Pricing Gubernatorial Election Uncertainty

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1. INTRODUCTION

On April 26, 2023, Disney filed a lawsuit against Florida Governor Ron DeSantis, accusing him of retaliating through government action following the company's opposition to a law that prohibited classroom discussions on sexual orientation or gender identity. This lawsuit came in response to what Disney alleges was a "targeted campaign of government retaliation" orchestrated by the Republican governor after their public dissent. However, Disney's legal battle is merely a single instance in a broader cultural conflict DeSantis has instigated within the business sector. His legislative actions include a 2020 law mandating certain private employers to verify the immigration status of their employees, a 2021 statute enabling Florida to sanction social media platforms for banning political candidates, and a recent call for political action against the environmental, social, and corporate governance (ESG) movement, which advocates for ethical and socially responsible investment practices. Despite these actions, DeSantis promotes himself as a champion of business, boasting of Florida's business-friendly climate and crediting himself with the economic rescue of local enterprises during the COVID-19 pandemic.

DeSantis's story exemplifies but one facet of the complicated relationship between business and politics. Political developments—from conflicts to international treaties—significantly affect business operations, influencing costs and profits. Other events, such as elections, are closely watched by companies and investors because of their important yet uncertain implications. Conversely, the business sector engages in politics through various means such as donations, lobbying, and, in some cases, bribery. Overall, anecdotal evidence suggests that politics matter a lot to business and the financial market, and existing research has provided theoretical and empirical justifications for these observations (for examples see (Pástor and Veronesi 2012, 2013; Julio and Yook 2012; Kelly, Pástor, and Veronesi 2016)). Empirical works, however, are not without their challenges. Existing evidence uses broad metrics that capture the effects of a variety of types of uncertainty (Baker, Bloom, and Davis 2016), and those focusing on national elections risks cannot fully separate the effects of the political cycles from the business cycles (Jens 2017). Traditional reliance on quarterly or monthly data may also distort findings, considering the financial market's vulnerability to numerous influences, with political factors being only one aspect.

Motivated by this puzzle, this paper examines how investors in the United States react when anticipating gubernatorial elections. Following existing finance theories that have examined events of similar natures such as corporate earnings calls and the Federal Reserve's Federal Open Market Committee (FOMC) meetings, I argue that if gubernatorial elections have direct effects on business performances and the financial market, investors should anticipate higher volatility prior to the election as they demand compensations for holding political risks. Although governors are rarely famous political figures in the country, state politics can have important impacts on company performances, and given the trend of executive aggrandizement at both the federal and state levels, governors could matter more to businesses within their jurisdictions than the average voter pays attention to. I also argue that because the financial market aggregates all beliefs and information, including the prior

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expectation of the election outcomes, investors should anticipate greater volatility when they expect more competitive and uncertain elections. Thus unlike previous works that have treated all elections as uncertain events, this paper argues that electoral competitiveness is the main driver of rising implied, or expected, volatilities.

To test my hypothesis, I turn to options data for all publicly traded companies in the United States in the narrow window around the 2020 and 2022 election days. I also use gubernatorial elections, which are staggered across the national economic and business cycles, to isolate the effects of political uncertainty. I use a difference-in-difference (DiD) framework to establish causality and conclude that investors do pay attention to gubernatorial elections as they can signal changes to regulatory environments. They perceive more potential election-induced volatility when the elections are more competitive and results are more uncertain. Using various measures constructed from pre-election polls as proxies for expected electoral competitiveness, I find that investors anticipate significant rises in asset volatility when the underlying company is exposed to a competitive gubernatorial election, suggesting that political uncertainty does exist even in cases of regular, constitutional executive turnover at the subnational level.

This paper contributes to the existing literature in several ways. First, I provide some of the first empirical evidence that investors in the United States are causally affected by state-level political uncertainty. By showing that competitive gubernatorial elections can impact investor sentiments and behaviors, I contribute to the debate regarding the role of regular, constitutional transfers of power. Although an important element of a well-functioning democratic system, which is less prone to irregular political instability, peaceful and constitutional turnovers of executive power can nevertheless dampen investment by introducing more political uncertainty. Second, this study presents a method to estimate the effects of political events such as elections. Borrowing from finance research that uses options data to examine the uncertainty effects of corporate earnings calls, I propose a new DiD framework that allows for more robust estimation and less stringent theoretical assumptions. Finally, this paper adds to the small collection of works that make theoretical and empirical connections between observed probabilities from polls and implied probabilities embedded in financial markets. It provides a generalizable theoretical framework and an empirical strategy to understand the role of political uncertainty in elections and leadership transitions in general. While this connection has been well-documented in the bond market, which is highly sensitive to the central bank's interest rates, few have identified similar relationships for political events and the equity market.

2. UNCERTAINTY AND INVESTMENT

For political scientists, the relationship between political uncertainty and investment poses an interesting puzzle as it addresses an age-old question in political economy: what causes economic development? Despite disagreement over the root cause of growth, many explanations identify investment as a key mechanism connecting institutions to economic performance (North 1990; Tavares and Wacziarg 2001; Acemoglu 2003). Empirical works also find that a more developed and better functioning financial system can deliver better economic outcomes by mobilizing capital for investment, mitigating information asymmetry, and improving corporate efficiencies (King and Levine 1993b, 1993a; Levine 1997; Pagano 1993). At the same time, stemming from the political instability theory that posits the adverse effects political instability has on development, a growing literature focuses on the impacts of political uncertainty or minor political instability (Alesina et al. 1996; Perotti 1996; Persson and Tabellini 1999). Equally interested in the puzzle, finance scholars have built on Bernanke's (1983) seminal work explaining patterns of irreversible investment under uncertainty and documented how various forms of uncertainty—commercial, economic, and political—shape the financial market.

2.1. Political Instability, Policy Uncertainty, and Economic Development

Most existing work on development finds a negative relationship between political stability and economic growth (Barro 1991; Gupta 1990; Barro 1996). Using various measures for political instability—including coups, revolutions, assassinations, purges, and major government crises—these works find that political instability, through its adverse effect on property rights, depress investment and growth (Gupta 1990; Barro 1991). Accounting for both constitutional and irregular changes in government, Alesina et al (1996) find that the effect of instability on growth is significant but weaker for regular and frequent executive turnovers common in industrial democracies. Using similar definitions and categorizations, however, Feng (1997) documents the opposite effects between violent, irregular turnovers and constitutional changes of power, arguing that minor government changes can enhance system adaptability.

Another group of scholars contends an indirect effect through the accumulation of physical capital, positing that regime instability creates a disincentive for investors to commit capital to unstable political environments, reducing domestic savings and inflow of foreign capital alike (Alesina and Perotti 1996; Benhabib and Rustichini 1996). Similar effects can be extended to government investment and expenditures as political instability leads to inefficient and myopic policy decisions by incumbent regimes. Frequent political turnovers create incentives for incumbent governments to incur excessive debt (Alesina and Tabellini 1989), reduce public investment (Persson and Tabellini 1999; Darby, Li, and Muscatelli 2004), and run down the economy's asset base (Devereux and Wen 1998). These policies can generate private capital outflows and depress domestic investment as the threat of future taxation looms.

Arguing that investors and entrepreneurs care more stability of economic policies than the stability of the regime itself, Aizenman and Marion (1993) find a negative relationship between policy uncertainty and investment and growth. The focus on policy rather than regime stability addresses both the challenge that democratic turnover signals a durable constitutional framework instead of political turmoil (Clague et al. 1996) and the argument that countries can suffer from unstable economic policies without facing imminent political collapse (Ali 2001). Examining the volatility of interest rates (Ingersoll and Ross 1992), exchange rates (Solimano 1989; Aizenman and Marion 1999), inflation (Al-Marhubi 1998), government consumption (Aizenman and Marion 1999), and overall economic output (Asteriou and Price 2005), theoretical and empirical works have found similar negative association between policy uncertainty and growth.

