When Prediction Markets Disagree: Cross-Platform Dispersion and Politically Sensitive Equity Volatility

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Abstract

We ask whether disagreement across prediction markets helps predict the volatility of politically sensitive equities. Using 5-minute odds from seven betting platforms and intraday equity data during the 2024 U.S. presidential election, we construct hourly measures of cross-platform dispersion and realized volatility. Higher disagreement predicts higher volatility in a partisan long–short portfolio—a one-standard-deviation increase raises spread volatility by 11% after controlling for broad realized and implied market volatility. A formal selectivity test confirms that this effect is significantly stronger for politically exposed equities than for the broad market. Local projections show the effect persists for roughly one trading day. Decomposing by platform type, the association is stronger for lower-information platforms than for price leaders—consistent with the view that dispersion reflects election-specific uncertainty rather than price-leader dynamics alone.

Keywords: Prediction Markets; Political Uncertainty; Equity Volatility; Disagreement; Price Discovery

JEL Classifications: G14; D72; G12

1 Introduction

During the 2024 U.S. presidential election, at least seven global platforms simultaneously quoted odds on the outcome. These platforms often disagreed. The cross-sectional standard deviation of implied Trump-win probabilities averaged 2.7 percentage points and exceeded 13 percentage points around major campaign events. This paper asks whether such cross-platform disagreement matters for equity markets.

A large literature shows that political uncertainty affects asset prices (Pástor and Veronesi, 2012, 2013; Kelly et al., 2016; Baker et al., 2016). A smaller literature studies information aggregation in prediction markets (Arrow et al., 2008; Wolfers and Zitzewitz, 2004). Yet the link between prediction-market *disagreement* and equity-market *volatility* remains unexplored—despite a natural theoretical motivation: when platforms disagree about the likely winner, the range of policy scenarios that equity investors must price widens, increasing the volatility of firms whose fortunes depend on the outcome.

We study this link with a selectivity design. If cross-platform disagreement captures election-specific uncertainty, it should predict the volatility of firms exposed to the electoral outcome more strongly than it predicts the volatility of the broad market. This is the pattern in the data. Disagreement strongly predicts the volatility of a partisan long–short equity spread, and a formal interaction test confirms this difference is statistically significant. Its relationship with broad market volatility is much weaker once standard controls are included. Local projections show this predictive effect persists for roughly one trading day, while the corresponding market-wide effect is small and imprecisely estimated.

Our contribution differs from work that links the level or change in a single platform's probability to equity returns (Addoum and Kumar, 2016; Aktuğ and Torul, 2026a). That channel asks *which way* the election is going. We study a second-moment object: *how much* markets disagree, and whether that disagreement predicts the volatility of politically exposed equities. The selectivity design helps separate election-specific uncertainty from broader confounds: if disagreement merely proxied for general news intensity or stale-quote dispersion, one would expect it to predict broad market volatility and partisan-spread volatility more similarly than we observe in the data. Accordingly, we interpret the evidence as documenting a selective predictive relation rather than as establishing a fully causal mechanism.[1]

[1] Our empirical design is informed by the market microstructure literature on price discovery across trading venues (Hasbrouck, 1995; Chakravarty et al., 2004).

2 Data

We combine prediction-market and equity-market data from January 22 to November 5, 2024.[2] Prediction-market quotes and equity prices are sampled at 5-minute intervals; realized volatility is computed from these returns within each trading hour. Baseline regressions use the hourly frequency to reduce microstructure noise and mitigate the effects of stale quotes.

Our prediction-market sample contains implied Trump-win probabilities from seven platforms: PolyMarket, Betfair, Bovada, BetOnline, William Hill, Unibet, and Everygame. To distinguish between leading and lagging venues, we use Gonzalo–Granger (GG) weights from a companion price-discovery exercise estimated at the 5-minute frequency (Gonzalo and Granger, 1995; Aktuğ and Torul, 2026b; Bossaerts et al., 2024). GG weights decompose the common efficient price into each venue's contribution: a platform with a large positive weight leads the discovery of new information, while one with a near-zero weight tends to follow.[3] PolyMarket, Betfair, and BetOnline receive positive and relatively large GG weights. Bovada, William Hill, Unibet, and Everygame receive near-zero or negative weights. We refer to these two groups as "price leaders" and "lower-information" platforms, recognizing that the classification rests on a statistical decomposition rather than direct observation of trader types.

