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### **Can Prediction Markets Scale in Both Liquidity and Forecasting Value?**

In April 2026, a U.S Army Special Forces soldier was charged with using classified information about an operation to capture Venezuelan President Nicolás Maduro to profit more than \$400,000 from a bet on Polymarket (U.S. Department of Justice, 2026). As prediction markets become more popular, cases like this raise a larger question about whether these markets are simply speculative platforms with regulatory risk or emerging tools for interpreting the future. With over \$5.9B now traded weekly across Polymarket and Kalshi, the two most popular platforms, prediction markets have drawn attention from consumer culture, politics, finance, journalism, and academia, but for differing reasons (DeFi Rate, 2026). To casual users, prediction markets are simply platforms to make bets with monetary value on their beliefs. To traders, they are emerging exchanges with value to be extracted. To researchers, journalists, and policymakers, they offer a potentially valuable forecasting tool to convert dispersed beliefs into a live probability estimate.

This forecasting value comes from the basic structure of a prediction market contract. In a typical event contract, users trade “Yes” and “No” positions tied to a specific future outcome. In the Maduro case, the soldier took “Yes” positions on contracts speculating on whether U.S. forces would enter Venezuela and whether Maduro would be removed from power by January 31, 2026. At the soldier’s time of purchase, the market priced the event at roughly 8¢, meaning

traders viewed it as unlikely to occur. If a “Yes” contract trades at 8¢, the market is assigning the event roughly an 8% chance of occurring. If the event becomes more likely, the price should rise; if it becomes less likely, the price should fall. The soldier clearly saw an opportunity to profit by buying before the market reflected his classified information. However, the price carried meaning beyond exploitation. For instance, a Venezuelan activist or journalist could interpret that probability as meaningful information about the likelihood of U.S. intervention and Venezuela’s political future.

The reason these prices matter is that they appear to offer more than speculation. If prediction market prices can be read as probabilities, then they may provide a measurable way to study what groups of people collectively believe about the future. This makes prediction markets especially valuable to researchers because their forecasts are not based on surveys, expert opinions, or individual predictions alone. Instead, they are built from trades where participants must attach money to their beliefs. However, those prices can only become meaningful forecasts if the markets have active traders. A market with minimal capital flow may show a price, but that price may reflect a few scattered bets rather than a reliable measure of collective belief. This creates the central question of prediction markets as they grow: can they become deeper, more active financial exchanges while still preserving the forecasting value that makes their prices useful in the first place? Before examining that tension, it is first necessary to understand whether prediction market probabilities have shown real forecasting power at all.

### **The Forecasting Promise of Prediction Markets**

Several studies provide empirical evidence into the actual accuracy of these probabilities, but from different lenses. While Arrow et al. emphasize prediction markets’ broad usefulness

across government and business, Berg et al. (2008) compare market forecasts directly against the most familiar alternative, being polls. They show that across 964 polls from the 1988 through 2004 U.S. presidential elections, the Iowa Electronic Markets were closer to the eventual two-party vote split 74% of the time and significantly outperformed polls in every election when forecasting more than 100 days in advance. This illustrates the general idea that when asked to put money on the line, the consensus is more accurate.

Additionally, there appears to be predictive value beyond this one-to-one price-to-probability lens, as Mohanty and Krishnamachari (2026) study how daily changes in Kalshi macro-market prices can predict future cryptocurrency volatility. More specifically, they find that an aggregation of Kalshi markets related to Federal Reserve policy contains information about future Bitcoin volatility, while an aggregation of CPI-related markets contains information about future volatility in alternative cryptocurrencies such as Ethereum, Solana, Cardano, and Chainlink. While Arrow et al., and Berg et al. focus directly on the probabilities, Mohanty and Krishnamachari focus on probability changes, revealing another layer in how prediction market prices can be used to predict.

Wolfers and Zitzewitz (2006) help explain why this move from probability levels to probability changes matters. Arrow et al. and Berg et al. largely depend on the idea that prediction market prices can be read as direct forecasts. Wolfers and Zitzewitz support this basic interpretation, arguing that prediction market prices “typically provide useful (albeit sometimes biased) estimates of average beliefs” about an event’s probability. However, their analysis also adds an important distinction that prices are not pure probabilities by default. One reason is that traders do not evaluate every contract in the same way. Around 50¢, the risk and reward of a contract are relatively balanced: a trader risks about 50¢ to make about 50¢. But near the