This strand of literature in the political economy of development intersects with a growing field in finance research that seeks to understand how uncertainty impacts investor behaviors and the financial market more broadly. Rather than relying on aggregate measures such as GDP and the overall size of private investment, these papers focus on the timing of investments as well as the prices of assets and their derivatives. Theoretically, the relationship between uncertainty and the timing of irreversible investment has been well documented (Bernanke 1983; Pindyck 1991). Because irreversible investments are sunk costs that cannot easily be disinvested, investors and firms have the incentive to wait for new information about future market conditions to arrive before committing resources. Relatedly, Pastór and Veronesi (2012; 2013) have shown that investors demand higher risk premia—or greater compensations—for holding risky assets during times of higher political uncertainty.

To test these theories, scholars have adopted two empirical strategies. The first identifies a series of uncertain events such as elections, summits, and conflicts. Scholars have documented that US federal elections heighten market anxiety (Goodell and Vähämaa 2013) and create higher short-term volatility (Li and Born 2006). Using cross-country panels, Julio and Yook (2012) show that firms delay investments during election years and Kelly et al. (2016) find that investors demand greater risk premia when facing national elections and important global summits. When facing local sources of policy uncertainty such as gubernatorial elections in the United States, firms also adopt more conservative corporate decisions in terms of investment (Jens 2017) and financing (Çolak, Durnev, and Qian 2017). The recent war between Ukraine and Russia also inspired a host of research examining the impact of international conflicts on the financial market.

The second approach relies on news articles or financial disclosure documents to construct continuous measures of uncertainty. Using text from the Wall Street Journal (WSJ), Manela and Moreira (2017) create an index of economic policy uncertainty. Expanding on previous efforts, Baker et al (2016) developed the popular proxy—the economic policy uncertainty (EPU) index—that takes into account newspaper coverage for policy-related economic uncertainty, the expiration schedule of federal tax codes, and disagreement among economic forecasters. Following their footsteps, numerous measures have been created to track EPU for specific countries and industries. Using a similar methodology, Hassan et al (2019) develop a measure for firm-level political risk using textual analysis of quarterly earnings conference call transcripts. Empirical work using these measures found similar results—firms face higher financing costs and adopt more conservative policies during times of heightened uncertainty (for examples, see (Gulen and Ion 2015; Brogaard and Detzel 2015; Bonaime, Gulen, and Ion 2018)).

Despite consistent results, empirical works confront several challenges. Theoretically, the role of politics remains under-examined. Studies using the EPU index naturally focus on macroeconomic policies, which are driven more by economic conditions rather than by government preferences and distribution of political power. Research identifying specific uncertain events such as national elections has also failed to disentangle the political factors from the economic effects. Because political cycles often coincide with economic and business cycles, changes in investors' expectations and behaviors may be driven by changing economic and business environments than by non-economic sources of uncertainty such as government regulations. Cross-country panels pose additional challenges as differences in political system and executive power can create heterogeneous treatment effects that are hard to estimate. Few existing studies have examined how political factors—from the different forms of government and variations in executive power to state capacity—matter in the relationship between political uncertainty and investment.

Methodologically, existing text-based indices cannot distinguish the expectation and resolution of uncertainty. Without identifying the context around which policy uncertainty is mentioned, the good news of fading uncertainty can be easily construed as bad news. Term frequency measures also do not necessarily translate into issue salience and magnitude. Moreover, most existing research relies on data aggregated at the annual, quarterly, or monthly level. Because political risks are but one of many, and arguably not the most important, factors investors and firms consider, such aggregation risk estimation errors as the presence of non-random noises can overpower the true effect and return biased results. This concern is more series when using firm-level data as idiosyncratic noises can be more pronounced.

By leveraging daily implied volatility before and after gubernatorial elections in the United States, this paper aims to present a better estimate of how investors react to potential changes in regulatory environments. Using subnational variations allows for larger samples, better comparisons, and less interference with the economic cycle effects. Using daily options data and a DiD framework also provides a better identification strategy that is less subject to other noises.

3. STATE POLITICS AND GUBERNATORIAL ELECTIONS

The decision to examine gubernatorial elections is not driven purely by methodological considerations. In American politics, the federalism system grants state governments tremendous power over key issues that affect business and investment (Robertson 2018). Compared to national elections, gubernatorial elections are less susceptible to national business and political cycles (Jens 2017), exhibit both cross-sectional and time-series variations (Gao, Murphy, and Qi 2019), and provide a larger sample to work with (Çolak, Durnev, and Qian 2017). Existing research on how gubernatorial elections shape investors' behaviors and corporate decisions has relied on the federalism argument and methodological justifications but has largely overlooked why investors should pay attention to gubernatorial elections in general when few governors garner public attention locally or nationally. Formally, state constitutions have left governors with little explicit power, and any unilateral power the governor possesses is subject to legislative constraints (Kousser and Philips 2012; Bolton and Thrower 2021).

Instead of assuming that state governments have consistently wielded important power and that governors are the powerful chief executives who can implement policies unilaterally, political scientists show that both relationships—federal versus local and executive versus legislative—evolve over time. When the framers crafted the US Constitution in the 18th century, they assumed that citizens' primary loyalties lie with the state they reside in and designed the separation of power so that most explicit policy-making power would rest with Congress and the executive should serve as a national tribune above party and faction (Skowronek 1997; Hopkins 2018). In modern times, however, both relationships have changed dramatically. While the formal distribution of power, outlined in the Constitution, largely remained, American political behavior has become nationalized and the executive has gained important agenda-setting and decision-making power.

Driven by political (Hopkins 2018), economic (McCarty, Poole, and Rosenthal 2008), and even technological (Darr, Hitt, and Dunaway 2018) factors, the nationalization of American politics can is evident in the declining heterogeneity in state party platforms (Hopkins 2018), waning voters' attachment to local identities (Wong 2010), and the partisan asymmetry of presidential reference in Congressional rhetoric (Noble 2023). The nationalization of politics, however, has not diminished the importance of state politics. Simultaneous political polarization produces legislative gridlocks in Congress (McCarty, Poole, and Rosenthal 2008), shifting policy debates and actions to state governments (Grumbach 2022). Thus while local issues are becoming less salient in public discourse, states are reemerging as key battlegrounds for national political debates.

At the same time, the expansion of executive power and gradual decline in legislative capacity give governors more control over policy agenda and outcomes (Bolton and Thrower 2021). Several constitutional reforms strengthened gubernatorial power at the expense of state legislatures (Conant 1988). Although efforts have been made to enhance legislative policy-making and resource capacity since the early 20th century, significant gaps remain. Since the 1990s, growth in salaries and staff resources have tapered off or reversed (Bolton and Thrower 2021; Squire 2012), and newly imposed legislative term limits only sabotage legislatures' attempts to constrain gubernatorial power (Kousser 2005).

The nationalization of American politics and expansion of executive power suggest that governors play important roles in setting policy agendas and driving political outcomes that have local and national implications. I therefore expect investors to pay attention to gubernatorial elections, as changes in governors and shifts in political power in state governments can have direct policy implications on business environments, economic uncertainty, and firm profitability, all of which affect investors' expected return from and volatility of their investments.

4. THEORY AND HYPOTHESES

4.1. Election as Dated Unknowns

Before formulating a theory on electoral uncertainty, it's essential to explore the different categories of uncertainty. While current studies, leveraging the categorization of risk factors, typically differentiate

TABLE 1. Caption

		Timing	
		Known	Unknown
Contents	Known		Recession, Layoff
	Unknown	Election, Summit	War, Natural Disaster

uncertainty by the activities they pertain to—whether financial, economic, or political—they often perceive the essence of uncertain events through a uniform lens—that is, they introduce new, previously undisclosed information to the market. Although this perspective is valid, it neglects significant nuances among uncertain events, potentially leading to incorrect assumptions about expectations and responses to information shock. As the financial market is forward-looking, any uncertainty reflects situations of imperfect or unknown information about the future, and any future events can be decomposed into two dimensions—timing and contents.