On the equity side, we use 5-minute prices for 71 publicly traded U.S. firms classified as Republican-leaning (36 firms) or Democrat-leaning (35 firms) using corporate PAC contribution data.[4] We construct equal-weighted RED and BLUE portfolios and define *SPREAD* as the RED-minus-BLUE return and *MKT* as the equal-weighted average across all 71 firms. Our benchmark implied-volatility control is VIXY, an exchange-traded product linked to short-term VIX futures that is available at intraday frequency.[5]

After merging and restricting to U.S. trading hours (13:30–20:00 UTC), the sample contains more than 15,000 five-minute observations, 1,402 hourly observations, and 201 daily observations. Summary statistics are in Table A.1 in the Appendix.

[2]The sample begins on January 22—the first trading day after Ron DeSantis withdrew from the Republican primary—to ensure that prediction-market prices reflect general-election uncertainty rather than primary-nomination dynamics.

[3]Because disagreement is measured as cross-sectional dispersion rather than deviations from a single platform's quote, our main results do not depend on the GG classification. The classification is used only in the supplementary decomposition in Table 2.

[4]The classification data are obtained from OpenSecrets.

[5]Results are materially unchanged when we replace VIXY with the standard CBOE VIX close-to-close change (Table 4). VIXY tracks expected volatility via VIX futures, so it may respond with a lag relative to spot-VIX shocks; this makes it a conservative control.

3 Methodology

At each 5-minute timestamp we measure disagreement as the cross-sectional standard deviation of Trump-win probabilities across the seven platforms:

$$\text{DISAGREE}_t = \text{SD}\big(p_{1,t}, \ldots, p_{7,t}\big). \tag{1}$$

We aggregate this measure to hourly frequency and relate it to hourly realized volatility. For each trading hour we compute the standard deviation of the twelve 5-minute log returns within that hour, separately for the partisan spread and the broad market portfolio.[6]

Our baseline specification is:

$$\ln\big(\text{SPREAD vol}_t\big) = \alpha + \beta\,\text{DISAGREE}_t + \gamma\,\ln\big(\text{MKT vol}_t\big) + \delta\,\ln\big(\text{VIXY}_t\big) + \varepsilon_t, \tag{2}$$

where standard errors use the Newey–West HAC estimator with the Andrews bandwidth (Newey and West, 1987). Including both realized market volatility and VIXY absorbs broad volatility conditions, so that β captures whether cross-platform dispersion contains additional information about politically exposed stocks.

To trace the dynamics we estimate local projections following Jordà (2005):

$$\overline{y}_{t,t+h} = \alpha_h + \beta_h\,\text{DISAGREE\_SHOCK}_t + \boldsymbol{\gamma}'_h \mathbf{Z}_t + \varepsilon_{t+h}, \tag{3}$$

where $\overline{y}_{t,t+h}$ is average log volatility from t to $t+h$, the shock is the standardized disagreement measure, and $\mathbf{Z}_t$ includes lagged volatility and lagged disagreement.[7]

To test the selectivity claim formally, we stack SPREAD and MKT volatility into a single panel and estimate:

$$\ln\big(\text{vol}_{i,t}\big) = \alpha + \beta_1\,\text{DISAGREE}_t + \beta_2\,D_i + \beta_3\,\text{DISAGREE}_t \times D_i + \boldsymbol{\gamma}'\mathbf{X}_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $D_i = 1$ for the partisan spread. In the controlled version, $\mathbf{X}_{i,t}$ includes $\ln(\text{VIXY}_t)$ interacted with D_i as a common implied-volatility control. (Realized market volatility cannot serve as a common control because it is the dependent variable for the $D_i = 0$ observations.) The coefficient β_3 tests whether disagreement predicts partisan-spread volatility significantly more than broad market volatility.

[6] Table 4 shows that conclusions are similar under alternative volatility proxies, including realized variance and mean absolute returns.

[7] The HAC bandwidth is set to $\max(h, \lfloor 4(T/100)^{2/9} \rfloor)$.

4 Results

4.1 Descriptive evidence

Figure 1 shows the disagreement measure over time. Cross-platform dispersion rises around major campaign events: the Trump assassination attempt, President Biden's withdrawal, and Vice President Harris's emergence as the Democratic nominee. Disagreement co-moves with the political environment.

