingly lower. But the *absolute* results are solid since the overall market has a positive expectation. In the last century, the U.S. stock market has generated gains of $91 trillion, relative to the monthly returns of U.S. Treasury bills.

The vast majority of bettors lose money and the vast majority of investors make money in the long run (even if they are unable to keep pace with index averages).

A handful of conclusions surfaced as a result of our analysis:

- **Prediction markets, sports betting markets, and parimutuel betting markets are quite accurate.** We measured accuracy by comparing implied probabilities based on market prices and objective outcomes. Some biases exist. The most prominent is the favorite-longshot bias, which shows that the probability of winning for a favorite as implied by the bets of participants understates the actual rate of success, and that the opposite is true for longshots, which win at a lower rate than their odds imply.

- **Benefits must be weighed against costs.** In any marketplace, the benefit of finding a mispricing has to be compared to the cost of action. The costs to participate in the markets we cover vary widely. But it is clear that the stock market, which is by far the largest of these markets, has the lowest costs.

- **There are multiple mechanisms for information aggregation.** We featured three of them: continuous double auction (used in most prediction markets and the stock market), bookmaking, and parimutuel pools. (Another approach, logarithmic market scoring rules, is also used in some niche prediction markets.) In auction markets, the price is set by the interaction of buyers and sellers. In bookmaking, bookmakers set the odds and prices and act as intermediaries. In a parimutuel pool, the odds are set by how bettors allocate wagers within a pool. While the approaches are different, each mechanism has proven to be accurate.

- **Diversity breakdowns differ.** Diversity is the condition of the wisdom of crowds that is most likely to be violated. The threat of correlated beliefs is much lower in markets with outcomes because wagers with odds or prices that veer too far off course materialize as losses. A review of the evidence shows that diversity breakdowns are relatively rare in those markets but can happen when uninformed but enthusiastic participants enter the market, such as what often occurs with Triple Crown contenders in American horse racing.

In contrast, diversity breakdowns are common in the stock market because the market is perpetual, which creates fertile ground for narratives to grow. Measuring diversity in the stock market can be difficult, but a combination of strong bullish or bearish sentiment and extreme valuations often provides opportunities to sell or buy.

- **Incentives matter.** The primary draw of these markets is to make money. But bettors report enjoying substantial nonmonetary benefits, including excitement and engagement. The prospect of making money also encourages the manipulation of outcomes. For example, one bettor appeared to have manipulated a weather station at Charles de Gaulle Airport to win a bet on the temperature in Paris on Polymarket.[119] Other bettors apparently manipulated streams on Spotify to win bets on the most played song in the month of June 2026.[120] Shenanigans such as these, along with the manipulation of outcomes in sports, will be difficult to manage.

- **Regulation can vary greatly.** The markets we reviewed have different regulators while the products they offer now overlap in practice. Prediction markets offering contracts in sports betting are the clearest example. The Commodity Futures Trading Commission oversees prediction markets, and state gaming commissions are the main regulators for sports betting. State governments also collect taxes on sports betting where it is legal. States have lost regulatory control and tax revenues as activity has migrated to prediction markets.

  This hodgepodge of regulatory oversight in the U.S. has led to legal battles, and participants should be aware that the regulatory environment can shift quickly based on the judgments of the judicial branch and changes in the executive and legislative branches.

Exhibit 14 summarizes some of the key topics for these markets.

Understanding how markets work is useful for evaluating how opportunities for excess returns arise. The wisdom of crowds is a powerful way to explain how markets capture known information, making them generally efficient (and hard to beat). Prices commonly reflect information.

The ability to compare information from different markets has never been better. For example, prediction markets now offer contracts tied to key performance indicators for companies, which may provide investors with an additional way to assess the expectations embedded in stock prices.

From time to time, beliefs and trading in the stock market become correlated and crowds amplify, rather than correct, errors. This is the madness of crowds. Such errors can generally persist because for a stock price there is no universally accepted value on a fixed date. Instead, stock prices depend on fluctuating expectations about future cash flows, risk, and investor behavior.