Table 1 presents a two-by-two framework that classifies future events according to prior knowledge of their timing and details. In the top left corner, we find events that are entirely predictable ("Dated Knowns"), carrying no uncertainty. Although such events do occur, they often provide minimal valuable information or are too vague for making practical forecasts.[1] Events with fixed dates but uncertain outcomes, like elections, summits, and corporate earnings calls, are categorized in the bottom left quadrant ("Dated Unknowns") due to their scheduled timings but unpredictable content. In contrast, events categorized as "Undated Knowns" and "Undated Unknowns" are characterized by their uncertain timings. While it is straightforward to distinguish events based on the knowledge of their timing—either the timing is known or not—the clarity regarding the content of events with unknown timings is often murky. Few events are ideal types that fit neatly into these categories, and the extent of our knowledge about what will happen can range widely, from specific future actions like a Federal Reserve's interest rate cuts to more vague possibilities like another global pandemic. Previous research has often overlooked the variations among uncertain events, particularly failing to acknowledge "Undated Knowns" and the critical temporal distinction between "Dated Unknowns" and "Undated Unknowns". By identifying elections as "Dated Unknowns", this paper emphasizes the important distinction between events with known and unknown timings, suggesting that this distinction significantly influences how investors formulate expectations and how new information impacts those expectations.

4.2. Modeling Electoral Uncertainty

Having established elections as "Dated Unknowns," I move on to a theory that explains how investors formulate and adjust their beliefs and expectations when they anticipate an election. Here it is important to reemphasize the key characteristics and implications for a future event with pre-determined timing. As the financial market is forward-looking, security prices reflect investors' expectations about future events. When an event with specified timing approaches, expectations about the outcome are incorporated into the prices. After the information is released, the prior is updated, and any incorrect

1. For instance, the assertion that someone will age by one year on their next birthday is an example of minimal information, while stating that someone will be elected the next president of the United States on November 5, 2024, makes the 2024 US presidential election appear predictable, yet diminishes its significance.

belief is corrected. The jump in prices thus reflects this adjustment in beliefs, both in direction and magnitude. In other words, for any "Dated Unknowns," we expect prices to reflect both *ex ante* anticipations and *ex post* adjustments, and given a narrow enough time window, the difference between them isolates the effects of specific events on individual assets as well as the entire market.

On election night, the announcement of the winner of the election injects new information into the market, prompting investors to update their priors. Given the potentially significant and long-term impacts of elections, the updates in belief can influence investor perceptions and financial markets in at least two discernible ways.

First, electoral outcomes can precipitate substantial jumps in stock prices. As aggregations of all available information of given public companies, stock prices reflect the discounted future value of their equities. New information about future government policies, economic conditions, and regulatory environments has direct implications on the costs and profits of future operations. When election results are revealed, investors update their calculations of firms' future values, driving current prices to reflect such adjustments.

Second, the uncertain nature of elections can lead to anxiety and volatility in financial markets. When investors anticipate a significant shift in stock prices following the announcement of election results, the forward-looking (or implied) volatility tends to increase before the election. This rise accounts for both the likelihood and potential magnitude of the price jump. Notably, implied volatility is characterized by two essential features: it is memoryless and operates on an *ex ante* basis. The memorylessness nature means that much like stock prices—which are theorized to operate independently of historical data and previous trends—implied volatility, derived from options contracts, does not rely on the past fluctuations of the securities in question. Its connection to historical patterns is confined solely to the propensity of volatility to continue, barring any external disruptions. Yet unlike the reactive nature of stock price movements, which adjust in response to new information about uncertain events, implied volatility is an *ex ante* indicator of event-driven uncertainty. It reflects anticipated changes rather than responding to events that have already happened. Thus, whereas stock prices react to information releases about uncertain events, implied volatility is influenced by the anticipation of these events as long as they are yet to occur.

As elections are uncertain events with pre-determined timing, implied volatility calculated from options that span those time windows should capture the anticipation that stock prices may respond to the announcement of electoral outcomes. Compared to the baseline level that does not incorporate political shocks, implied volatility exposed to electoral uncertainty should be higher to account for the potential jumps in stock prices. The size of this difference, whether in absolute or relative terms, is driven by the anticipated competitiveness of the race. The importance of this theoretical claim is that if the stocks and options contracts are priced correctly, the election-induced increase in implied volatility does not depend on either the *ex post* outcomes or whether an incumbent is seeking reelection.

To illustrate this, suppose we consider a simplified scenario with one investor, one stock, two candidates (candidate 1 and candidate 2), and one plurality election result set to be announced at time $t = \tau$. At time $t = \tau$, the announcement of the election outcome moves the price of the stock of P_{τ^-} to P_{τ^+}, and the jump in stock price is $Z_j = P_{\tau^+} - P_{\tau^-}$. Prior the the election, the investor forms an expectation, and because P_{τ^-} is observable at time $t = \tau^-$, the expected jump can be written as

$$E^{\mathbb{P}}[Z_j] = E^{\mathbb{P}}[P_{\tau^+} - P_{\tau^-}] \tag{1}$$

where $\mathbb{P}$ is the physical probability measure[2]. The variable of interest, the volatility of Z_j, $\sigma_j^{\mathbb{P}}$, captures

2. This is emphasized to distinguish physical probability measure from the risk-neutral probability measure $\mathbb{Q}$, which is used in option pricing models and discussed more in Appendix A.

ex ante anticipated uncertainty about the equity price response to the electoral outcome:

$$\sigma_j^{\mathbb{P}} = std^{\mathbb{P}}(Z_j|\mathcal{F}_{\tau^-}) \tag{2}$$

Here $\mathcal{F}_t$ is the σ-field that contains all information up to time t. This means that the anticipated uncertainty is measured with only information available prior to the release of new information at time τ.

Now suppose there exists a function $f(X) : \mathbb{R}^d \longrightarrow \mathbb{R}$ that maps any candidate to the post-election stock prices given their victory. The function needs not to be specified but can include factors such as the candidate's party identity, the incumbency status, and campaign platforms. Assuming f, we have

$$f(X_{C_i}) = P_{\tau^+C_i} = E^{\mathbb{P}}[P_{\tau^+}|\text{Candidate i Wins}] \tag{3}$$

where X_{C_i} are the factors for candidate i, and $P_{\tau^+C_i}$ is post-election stock price if candidate i wins. In simpler words, the equations state that the price of the stock under different potential scenarios is already priced prior to the outcomes being revealed.[3] This claim is non-trivial because it states that the uncertainty about the election does not stem from the unknown distribution of candidate true types or preferences, but simply from the unpredictability of which outcome will transpire.

Having established the formula that maps electoral outcomes to reactions in the equity price, we can consider the election response model as

$$Z_j = \alpha + \beta(X_{\tau^+} - E^{\mathbb{P}}[X_{\tau^+}]) \tag{5}$$

where X_{τ^+} are the factors for the winning candidate, and $E^{\mathbb{P}}[X_{\tau^+}]$ are the pre-election estimates of those factors. Under a plurality system with two candidates, there are only two possible electoral outcomes, so we can rewrite $E^{\mathbb{P}}[X_{\tau^+}]$ by assuming that the investor anticipates candidate 1 to win with probability p and lose with probability $1 - p$

$$\begin{aligned} E^{\mathbb{P}}[X_{\tau^+}] &= E^{\mathbb{P}}[X_{\tau^+}|\text{Candidate 1 Wins}]P(\text{Candidate 1 Wins}) \\ &\quad + E^{\mathbb{P}}[X_{\tau^+}|\text{Candidate 2 Wins}]P(\text{Candidate 2 Wins}) \\ &= p \cdot X_{\tau^+C_1} + (1-p) \cdot X_{\tau^+C_2} \end{aligned} \tag{6}$$

While the resulting factors vector can be difficult to interpret because there exists no such candidate, it is merely an artificially constructed object reflecting investor's beliefs when hedging against different potential outcomes.