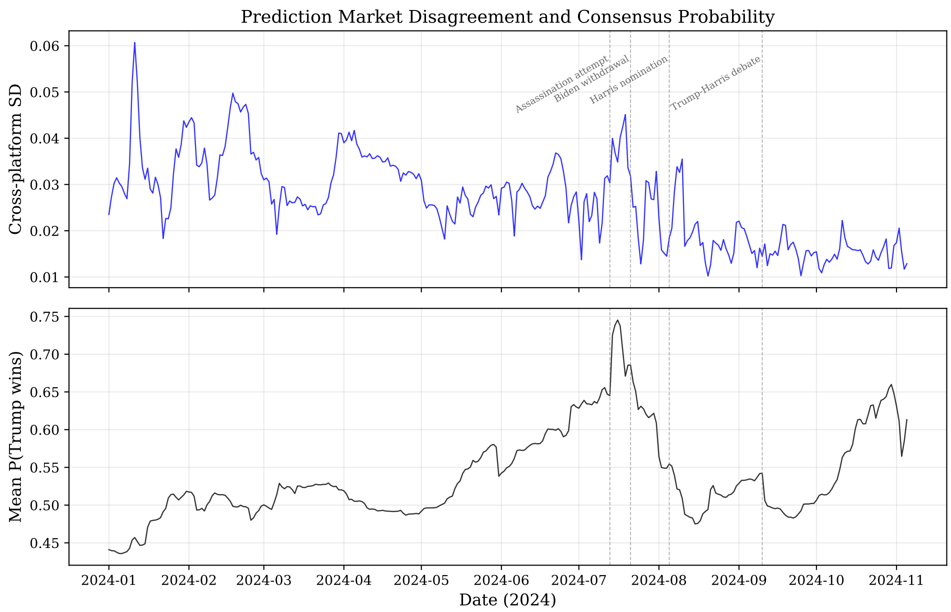

Figure 1: Prediction Market Disagreement and Consensus Probability

Notes: The top panel shows the daily mean cross-platform standard deviation of Trump-win probabilities. The bottom panel shows the daily mean probability across seven platforms. Dashed lines mark key events.

4.2 Core selectivity

Table 1 presents the main results. Column (1) shows that higher disagreement predicts higher volatility in the partisan spread. Column (2) reports a much weaker relationship for broad market volatility. In Columns (3) and (4), the disagreement coefficient remains large and significant after controlling for both realized market-wide volatility and implied volatility. Adding a control for the mechanical level of probability uncertainty—which peaks when probabilities are near 50%—does not change the result.

The selectivity test in Equation (4) confirms this pattern formally. The interaction coefficient $\hat{\beta}_3$ is significant in both uncontrolled ($t = 3.76$) and controlled ($t = 3.85$) specifications: disagreement predicts partisan-spread volatility significantly more than broad market volatility.

In terms of magnitude, a one-standard-deviation increase in disagreement (0.93 percentage points) is associated with a 17% increase in partisan-spread volatility in the uncontrolled specification and an 11% increase after absorbing broad market volatility.[8]

Table 1: Prediction Market Disagreement and Equity Volatility

	(1) SPREAD vol	(2) MKT vol	(3) SPREAD vol	(4) SPREAD vol
Disagreement	17.990***	6.347***	12.107***	12.466***
	(8.93)	(2.99)	(6.69)	(6.78)
ln(MKT vol)			0.711***	0.716***
			(26.29)	(26.38)
Prob. uncertainty				3.563**
				(2.19)
ln(VIXY)			0.453**	0.294
			(2.49)	(1.43)
Observations	1401	1401	1401	1401
R^2	0.0648	0.0113	0.4517	0.4538

Selectivity test: H_0: $\beta_{SPREAD} = \beta_{MKT}$
Uncontrolled: $\hat{\beta}_{\text{interact}} = 11.644$, $t = 3.76^{***}$
Controlled: $\hat{\beta}_{\text{interact}} = 11.360$, $t = 3.85^{***}$

Notes: Dependent variable is ln(realized volatility) at hourly frequency. Disagreement is the cross-sectional standard deviation of probability levels across 7 prediction market platforms. Prob. uncertainty = $0.25 - (\bar{p} - 0.5)^2$. HAC (Newey–West) standard errors; t-statistics in parentheses. The selectivity test reports the coefficient on Disagree × SPREAD from a stacked regression of ln(vol) on disagreement, a SPREAD indicator, and their interaction. The controlled version adds ln(VIXY) interacted with the indicator as a common implied-volatility control. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

4.3 Price leaders vs. lower-information platforms

Table 2 decomposes disagreement by platform type. In a joint regression, disagreement among lower-information platforms is more strongly associated with partisan volatility than disagreement among price leaders. One possible interpretation is that slower-updating venues reflect broader public uncertainty that correlates with equity-relevant risk, whereas price leaders converge quickly and contribute less marginal dispersion. This result is suggestive rather than definitive: it does not rule out alternative explanations related to differences in liquidity, clientele, or updating frequency across platform types.