Exhibit 14: Comparison of Prediction, Sports Betting, Parimutuel, and Stock Markets

Market	Accuracy	Aggregation Mechanism	Role of Intermediary	Diversity Breakdowns	Cost to Participate	Where the Wisdom Comes From
Prediction Market	Very well calibrated. Observed frequency of outcomes close to probabilities implied by prices. Accuracy can be compromised by thin markets.	Continuous double auction. For binary contracts, price approximately reflects probability before costs.	Platforms match orders, handle settlement, and charge fees. They generally do not take directional risk.	Partisan participants can create short-term movement.	Some charge fees for trades or withdrawals. Customers may not receive interest on cash balances.	Broad, diverse participation with skin in the game; arbitrageurs pull price toward truth.
Sports Betting Market	Very well calibrated, with high correlation between probability implied by odds and win rate. Evidence of favorite-longshot, home-team, and recency biases, but they vary by sport.	Bookmaker line with small and infrequent revisions throughout the week. Odds approximately reflect probability before costs.	Bookmaker takes the other side, manages risk, and may balance exposure or shift prices to exploit bettor biases.	Limited because bookmakers set and adjust the odds and outcomes are independent of implied probabilities.	Vigorish varies by sport, market, and type of wager, but it is around 4-5% for straight bets and higher for parlays.	Bookmakers who take into consideration bets by smart money.
Parimutuel Market	Very well calibrated, with high correlation between probability implied by odds and win rate. Evidence of favorite-longshot bias.	Gross bet distribution determines implied probabilities. Payout odds reflect the takeout.	None. Track is an operator and not a counterparty. Payouts are after a takeout.	Manipulations move odds in the short term but do not persist. Periodically, large money comes in on a favorite such as a Triple Crown candidate.	Takeout rate 15-24% depending on pool. Low end for win, place, and show pools and higher for exotic pools.	Aggregation of all bets, with smart money tending to come in late if advantageous.
Stock Market	Efficiency difficult to quantify. Hard to generate excess returns, but markets veer to booms and busts from time to time.	Continuous double auction. Most liquid of markets.	Market makers, specialists, and high-frequency traders. Most liquidity providers seek to maintain no net exposure.	Correlated beliefs, narratives can dominate, short-term investors fail to discount future cash flows, and diversity breakdown effects are often non-linear.	Cost for institutions is commission and market impact. Often zero explicit commissions for retail investors. Relatively low.	Diverse investors (time horizon, sophistication, decision rules). Payoffs for producing costly information. Arbitrageurs push price toward fundamentals.

Source: Counterpoint Global.

Appendix A: How Crowds Solve Needle-in-the-Haystack Problems

With a needle-in-a-haystack problem, there is an answer known to some members of the collective. Think of a large group playing *Trivial Pursuit,* a board game where winning requires answering trivia correctly. For any given question, only a subset of the group may know the answer, and those individuals are likely to differ across questions. Seeing the value of diversity in this setting is easy.

What is remarkable is that when all within the collective participate, the correct answer emerges even when only a few individuals know it.

James Surowiecki illustrates this with the game show *Who Wants to Be a Millionaire?*[121] In this program, the host asks the contestant a series of multiple-choice questions that become more difficult over time. Answering them all correctly results in a $1 million prize.

The creators added some wrinkles to encourage viewer engagement. When stumped by a question, contestants can seek help through one of three options: remove two of the four possible answers creating a fifty-fifty chance of success, call a pre-selected friend or relative for guidance, or poll the studio audience.

Contestants answered correctly on about two-thirds of attempts after consultation with their smart contact. But the poll of the audience produced the correct answer more than 90 percent of the time. The crowd was a lot wiser than the individual.

The Condorcet Jury Theorem, developed by Marquis de Condorcet, a French philosopher, political economist, and mathematician, is one way to explain this result.[122]

The theorem shows that if each member of a group has an independent probability of choosing the correct answer greater than 50 percent, and the response is tabulated using majority rule, the likelihood of finding the right answer rises toward 100 percent as the size of the group increases.