Having established the link between election outcomes and equity price responses, the variance due to the information released on election night is

$$\begin{aligned} \left(\sigma_j^{\mathbb{P}}\right)^2 &= \beta^2 var\left(P_{\tau^+} - E^{\mathbb{P}}[X_{\tau^+}]\middle|\mathcal{F}_{\tau^-}\right) \\ &= \beta^2\left(E\left[(P_{\tau^+} - E^{\mathbb{P}}[X_{\tau^+}])^2\middle|\mathcal{F}_{\tau^-}\right] - E\left[P_{\tau^+} - E^{\mathbb{P}}[X_{\tau^+}]\middle|\mathcal{F}_{\tau^-}\right]^2\right) \\ &= \beta^2 p(1-p)(X_{\tau^+C_1} - X_{\tau^+C_2})^2 \end{aligned} \tag{7}$$

3. The proof of this can be quite simple using basic σ-algebra. Let $\mathcal{F}_t$ be the σ-field that contains all information up to time t. Because we can model stock prices as a stochastic process, we can say that stock price at any time $\tilde{t}$ is $\mathcal{F}_{\tilde{t}}$-measurable. This gives us $E[P_{\tilde{t}}|\mathcal{F}_{\tilde{t}}] = P_{\tilde{t}}$. As the election outcome is the only information to be revealed between τ^- and τ^+, $\mathcal{F}_{t^+}$ is the addition of the news about the winning candidate to $\mathcal{F}_{t^-}$. We thus have the following:

$$E[P_{\tau^+}|\mathcal{F}_{t^-}, \text{ Candidate i Wins}] = E[P_{\tau^+}|\mathcal{F}_{\tau^+C_i}] = P_{\tau^+C_i} \tag{4}$$

where i is the index of the winning candidate and $\mathcal{F}_{t^+C_i}$ is the σ-field at time τ^+ if Candidate i wins.

The derivation of (7) is trivial after applying (6), but the result yields two important implications. First, the exact values of $X_{\tau^+C_1}$ and $X_{\tau^+C_2}$ are unimportant as long as we know their differences. This means that electoral uncertainty is driven by policy divergence and political polarization between the candidates. Incumbency status, though may act as a factor in X, has no direct effect on the variance. Second, holding the candidates' differences fixed, the size of the expected jump has a non-linear relationship with p, it has two minima at $p = 0$ and $p = 1$, when the election is perfectly predictable, and a maximum at $p = 0.5$, when the outcome is most uncertain. Thus I expect implied volatility measure to be higher when candidates are more polarized on issues relevant to the company and when the election is more competitive.

4.3. Hypotheses

Motivated by existing research and the theoretical model, I propose the following two hypotheses for gubernatorial elections in the United States.

Hypothesis 1 (H1): *Political uncertainty is priced in the option market as investors anticipate greater volatility when facing an upcoming election*

Hypothesis 2 (H2): *Political uncertainty is priced in the option market as investors anticipate greater volatility when expecting a more uncertain election*

Both share the null hypothesis that investors do not price political uncertainty arising from gubernatorial elections, but the two differ in that the second hypothesis sees facing a predictable election as equivalent to expecting no election. Guided by the theory, I expect to find no support for H1 but evidence for H2; however, if neither hypothesis holds, I cannot assert the null hypothesis confidently because other factors—such as whether an incumbent is seeking reelection—may be driving the political uncertainty effect and I cannot find an exhaustive set to rule out all possibilities.

5. RESEARCH DESIGN

I construct a dataset of gubernatorial elections, firm-level option prices, and macroeconomic variables. In this section, I will describe the dataset and introduce the key variables used in the empirical analysis. The dependent variable is an option-market quantity, calculated from option contract prices and captures the price risk of stocks attributed to electoral uncertainty. A series of independent variables, calculated from pre-election polls, are designed to capture uncertainty about election outcomes.

5.1. Options

The main source of the option data is OptionMetrics. I use the daily data on 30-day and 60-day implied volatilities at the firm level. The implied volatility measures are calculated by OptionMetrics using the standard optioning pricing interpolation method. The sample includes all publicly traded companies headquartered and listed in the United States with actively traded option contracts. I include data from the 2020 and 2022 gubernatorial elections, and for each election, I collect implied volatility data on the day of the election and the day after the election. Because election results are announced after market trading hours, the two data points correspond to the pre- and post-election measures.

For each stock on a given day, OptionMetrics records the implied volatilities derived from the call contracts and the put contracts. Because American options can be exercised at any time before their expiration dates, slight discrepancies between the put and call implied volatilities often arise. This paper uses the averages between the two measures, but the results are not sensitive to this choice.

After obtaining the implied volatility data, I construct the volatility term structure estimator following the formula by Dubinsky et al (2019) and Smith and So (2022). The estimator, a time-weighted difference between the 30-day and 60-day implied volatilities of a given stock on the same day, measures the expected variance in price movement due to the unobserved event. Specifically, let $\mathbb{Q}$ be a risk-neutral probability measure under which discounted prices are martingales[4]. Given two options with time to maturity $\tau_1$and τ_2 ($\tau_1 < \tau_2$), $\sigma_j^{\mathbb{Q}}$—a risk-neutral measure of the variance derived in (7)—can be estimated as

$$\left(\sigma_j^{\mathbb{Q}}\right)^2 = \frac{\sigma_{t,\tau_1}^2 - \sigma_{t,\tau_2}^2}{\tau_1^{-1} - \tau_2^{-1}} \tag{8}$$

where $\sigma_{t,T}$ is the implied volatility at time t with time to maturity T.

Because volatility or systematic risk is not uniformly distributed across companies, comparing absolute measures such as the term structure risks fails to capture the effect of electoral uncertainty. As an alternative measure, this paper also considers the relative variance jump (RVJ), following the approach of Iselin and Van Buskirk (2024). The relative measure is calculated by first subtracting the expected jump variance from the 30-day implied variance to obtain the baseline variance and then scaling the expected jump variance by its baseline

$$\begin{aligned} \sigma_{\text{baseline}}^2 &= \frac{\sigma_{t,30}^2}{252} - \frac{(\sigma_j^{\mathbb{Q}})^2}{30} \\ \text{RVJ} &= \frac{(\sigma_j^{\mathbb{Q}})^2}{\sigma_{\text{baseline}}^2} \end{aligned} \tag{9}$$

The derivations for both measures are formally presented and discussed in Appendix A.

As Dubinsky et al (2019) show with earnings call data, the term estimator is robust to multiple stochastic factors that may create biases, but one challenge that is particularly salient for political events such as elections is the influence of other uncertain events scheduled around the same time. To derive the term estimator in (8), one key assumption is the absence of other scheduled uncertain events before the maturity of the longer option contract (τ_2). In the case of earnings announcements, companies hold these events once a quarter and on different dates. While some companies may hold earning calls right before the release of key economic data or the announcement of electoral outcomes, the bias is not systematic. The effects of economic indicators and political transitions on the value of a company are also rarely as significant as the effects on its own financial health and prospects.

The same bias, however, can hardly be ignored for political events such as elections. Because gubernatorial elections in the United States are scheduled every 4 years (2 for Vermont and New Hampshire) on the Tuesday next after the first Monday in November—which falls between November 2 and November 8—firm-level biases can be systematic for companies that have earnings announcements in late November and December every year. Second, the biases induced by earnings calls, arguably the most important uncertain event for all companies, can easily outweigh the effect of state-level electoral uncertainty. Finally, because implied volatility does not depend on past events, the bias is non-randomly assigned to companies with post-election earnings announcements and is always positive, so increasing the sample size will do little to remedy this problem.

To derive more robust measures for both estimators, this paper proposes a difference-in-difference (DiD) design. Figure 1 shows the treatment assignment—only companies exposed to uncertain gubernatorial elections in the pre-election period are treated. The treatment is a continuous measure of anticipated electoral uncertainty and competitiveness, and the DiD estimator compares the term estimator across treatment status before and after the announcement of electoral outcomes.