[8] With ln(vol) as the dependent variable, the percentage effect is $\exp(\hat{\beta} \times \sigma_{\text{disagree}}) - 1$, or approximately $\hat{\beta} \times \sigma_{\text{disagree}}$ for small values.

Table 2: Informed vs. Noise Platform Disagreement

	(1) Joint	(2) Informed only	(3) Noise only
Informed disagreement	5.133***	9.060***	
	(3.92)	(6.31)	
Noise disagreement	13.555***		15.759***
	(7.66)		(9.53)
Observations	1379	1379	1379
R^2	0.0893	0.0384	0.0785

Notes: Dependent variable is ln(SPREAD vol) at hourly frequency. Informed platforms (GG weight $\psi > 0.05$): PolyMarket, Betfair, BetOnline. Noise platforms ($\psi \leq 0.05$): Bovada, William Hill, Unibet, Everygame. HAC standard errors; t-statistics in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

4.4 Dynamic effects

Figure 2 displays local-projection impulse responses. Panel A shows that a disagreement shock is followed by persistently higher volatility in the partisan spread over roughly the next trading day. The persistence is consistent with the slow-moving nature of disagreement itself (half-life ≈ 33 hours): because platforms do not converge immediately, the uncertainty that disagreement proxies for remains elevated over multiple hours. Panel B shows a much smaller and more imprecisely estimated response for broad market volatility. The contrast reinforces the selectivity finding: cross-platform dispersion is tied to election-sensitive assets, not to market-wide conditions.

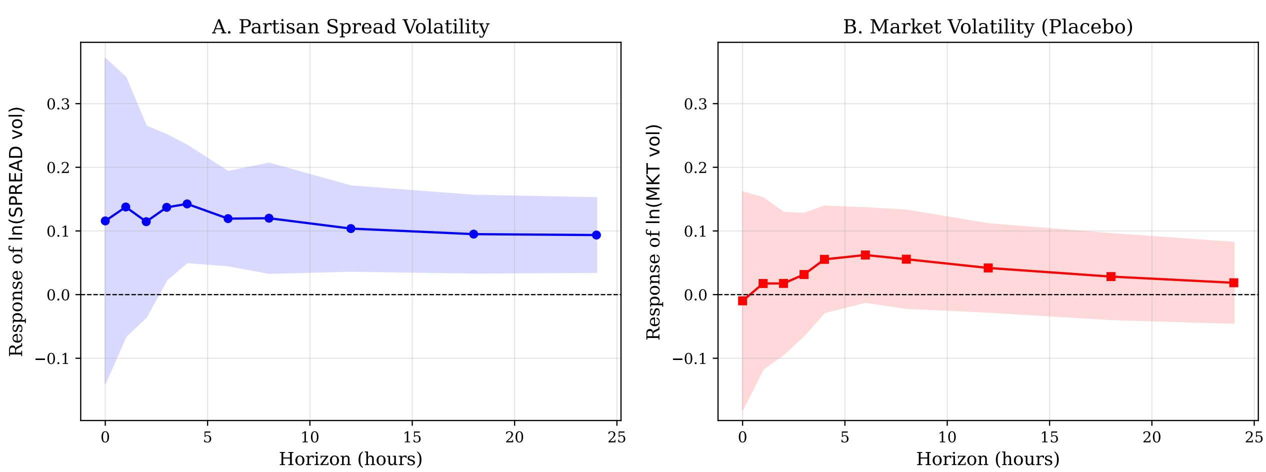

Figure 2: Local Projection IRFs: Disagreement Shock → Volatility

Notes: Responses to a one-standard-deviation disagreement shock. Controls include lagged log volatility and lagged disagreement. Shaded areas denote 95% confidence intervals based on HAC standard errors. Horizons are in hours.

4.5 Predictive ordering and persistence

Table 3 reports Granger-causality tests. Lagged disagreement helps predict partisan-spread volatility. Lagged volatility does not predict disagreement. We take this as evidence about temporal ordering, not as a stand-alone causal claim. An AR(1) specification indicates that disagreement is highly persistent, with an implied half-life of approximately 33 hours.