extremes, the trade feels different. A 97¢ contract may still be profitable if the event is actually more than 97% likely, but the trader is risking 97¢ to make only 3¢. Even if the chance of losing is small, the loss is large relative to the possible gain. Because risk-averse traders may demand compensation for bearing that downside, high-probability contracts can trade below their true likelihood, while low-probability contracts can trade above theirs. This pattern is called the favorite-longshot bias. Whelan and Bürgi (2026) find evidence of this phenomenon across more than 300,000 Kalshi contracts, suggesting that prediction markets can be informative while still being shaped by risk preferences and trader behavior. This is where Mohanty and Krishnamachari's use of daily probability changes becomes especially interesting. If price levels may contain risk premia or other distortions, then studying how prices move day to day can reveal a different kind of forecasting power. Although these studies use the probabilities in different ways, they support a general thesis backed by empirical evidence that prediction markets hold value in their ability to predict.

### **Why Liquidity is Necessary**

The forecasting value of prediction markets depends on more than whether traders have good information; it also depends on whether there is enough liquidity for that information to enter prices cleanly. Liquidity means that users can easily buy or sell. Levine (2026) makes this point by comparing prediction markets to stock markets. Although these markets may appear peer-to-peer, most users are not directly finding another individual with the opposite belief. Instead, they often trade against professional market makers, who continuously post prices where others can trade. Thus, they provide liquidity into markets. This connects directly to Palumbo's

(2026) microstructure analysis, demonstrating that market makers are the mechanism that allows individual beliefs to become tradeable prices.

However, Levine and Palumbo both complicate the idea that liquidity is easy to supply. In traditional financial markets, market makers can often hedge positions with related assets, but Palumbo notes that event contracts have binary resolution and “no underlying,” meaning that there is often no obvious asset to hedge against. As a result, they may absorb demand imbalances and hold outcome-dependent exposure through resolution. Liquidity is necessary because traders need someone to trade against, but that liquidity requires market-makers willing to bear terminal risk.

Smart et al. (2026) shows why the absence of strong liquidity can damage forecasting accuracy. If a market is thin (low-liquidity), a “whale,” a trader with a lot of capital, can temporarily distort prices, especially when other traders herd toward the market price or update their beliefs slowly. This connects back to Levine and Palumbo because all three studies show that prices are shaped by who has capital and who absorbs order flow. Without enough liquidity providers to counteract large trades, prices may reflect concentrated pressure rather than collective belief. Therefore, liquidity is not just useful for smoother trading; it is necessary for prediction markets to remain credible forecasting tools.

### **When Liquidity Becomes Financialization**

As liquidity becomes more central to prediction markets, the markets begin to look less like simple forecasting tools and more like financial exchanges built around risk transfer. Dalen (2026b) makes this shift explicit, arguing that prediction markets are “starting to look less like crowd polls and more like electronic markets.” This is where liquidity becomes financialization.

The same institutional liquidity that can make markets easier to trade can also make prices less purely crowd-driven. Dalen (2026b) states that “the first and clearest gains from institutional liquidity are more likely to appear in execution quality than in forecasting performance.” If market makers face volatility and cross-event risks, then they need standardized models for hedging and transferring those risks (Dalen, 2026a). Thus, Palumbo’s belief that market making in prediction markets resembles insurance underwriting directly corresponds to Dalen’s models. The result is that liquidity may make prediction markets more tradeable, but it also financializes their prices. Instead of reflecting only the “wisdom of the crowd,” prices may increasingly incorporate the compensation required for market-makers to bear event risk in order for liquidity to increase.

## **Conclusion**

The sources examined in this paper show that prediction markets occupy an unusual position between forecasting tools and financial exchanges. The early promise of prediction markets lies in their ability to turn scattered beliefs into probability-like prices. However, there is a central tension in what it takes for that predictive value to scale. Greater liquidity is necessary because thin markets can be noisy, hard to trade, and vulnerable to whales. At the same time, liquidity does not appear automatically. It depends on market makers who are willing to absorb order flow and bear event risk. The markets need liquidity to become reliable and widely usable, but the process of creating that liquidity may change what their prices mean. A prediction market price may still be informative, but it may no longer represent only collective belief. Therefore, the question is not simply whether prediction markets can forecast. The more important question

is whether they can scale into liquid financial exchanges without losing the forecasting clarity that made them valuable in the first place.

Future research should examine how emerging prediction market funds, research labs, and startups approach market-making in ways that are unique to event contracts. As prediction market companies continue to grow, analyzing how they adopt existing financial exchange infrastructure while developing models specific to event contracts may help answer whether liquidity can scale without weakening forecasting value.

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AI Statement: No AI was used.