4. The risk-neutral measure takes into account investors' risk preference. By the fundamental theorem of asset pricing, the condition of no arbitrage and the complete market is equivalent to the existence of a unique risk-neutral measure $\mathbb{Q}$ that is equivalent to the original physical probability measure $\mathbb{P}$.

FIGURE 1. DiD Treatment Assignment

DiD.png

Despite potential challenges common to DiD methods, the simple setup is robust to many potential violations of assumptions. First, the memorylessness of implied volatility is helpful for causal identification as the pre-trend does not affect the treatment status or the estimator derived from implied volatilities. Second, the possibility that electoral uncertainty is not fully resolved on election nights can introduce carryover effects, making the cell on the bottom right an imperfect control. This concern, however, will only cause an underestimation of the DiD estimator, making it harder to justify a null effect. Finally, the decision to match firms to states based on the locations of their headquarters may introduce problems akin to spillover effects. As larger companies can have presence and operations in multiple states and be exposed to multiple regulatory environments, some units in the control group may also be treated. This concern is also alleviated by the fact that it only biases the DiD estimator downward, making it harder to reject a null hypothesis. This means that if the DiD estimator is positive and statistically significant, the result should be robust to carryover and spillover concerns.

5.2. Electoral Uncertainty

To measure anticipated electoral uncertainty, I manually collect election poll data from 538, a political analysis site that records all gubernatorial election polls since 2018. For each poll, I collect both the outcomes and the margins of error. As public opinion about candidates can change, this paper only considers polls conducted within a month of the election days. For the 2020 and 2022 gubernatorial elections, the number of relevant polls ranges from 1 to 33 as more competitive elections receive more media and public attention. To aggregate these polls, I adopt three main approaches—approximation with the last poll results, aggregation through inverse variance weighting, and mathematical transformation to ensure a 0 lower bound.

In the first approach, I use the poll results and margin of error to calculate the predicted probabilities for the projected runner-up to win the election or lose within 1% and 2% margins. In the second approach, I calculate an aggregate mean and standard deviation for all the polls and compute the same predicted probabilities for the predicted runner-up as in the first approach. Finally, I calculate the average margin between the projected winner and runner-up and perform mathematical transformation as electoral uncertainty or competitiveness should be bounded from below by 0 and a higher average margin translates to a lower degree of uncertainty. In this paper I consider two transformation techniques—negative exponential ($e^{-\text{margin}} \in (0, 1]$) and multiplicative inverse ($\frac{1}{\text{margin}} \in (0, \infty)$). All three methods are discussed further in Appendix B, and to evaluate whether these measures adequately capture public expectation of electoral competitiveness, I calculate their Pearson and Spearman's Rank correlation with analysts projections.[5] Variations exist between these measures but their correlations

5. Sources of these reports include *The Cook Political Report*, Insider Elections, Larry J. Sabato's Crystal Ball, Politico, Daily Kos, Fox News, 538, RealClearPolitics (RCP), and 270toWin.

are high and collectively they form a good indicator of public expectation prior to the election.

6. EMPIRICAL RESULTS

In this section, I detail the sample and empirically implement the proposed term estimator and relative value jump (RVJ) measure. I then employ the DiD framework to test the two hypotheses outlined above. To preview the results, I find empirical support for H2 with no evidence for H1. This substantiates my theory that political uncertainty about the future regulatory environment is priced in the options market but only when investors anticipate a competitive election with uncertain results.

6.1. Data and Summary Statistics

This paper examines the jump in variance driven by gubernatorial elections in 2020 and 2022. 11 and 37 elections were held in 2020 and 2022, with varying degrees of competitiveness.[6] After obtaining implied volatilities data from OptionMetrics, I match firms to states by the location of their headquarters, effectively filtering our foreign companies and Exchange-Traded Funds (ETFs) that simulate a basket of securities. I am left with a total of 2,383 firms, many of which appear to have data in both years.

Table 2 shows the descriptive statistics for the implied volatility and electoral uncertainty measures. One can see that the majority of gubernatorial elections in 2020 and 2022 are not very highly competitive, but elections in a few states—such as Wisconsin, Arizona, and Nevada—are hotly contested. The two jump variance measures are right-skewed. While this is not unusual as variances are bounded by 0 from below and previous research has documented similar patterns (Iselin and Van Buskirk 2024), the presence of extreme outliers may signal measurement errors and can bias the DiD results. Potential challenges and solutions are discussed further in section 6.3.

6.2. Pricing Electoral Uncertainty

To test H1 and H2, I perform a series of DiD estimations using the following model specification:

$$\begin{aligned} JumpVariance_{it} = {} & \beta_0 + \beta_1 Pre_{it} + \beta_2 Treat_{it} \\ & + \beta_3 Pre_{it} \times Treat_{it} + \alpha_{year} + \gamma_{sector} + \varepsilon_{it} \end{aligned} \tag{10}$$

$JumpVariance_{it}$ is the implied or relative jump variance. $Pre_{it} = 1$ for period before election and $Pre_{it} = 0$ for period after election. $Treat_{it}$ is the assigned continuous treatment measure to unit i at time t. α_{year} and γ_{sector} are the year and sector fixed effects. A positive and statistically significant β_3 for the model interacts with the election treatment dummy and the period effect lends support for H1. Positive and statistically significant β_3s for models that interact with the electoral uncertainty treatment and the period effect lends support for H2. It is also important to note that it is theoretically improbable to observe statistically significant and negative effects because that would mean an uncertain event is more predictable than a guaranteed outcome, which is logically impossible.

Further, the inclusion of 2020 data may introduce non-random noises to the DiD estimator as the presidential election coincided with gubernatorial elections. If the heterogeneous effect of presidential electoral uncertainty is not balanced between treated and control groups in our sample, the regression results can be biased. As an additional check, I also include two models with the same specifications but restrict the sample to only 2022. Four regression tables are presented in Appendix C. All models include year and sector fixed effects where appropriate, and the standard errors are clustered at the state level. Figure 2 and 3 plot the DiD coefficients for all 36 models. In Figure 2, the dependent variable is the absolute measure, implied variance jump, and in Figure 3, the dependent variable is the scaled relative variance jump. Full sample results are presented in blue and the 2022 sample results are presented in red. The horizontal lines show 95% confidence intervals.

6. The 37 elections in 2022 include 36 gubernatorial elections and 1 mayoral election in Washington D.C.

FIGURE 2. DiD Estimators for Implied Variance Jump

IVJ Coef Plots.png

FIGURE 3. DiD Estimators for Relative Variance Jump

RVJ Coef Plots.png

TABLE 2. Descriptive Statistics

Panel A: Full Sample	N	Mean	SD	Median	Max
Implied volatility measures					
Implied jump variance	6605	0.010	0.028	0.004	0.675
Relative jump variance	6605	10.150	24.745	3.891	427.748
Electoral uncertainty measures					
0% margin (last)	6605	0.009	0.039	0	0.363
1% margin (last)	6605	0.013	0.055	0	0.496
2% margin (last)	6605	0.020	0.075	0	0.628
0% margin (all)	6605	0.003	0.028	0	0.322
1% margin (all)	6605	0.007	0.067	0	0.759
2% margin (all)	6605	0.012	0.094	0	0.969
Negative exponents	6605	0.0072	0.059	0	0.673
Multiplicative Inverse	6605	0.058	0.225	0	2.52

Panel B: Gubernatorial Elections Sample	N	Mean	SD	Median	P75
0% margin (last)	48	0.036	0.073	0	0.026
1% margin (last)	48	0.056	0.105	0.001	0.048
2% margin (last)	48	0.081	0.143	0.002	0.085
0% margin (all)	48	0.010	0.049	0	0
1% margin (all)	48	0.030	0.123	0	0
2% margin (all)	48	0.060	0.189	0	0
Negative exponents	48	0.027	0.105	0	0.001
Multiplicative Inverse	48	0.168	0.374	0.065	0.138

Note: The eight electoral uncertainty measures have different theoretical bounds. The two 0% margin variables are bounded by $[0, 0.5]$, The other four % margin variables are bounded by $[0, 1)$. The negative exponents variable is bounded by $(0, 1]$, and the multiplicative inverse variable is bounded by $(0, \infty)$. The different scales do not interfere with causal identification but make interpretation slightly more challenging

The regression results show no support for H1 and substantial support for H2. In three of the four specifications, the DiD coefficients for election treatment are statistically insignificant, and in the full sample RVJ model, the estimator is negative, which, as discussed earlier, is logically improbable and may indicate measurement errors. For the rest eight IVJ models, the DiD estimators for the electoral uncertainty treatments are mostly positive but statistically insignificant, with the exception of the three last sample measures. However, if we examine the RVJ models, all DiD estimators, with rare exceptions, are positive and statistically significant across both samples. Considering that the eight measures constructed to approximate anticipated electoral uncertainty consider different relationships between poll results and investors' expectations and have strong correlations with holistic estimates from political analysts, the observed positive effects in the RVJ models are quite robust. Further, as discussed in the research design section, potential identification challenges will only underestimate the DiD estimators in my models, indicating that the true effect may be even more salient.