Table 3: Granger Causality Tests (Hourly)

	Disagreement → SPREAD vol		SPREAD vol → Disagreement	
Lags	F-stat	p-value	F-stat	p-value
1	48.05***	0.0000	0.70	0.4016
2	30.11***	0.0000	0.32	0.7231
3	25.73***	0.0000	0.77	0.5134
4	21.29***	0.0000	0.78	0.5384
5	15.19***	0.0000	0.63	0.6795
6	7.65***	0.0000	1.57	0.1521

Notes: F-tests from hourly VAR. Null: lagged values of the row variable do not Granger-cause the column variable. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

5 Robustness

Table 4 consolidates the robustness checks.

The results survive changes in how disagreement and volatility are measured. Replacing the cross-sectional standard deviation with the range, interquartile range, coefficient of variation, or Gini coefficient does not alter the qualitative finding. Nor does replacing realized volatility with realized variance or mean absolute returns.

The conclusions hold at the daily frequency. Disagreement predicts partisan-spread volatility and remains informative after controlling for market-wide volatility. The results are similar whether the daily implied-volatility control is VIXY or the standard CBOE VIX close.

In subsamples, disagreement positively predicts partisan-spread volatility both before and after the assassination attempt of July 13, though the coefficient is larger in the first half of the sample when cross-platform variation in disagreement was roughly twice as high.

The estimates are not driven by any single platform. Leave-one-out exercises preserve the main result. A block bootstrap delivers confidence intervals that exclude zero, and a time-series permutation test that randomly shuffles disagreement across hours yields $p < 0.001$ in both uncontrolled and controlled specifications. Newey–West inference is stable across bandwidth choices. We find no strong asymmetry depending on whether Trump is leading or trailing, and the relationship holds across different intraday windows. A nine-market specification that adds Kalshi and Pinnacle is considerably noisier, consistent with its much smaller usable sample.

Replacing contemporaneous disagreement with its one-hour lag yields nearly identical point estimates, confirming that the relationship is predictive rather than merely contemporaneous. Including a lagged dependent variable to absorb volatility persistence reduces the coefficient modestly ($\hat{\beta} = 10.07$, $t = 5.99$) but it remains highly significant. Hour-of-day and day-of-week fixed effects produce similar results ($\hat{\beta} \approx 13$, $t > 8$), ruling out intraday seasonality. Two-way clustering by date and hour of day yields a t-statistic of 8.15, larger than the HAC baseline. A kitchen-sink specification that includes all controls, both sets of fixed effects, and a lagged dependent variable simultaneously renders the coefficient insignificant, likely reflecting severe multicollinearity: the hourly autocorrelation of disagreement exceeds 0.97, so contemporaneous and lagged disagreement are nearly indistinguishable. Each component remains robust when introduced separately in the specifications above.

Taken together, the lagged-disagreement, fixed-effects, alternative-measure, leave-one-out, and permutation specifications indicate that the core finding is stable across timing assumptions, control sets, and measurement choices.