The Condorcet Jury Theorem has some useful applications, but there is a simpler way to show why the crowd is wise in this case.

Here is an example that Scott Page presents in his book, *The Difference*.[123] He suggests asking a collective this question about the Monkees, a 1960s pop band:

Which person from the following list was not a member of the Monkees?

A. Peter Tork
B. Davy Jones
C. Roger Noll
D. Michael Nesmith

Roger Noll, a Stanford economist, was not part of the band. Page imagines a crowd of 100 people with the following distribution of knowledge:

- 7 know all 3 of the listed Monkees
- 10 know 2 of the listed Monkees
- 15 know 1 of the listed Monkees
- 68 have no clue

Only seven percent of the individuals know the answer, and more than two-thirds know nothing of the topic. Page assumes that those who do not know the answer vote at random. The Condorcet Jury Theorem does not apply because only a small minority knows the answer.

Still, the crowd has no problem identifying Noll as the non-Monkee. Here's the summary:

- All 7 who know all of the listed Monkees vote for Noll;
- 5 of the 10 who know 2 of the listed Monkees vote for Noll;
- 5 of the 15 who know 1 of the listed Monkees vote for Noll; and
- 17 of the 68 clueless vote for Noll.

Noll collects 34 votes and each of the other choices 22 votes. The crowd identifies him by a comfortable margin.

Random errors cancel out one another in this case, which allows the correct answer to surface. The result holds with an even greater number of clueless individuals, but the percentage margin by which Noll is identified goes down.

If getting to the right answer is so easy, it is fair to ask why the studio crowd was not correct all of the time.

The amount of randomness and the percentage of the crowd who know the answer are the two key variables. Randomness is more important than accuracy. With random responses that are unbiased and independent, only a small share of the population with the correct answer is necessary to generate an accurate crowd response. The answers are still good, if not perfect, when replies are not totally random.

Many of these problems exist but most do not require collectives because they are solved easily using technology such as search engines and GenAI.

Appendix B: The Math of the Diversity Prediction Theorem Applied to the Ox

Galton provided some data in his original articles, but later Kenneth Wallis, an econometrician, found all 787 of the slips used in Galton's experiments.[124] This allows us to apply the math of the diversity prediction theorem to the full sample.

Recall the equation:

Collective error = average individual error – prediction diversity

Individual error is the squared difference between the actual weight and an individual's guess. Squaring the difference makes guesses that are too high or low by the same amount equal to one another. For example, one person guessed 1,107, or 90 pounds too low. Another guessed 1,287, or 90 pounds too high. Both of their individual errors were 8,100 (90^2).

The average individual error for the full sample was 5,408.2.

Prediction diversity is measured by calculating the squared difference between the average guess and each individual's guess, and then taking the average of those. In this case, the average guess of 1,197 was nearly identical to the actual weight. This calculation has a little rounding. The person who guessed 1,107 was 89.7 off the average, or 8,047.9 (89.7^2) when squared. The person who guessed 1,287 was 90.3 pounds from the average, or 8,152.2 (90.3^2) when squared.

The prediction diversity was 5,408.1.

The collective error was therefore 0.1 (0.1 = 5,408.2 – 5,408.1).

We do a similar exercise with students at Columbia Business School, who estimate the number of jelly beans in a jar. The sample sizes are much smaller, typically in the range of 50 to 70, but the average guess is consistently within 5 percent of the correct answer.

Notwithstanding Galton's comments that the participants were "probably guided by such information as they might pick up, and by their own fancies," the collective accuracy was very high. Indeed, a reader wrote a letter to the editor pointing that out in response to Galton's analysis.[125]

To provide some sense of this, we calculated the average absolute value of each individual error on a percentage basis. For Galton's experiment it was 4.4 percent. For the jelly bean experiments it is closer to 40 percent (for instance, it was 39.4 percent for the Columbia Business School students in the class in 2026).

Galton was likely drawing on a group that was more informed than typical. But the math of the diversity prediction theorem still works. The crowd beats the average person in the crowd.

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