6.3. Measurement Challenges

Despite the confidence that the bias from various measurement errors will only underestimate the DiD estimator and make it harder to reject the null hypothesis, it is important to discuss the sources of potential measurement errors and ways to make the estimators more robust. First, the assignment to treatment relies on matching the locations of firms' headquarters, which can create problems similar to a spillover effect. While the treated units are almost always treated because headquarters locations have tax and regulatory implications and most firms have the largest physical presence in their headquarters states, many control units can also receive, at least partial, treatment effects when they operate in multiple states and adhere to different labor and environmental regulations. One way to account for this is to approximate firms' geographical exposure from their public disclosure documents. Jens (2017), for example, counts the number of mentions of states and municipalities in companies' annual 10-K reports. Similar methods can be applied to create more accurate measures of firms' geographical exposure to regulatory environments.

Second, the implied volatility data is collected daily at market closing, and even within the one-day interval, new information apart from electoral outcomes can arrive and influence the option prices and implied volatilities. These non-random noises can also bias our results because the estimator will be capturing more than electoral uncertainty. The unique memoryless and stochastic nature of implied volatilities means that the parallel trend assumption for a traditional DiD model can never be satisfied. Instead, the robustness of the estimator relies on narrowing the time difference such that the treatment is the only time-varying factor. Under this condition, the daily frequency of options data can create serious problems, especially when the arrival of new information impacts firms differently between the treatment and the control groups. An alternative approach is to use minute-by-minute data instead. Because election outcomes are announced after the market closes, I will compare implied volatilities at closing time on election day and at opening time on the next. Although this is not perfect—other events may also occur on election nights—they are much rarer compared to trading hours and easier to control.

Finally, many option contracts can be highly illiquid, which means that trades are infrequent and prices can be outdated and not reflect the most updated investor expectations. Most existing options research has faced similar challenges. Previously, scholars have restricted the same to the most liquid firms (Dubinsky et al. 2019) or filtered out companies with few trades (Smith and So 2022; Iselin and Van Buskirk 2024). While the current options data do not include relevant information to determine the quality of the implied volatility measures, similar filtering can be accomplished with more comprehensive data to ensure the DiD estimator indeed captures the pre-election and post-election differences in investors' beliefs and expectations. I can then partition the sample by option liquidity to ensure that the results are robust and not driven by companies with illiquid options.

7. CONCLUSION

Building on asset pricing theories, propose a model of pricing electoral uncertainty that directly depends on the prior anticipation of electoral competitiveness. To better understand the effects of political uncertainty on investors' beliefs and behaviors, I propose a DiD model to establish a causal effect using US gubernatorial elections as my sample. I provide evidence that the implied volatility of firms in states about to experience a competitive election is higher than that of firms in states with highly predictable elections or no elections. The results provide some empirical evidence that investors in the United States are indeed affected by political uncertainty, rather than general economic uncertainty. Using several continuous measures to capture electoral competitiveness, I also show that the effect is not driven by political events in general but only those that are not easily predictable.

Despite strong belief in the robustness of the DiD estimator—many challenges to the estimation strategy only threaten to bias the estimator downward—a better design will address many potential measurement errors. A more robust causal design will also allow me to delve further into some heterogeneous treatment effects—including how different types of exposures, sensitivities to government policies and regulations, and firm characteristics—impact how investors evaluate and price political uncertainty.

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A. IMPLIED VOLATILITY TERM ESTIMATOR AND DIFFERENCE-IN-DIFFERENCE (DID) ESTIMATOR

This section introduces the finance theory of this paper and discusses how option prices can be used to measure the jump in implied variance due to an anticipated information event. My model takes as given the firm's stock-price process, as is the norm in the option-pricing literature, including relevant studies of option prices surrounding information events (Kelly, Pástor, and Veronesi 2016; Dubinsky et al. 2019; Smith and So 2022; Iselin and Van Buskirk 2024). As stock prices respond to events that convey information about the riskiness of a firm's fundamental value, directly modeling the price process enables a general and intuitive derivation without needing to place specific assumptions on the features of each individual firm.

Modeling Shocks in the Financial Market

Consider a firm whose stock is continuously traded over a period $[0, \infty)$. First, following the Black-Scholes assumption of constant volatility and no discrete jump in prices, we can define the movement of stock prices as the following stochastic differential equation (SDE):

$$\frac{dS_t}{S_t} = \mu d_t + \sigma dW_t \tag{11}$$

where S_t is the price of the stock at time t, μ and σ are the expected return and volatility of the asset, and $(W_t)_{t\geq 0}$ is a Brownian motion. It is known that this equation has a unique solution

$$S_t = S_0 \exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W_t\right) \tag{12}$$

Now, to account for discrete jump in stock prices from information events such as elections, the Merton's jump-diffusion model introduces a Poisson process to describe the arrival of these events, with the following SDE:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t + dJ_t \tag{13}$$

where $(W_t)_{t\geq 0}$ is a Brownian motion and $(J_t)_{t\geq 0}$ is the Poisson process with the form

$$\begin{aligned} J_t &= \sum_{i=1}^{N_t} (Y_i - 1), \\ Y_i &= 1 + \frac{dS_{T_i}}{S_{T_i}} \end{aligned} \tag{14}$$

being the ratio associated with the i-th jump along the path of the stock price, happened at random time $T_i > 0$. I assume that the random variables $\{Y_i\}$ are i.i.d. and independent of both W_t and N_t, the latter of which is a Poisson process with intensity $\lambda > 0$ and counts the number of jumps prior to time t: $N_t = \sum_i \mathbb{1}_{[}\tau_i \leq t]$ where $\mathbb{1}$ is the indicator function and τ_j is an increasing sequence of stopping times representing anticipated information events.

Following Merton (1976) and Gugole (2016), I assume Y_i has log-normal distribution with fixed parameters

$$V_i = \log Y_i \sim \mathcal{N}(m, \delta^2) \tag{15}$$

It follows that

$$
\begin{aligned}
E[J_t] &= \lambda k t \\
k = E[Y_i - 1] &= e^{m+\frac{\delta^2}{2}} - 1
\end{aligned}
\tag{16}
$$

While the original Merton model only considers one type of event with fixed parameters modeling its discrete arrivals and the distribution of its jump size, we can easily relax this constraint and allow multiple jump events. This is relevant in the study of electoral uncertainty as other significant financial and economic events can occur within small time windows. Instead we consider L types of information events, each with a distinct intensity $\lambda_l > 0$, counter $N_{;t}$, and log-normal distribution parameters m_l and δ_l. We also assume that all jumps Y are independent from each other, the Brownian motion W_t, and all Poisson processes. We can thus rewrite the SDE as

$$
\frac{dS_t}{S_t} = \mu dt + \sigma dW_t + \sum_{l=1}^{L} dJ_{l,t} \tag{17}
$$

where $(J_{l,t})_{t\geq 0}$ is the s-th Poisson process with the form

$$
J_{l,t} = \sum_{i=1}^{N_{l,t}} (Y_{l,i} - 1) \tag{18}
$$

and $Y_{l,i}$ is the ratio associated with the i-th jump along the path of the stock caused by event s happened at random time $T_{is} > 0$. We thus have

$$
\begin{aligned}
V_{l,i} &= \log Y_{l,i} \sim \mathcal{N}(m_l, \delta_l^2) \\
E[J_{l,t}] &= \lambda_l k_l t \\
k_l = E[Y_{l,i} - 1] &= e^{m_l+\frac{\delta_l^2}{2}} - 1
\end{aligned}
\tag{19}
$$