Table 4: Robustness Summary

Specification	$\hat{\beta}$	t	p	N	R^2
Panel A: Subsamples					
Pre-assassination (Jan–Jul 12)	19.899***	5.91	0.000	834	0.045
Post-assassination (Jul 13+)	7.455**	2.56	0.010	567	0.008
Pre-Biden (Jan–Jul 20)	18.693***	5.72	0.000	869	0.040
Post-Biden (Jul 22+)	6.001	1.28	0.202	532	0.003
Early campaign (Jan–Jun)	17.486***	4.82	0.000	771	0.032
Late campaign (Sep–Nov)	6.242	0.64	0.523	322	0.001
Panel B: Alternative disagreement measures					
Range	5.872***	7.53	0.000	1401	0.047
IQR	10.937***	7.32	0.000	1401	0.055
Coeff. of variation	10.050***	10.07	0.000	1401	0.082
Gini	22.222***	10.79	0.000	1401	0.086
Log disagreement	0.408***	8.32	0.000	1401	0.059
Panel C: Alternative volatility measures					
ln(SD) [baseline]	17.990***	8.93	0.000	1401	0.065
ln(RV)	36.460***	9.61	0.000	1401	0.085
ln(|ret|)	17.366***	9.06	0.000	1401	0.065
Panel D: Daily frequency					
SPREAD vol	22.816***	5.97	0.000	201	0.237
Controlled (VIXY)	16.158***	5.22	0.000	201	0.468
Controlled (VIXCLS)	12.794***	3.26	0.001	201	0.412
Panel E: Predictive specifications					
Lagged disagree	18.071***	9.04	0.000	1400	0.066
Lagged + controls	12.041***	6.64	0.000	1400	0.450
Lagged + controls + LDV	10.072***	5.99	0.000	1400	0.468
Panel F: Fixed effects & clustering					
Hour-of-day FE + controls	13.250***	8.53	0.000	1401	0.681
Day-of-week FE + controls	12.343***	6.93	0.000	1401	0.457
Both FE + controls	13.352***	8.70	0.000	1401	0.684
Kitchen sink (all + LDV + FE)	5.533	1.08	0.281	1400	0.704
Two-way clustered SEs	12.107***	8.15	0.000	1401	0.452
Panel G: Inference & sensitivity					
Block bootstrap	18.528***	6.48	0.000	1401	–
Asymmetry: interaction	−6.223	−1.53	0.125	1401	0.071
LOO: drop PolyMarket	16.185***	9.14	0.000	1402	0.066
LOO: drop Betfair	12.563***	4.47	0.000	1402	0.024
LOO: drop Bovada	14.985***	8.07	0.000	1402	0.057
LOO: drop BetOnline	16.780***	9.31	0.000	1402	0.075
LOO: drop William Hill	16.048***	7.74	0.000	1402	0.053
LOO: drop Unibet	15.440***	7.33	0.000	1402	0.052
LOO: drop Everygame	17.640***	8.76	0.000	1402	0.064
9-market spec	−17.220	−1.38	0.166	161	0.013
Panel H: Trading hours					
Full (9:30–16:00)	17.859***	8.79	0.000	1402	0.063
Excl. open/close	18.632***	8.50	0.000	1205	0.101
Morning (9:30–12:30)	20.113***	6.97	0.000	804	0.074
Afternoon (12:30–16:00)	15.173***	7.49	0.000	603	0.138

Notes: Each row reports the coefficient on the disagreement measure in a regression of ln(SPREAD vol) on disagreement. HAC standard errors unless otherwise noted. “Predictive” rows use lagged disagreement; “FE” rows include fixed effects with full controls (MKT vol + VIXY); “Kitchen sink” adds all controls, both FE sets, and a lagged dependent variable; “Two-way clustered” uses Cameron–Gelbach–Miller (2011) SEs clustered by date and hour of day. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6 Conclusion

We show that disagreement across prediction-market venues contains incremental information about the volatility of politically exposed equities. Our evidence comes from a single, highly salient election, so the results should be interpreted as evidence from an important episode rather than as a universal pattern. Within that setting, a formal selectivity test confirms the effect is significantly stronger for a partisan long–short portfolio than for the broad market. The incremental effect—an 11% increase in spread volatility per one-standard-deviation rise in disagreement, after absorbing broad market conditions—persists for roughly one trading day and survives intraday fixed effects and a lagged dependent variable. These findings suggest that cross-venue dispersion—not only consensus probabilities—can serve as a real-time, high-frequency measure of political uncertainty relevant for asset pricing and risk management. Whether this relationship extends to other high-stakes political events where multiple liquid prediction markets coexist remains an open question for future work.

A Appendix

Table A.1: Summary Statistics

Variable	*N*	Mean	SD	Min	Max
Panel A: Hourly					
Disagreement (SD)	1402	0.0254	0.0093	0.0035	0.0477
Disagreement (range)	1402	0.0658	0.0243	0.0080	0.1328
SPREAD vol (hourly)	1402	0.0581	0.0592	0.0103	0.7439
MKT vol (hourly)	1402	0.0634	0.0426	0.0111	0.3690
Mean probability	1402	0.5448	0.0576	0.4717	0.7467
Panel B: Daily					
Disagreement (SD)	201	0.0256	0.0091	0.0102	0.0475
SPREAD vol (daily)	201	0.0642	0.0353	0.0280	0.2999
MKT vol (daily)	201	0.0675	0.0220	0.0332	0.1926

Notes: Hourly realized volatility is the within-hour standard deviation of 5-minute log returns. Disagreement is the cross-sectional standard deviation of probability levels across 7 platforms. Sample: January 22–November 5, 2024 (U.S. trading hours).

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