Using this, we can obtain a unique solution for the modified Merton model

$$
S_t = S_0 \exp\left\{\sigma W_t + \left(\mu - \sum_{l=1}^{L} \lambda_l k_l - \frac{1}{2}\sigma^2\right)t\right\} \prod_{l=1}^{L} \prod_{i=1}^{N_{l,t}} Y_{l,i} \tag{20}
$$

Now consider a time frame $[0, T]$ such that we have an option contract expiring at time T, we can calculate the log-return for the for the modified Merton model, conditional on the event $N_{l,t} = j_l$ for $0 \leq t \leq T$, we can write

$$
\begin{aligned}
\log\left(\frac{S_t}{S_0}\right) &= \sigma W_t + \left(\mu - \sum_{l=1}^{L} \lambda_l k_l - \frac{1}{2}\sigma^2\right)t + \sum_{l=1}^{L} \sum_{i=1}^{j_l} V_{l,i} \\
&\sim \mathcal{N}\left(\left(\mu - \sum_{l=1}^{L} \lambda_l k_l - \frac{1}{2}\sigma^2\right)t + \sum_{l=1}^{L} j_l m_l, \sigma^2 t + \sum_{l=1}^{L} j_l \delta_l^2\right)
\end{aligned}
\tag{21}
$$

Following the original Merton model calculations presented by Gugole (2016), we can define a risk-neutral probability measure $\mathbb{Q}$ and model the dynamics of the stock process under $\mathbb{Q}$ as

$$S_t = S_0 \exp\left\{\sigma W_t^{\mathbb{Q}} + \left(r - \sum_{l=1}^{L} \lambda_l^{\mathbb{Q}} k_l^{\mathbb{Q}} - \frac{1}{2}\sigma^2\right)\right\} \prod_{l=1}^{L} \prod_{i=1}^{N_{l,t}} Y_{l,i}^{\mathbb{Q}},\ 0 \leq t \leq T \tag{22}$$

where r is the risk-free rate. It follows that for a European option with time to maturity $\tau = T - t$, the implied variance measure can be derived as

$$\sigma_{t,\tau}^2 = \sigma^2 + \tau^{-1} \sum_{l=1}^{L} j_l \left(\delta_l^{\mathbb{Q}}\right)^2 \tag{23}$$

Now, to consider a gubernatorial election specifically, let A be the set of anticipate event types that will occur between time $[t, T]$. I will also relabel the implied electoral jump variance as $\sigma_j^{\mathbb{Q}}$ to separate it from other events. Assuming the gubernatorial election is the only event that occurs at time t, the pre-election implied variance is given as

$$\sigma_{t^-,\tau}^2 = \sigma^2 + \tau^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \tau^{-1} \sum_{l \in A} j_l \left(\delta_l^{\mathbb{Q}}\right)^2 \tag{24}$$

If we follow Dubinsky et al (2019)'s assumption that $A = \varnothing$, the two equations can be simplified as

$$\sigma_{t^-,\tau}^2 = \sigma^2 + \tau^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2 \tag{25}$$

By observing two pre-election implied volatilities with different time to maturity $\tau_1 < \tau_2$, we can derive the term estimator at time t

$$\left(\sigma_j^{\mathbb{Q}}\right)^2 = \frac{\sigma_{t,\tau_1}^2 - \sigma_{t,\tau_2}^2}{\tau_1^{-1} - \tau_2^{-1}} \tag{26}$$

If we relax the $A = \varnothing$ assumption, the pre-election term estimator will be biased.

$$\left(\sigma_{term,t^-}^{\mathbb{Q}}\right)^2 = \frac{\sigma_{t^-,\tau_1}^2 - \sigma_{t^-,\tau_2}^2}{\tau_1^{-1} - \tau_2^{-1}} = \left(\sigma_j^{\mathbb{Q}}\right)^2 + \sum_{l \in A} j_l \left(\delta_l^{\mathbb{Q}}\right)^2 \tag{27}$$

To derive an unbiased measure, we first observe that the post-election implied variance measure is

$$\sigma_{t^+,\tau}^2 = \sigma^2 + \tau^{-1} \sum_{l \in A} j_l \left(\delta_l^{\mathbb{Q}}\right)^2 \tag{28}$$

While it seems that the difference between the pre- and post-electoral implied variance can cancel out both the diffusive varaince σ^2 and the addition jump variance $\sum_{l \in A} j_l \left(\delta_l^{\mathbb{Q}}\right)^2$, leaving only our parameter of interest, $\left(\sigma_j^{\mathbb{Q}}\right)^2$, this is problematic because the time-series estimator is less robust than the term estimator and errors can be introduced when the election shifts the diffusive variance from σ^2 to $\tilde{\sigma}^2$ (Dubinsky et al. 2019; Smith and So 2022).

Instead, assuming that the election causes a shift in diffusive volatility from σ^2 to $\tilde{\sigma}^2$, the post-election term estimator is

$$\left(\sigma_{term,t^+}^{\mathbb{Q}}\right)^2 = \frac{\sigma_{t^+,\tau_1}^2 - \sigma_{t^+,\tau_2}^2}{\tau_1^{-1} - \tau_2^{-1}} = \tau^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2 \tag{29}$$

By subtracting (29) from (27), we can obtain an unbiased measure of the implied electoral jump variance.

$$
\begin{aligned}
\left(\sigma_j^{\mathbb{Q}}\right)^2 &= \frac{\sigma^2_{t^-,\tau_1} - \sigma^2_{t^-,\tau_2}}{\tau_1^{-1} - \tau_2^{-1}} - \frac{\sigma^2_{t^+,\tau_1} - \sigma^2_{t^+,\tau_2}}{\tau_1^{-1} - \tau_2^{-1}} \\
&= \left(\sigma^{\mathbb{Q}}_{term,t^-}\right)^2 - \left(\sigma^{\mathbb{Q}}_{term,t^+}\right)^2
\end{aligned}
\tag{30}
$$

Here the validity of the DiD estimator relies on two assumptions. First, no information about other anticipated events belonging to A is released at time t. Second, the announcement of election results is not correlated with any anticipated information to be released at events belonging to A. We can see that this is a much weaker assumption that the one necessary to derive an unbiased time-series estimator.

Scaled DiD Estimator

The DiD estimator derived in (30) is an absolute measure, capturing the increase in variance driven by electoral uncertainty. Because companies differ in riskiness, an absolute measure may not fully capture the effect. To illustrate this, consider two stocks with different diffusive or baseline implied volatility, 20% and 50% over the next month. This means that the market expects that a one standard deviation move over the next month will be plus or minus 20% and 50%, respectively. Their implied variances, 0.04 and 0.25, are calculated as the square term of the implied volatility. Now consider a shock in of size 0.11, increasing the implied variance to 0.15 and 0.36, respectively. This brings the new implied volatility to 38.7% and 60%, meaning that the same shock, in absolute term, makes the less risky asset almost twice as volatile while only making the more risky asset 20% more volatile. In reality, information events may impact assets with different levels of riskiness on a relative scale.

To calculate the relative measure, I follow Iselin and Van Buskirk (2024) by first deriving the baseline or diffusive volatility. From (24) and (27), we can derive the pre-election baseline variance as the difference between the implied volatility and time-scaled term estimator

$$
\begin{aligned}
\sigma^2 &= \sigma^2_{t^-,\tau} - \tau^{-1}\left(\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sum_{l \in A} j_l \left(\delta_l^{\mathbb{Q}}\right)^2\right) \\
&= \sigma^2_{t^-,\tau} - \tau^{-1}\left(\sigma^{\mathbb{Q}}_{term,t^-}\right)^2
\end{aligned}
\tag{31}
$$

And the same logic can be applied to derive the post-election baseline. I then use the baseline variance and the term estimator to calculate the relative variance jump (RVJ)

$$
RVJ_t = \frac{\left(\sigma^{\mathbb{Q}}_{term,t}\right)^2}{\sigma^2} \tag{32}
$$

which, similar to the term estimator, include both the effect of the election and other potential independent information events, so a DiD estimator is constructed to extract the relative effect of the election

$$
RVJ^{DiD} = \frac{\left(\sigma^{\mathbb{Q}}_{term,t^-}\right)^2}{\sigma^2} - \frac{\left(\sigma^{\mathbb{Q}}_{term,t^+}\right)^2}{\sigma^2} = \frac{\left(\sigma_j^{\mathbb{Q}}\right)^2}{\sigma^2} \tag{33}
$$

B. CORRELATION MATRICES OF ELECTORAL UNCERTAINTY ESTIMATES

Using the two approaches described in the paper, I calculated in total 8 measures to capture electoral uncertainty. This appendix presents the specific method for their derivations and examines similarities between measures.

Last Sample Predicted Probability

The first three measures are calculated using only the last available sample for each gubernatorial election, regardless of sample size. Because these samples reflect public opinions closest to the actual election, they are more likely to serve as the basis of investors' expectations than earlier poll results.

The predicted probability measures are obtained by calculating the probability of the less favored candidate winning the election, losing within 1% margin, and losing within 2% margin, given their support level and the margins of error of the polls. The simple calculation assumes normal sample distribution and involves taking an integral of the density function

$$P_m = \int_m^\infty \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{\sigma^2}} dx \tag{34}$$

where $m \in \{0.5, 0.495, 0.49\}$ is the share of vote the candidate need to pass the threshold, and μ and σ are the mean and standard deviation derived from the poll results and margin of error.

Full Sample Predicted Probability

The next three measures are constructed similarly using the same threshold and formula, but differs in that it takes more polls into account. To aggregate all survey results conducted within a month of the election days, I use inverse variance weighting to derive an aggregate mean and standard deviation measure to approximate the population distribution of support for the less favored candidate. The inverse variance weighting method gives more precise estimates—poll results with larger sample sizes—higher weights, and given a series of mean μ and standard deviation σ derived from poll results and margins of error, the aggregated mean and standard deviation are calculated as

$$\begin{aligned} \hat{\mu} &= \frac{\sum_i y_i/\sigma_i^2}{\sum_i 1/\sigma_i^2} \\ \hat{\sigma} &= \frac{1}{\sqrt{\sum_i 1/\sigma_i^2}} \end{aligned} \tag{35}$$

The predicted probabilities are calculating using (34) with $\hat{\mu}$ and $\hat{\sigma}$.

Transformation of Margins

Finally, the last two measures are calculated using mathematical transformation on the average poll margins between the projected winner and runner-up. Logically, a larger poll margin should indicate less uncertainty about the electoral outcome, with uncertain approaches 0 asymptotically as poll margin increases. To better capture this relationship, I consider two monotonic functions that converges to 0 from above on the interval $[0, \infty)$—the negative exponential function e^{-x} and the multiplicative inverse function $1/x$. I consider both functions because of their different properties. Because the multiplicative inverse function is not bounded from above, when elections are hotly contested, the two measures will differ significantly. Including both ensures that any relationship I observe is not driven by artificial constructions.

Similarities across Various Measures

To assess how consistent my measures for electoral uncertainty are, Figure 4 and 5 show Pearson and Spearman's rank correlation matrices for 2020 and 2022 gubernatorial elections. I also include predictions published by political analysts that consider factors such as the strength of the candidates and the partisan leanings of the state. These predictions range from "toss up" where no candidate has a clear advantage to "solid" or "safe" where one candidate has near-certain chance of victory. They provide a discrete index that capture anticipated electoral competitiveness and can serve as a benchmark to compare my measures.

FIGURE 4. Correlation Matrix for 2020 Gubernatorial Elections

2020pearson.png

2020spearman.png

From the figures, the 8 measures have relatively high correlations, especially among those derived using the same approaches. While some have lower correlation score with analysts predictions, the potential mismatch can be resolved by including multiple measures as robustness checks.

FIGURE 5. Correlation Matrix for 2020 Gubernatorial Elections

2022pearson.png

2022spearman.png

C. REGRESSION RESULTS

TABLE 3. Implied Variance Jump (Full Sample)

	Dependent variable:								
	Implied Variance Jump								
	Election	All Samples			Last Sample			Transformation	
		0%	1%	2%	0%	1%	2%	e^{-x}	$1/x$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Treat	0.001	-0.010^{***}	-0.005^{***}	-0.004^{***}	-0.016^{***}	-0.012^{***}	-0.009^{***}	-0.006^{***}	-0.002^{**}
	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
Pre×Treat	−0.00003	0.002	0.001	0.0001	0.018^{***}	0.012^{***}	0.009^{**}	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.006)	(0.004)	(0.004)	(0.001)	(0.001)
Constant	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}	0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	6,605	6,605	6,605	6,605	6,605	6,605	6,605	6,605	6,605
Adjusted R^2	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 4. Relative Variance Jump (Full Sample)

	Dependent variable:								
	Relative Variance Jump								
	Election	All Samples			Last Sample			Transformation	
		0%	1%	2%	0%	1%	2%	e^{-x}	$1/x$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre	1.134**	0.291	0.290	0.282	0.137	0.126	0.116	0.278	0.261
	(0.573)	(0.541)	(0.542)	(0.545)	(0.540)	(0.542)	(0.546)	(0.542)	(0.548)
Treat	0.797	−9.031***	−4.222***	−4.111**	−19.284***	−14.033***	−10.745***	−5.731***	−1.306**
	(0.971)	(2.757)	(1.467)	(1.844)	(4.036)	(3.169)	(2.633)	(2.112)	(0.524)
Pre×Treat	−1.968*	13.895***	5.329**	3.492	22.040***	14.962***	10.609***	7.237***	1.125
	(1.050)	(4.343)	(2.485)	(2.585)	(4.840)	(3.955)	(3.413)	(1.797)	(1.172)
Constant	4.745***	5.169***	5.172***	5.192***	5.298***	5.317***	5.338***	5.182***	5.200***
	(0.723)	(0.672)	(0.672)	(0.672)	(0.670)	(0.672)	(0.675)	(0.672)	(0.676)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	6,605	6,605	6,605	6,605	6,605	6,605	6,605	6,605	6,605
Adjusted R^2	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 5. Implied Variance Jump (2022 Sample)

	Dependent variable:								
	Implied Variance Jump								
	Election	All Samples			Last Sample			Transformation	
		0%	1%	2%	0%	1%	2%	e^{-x}	$1/x$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre	−0.001	0.0001	0.0001	0.0001	−0.0002	−0.0003	−0.0003	0.0001	0.00005
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Treat	0.001	−0.008***	−0.004***	−0.004***	−0.013***	−0.009***	−0.007***	−0.005***	−0.001**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Pre×Treat	0.001	0.004	0.002	0.001	0.021***	0.015***	0.012***	0.002	0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.006)	(0.005)	(0.004)	(0.002)	(0.001)
Constant	0.009***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2,801	2,801	2,801	2,801	2,801	2,801	2,801	2,801	2,801
Adjusted R^2	0.051	0.050	0.050	0.051	0.051	0.051	0.051	0.051	0.050

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 6. Relative Variance Jump (2022 Sample)

	Dependent variable:								
	Relative Jump Variance								
	Election	All Samples			Last Sample			Transformation	
		0%	1%	2%	0%	1%	2%	e^{-x}	$1/x$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pre	1.500	−1.044	−1.051	−1.091	−1.483	−1.525	−1.574	−1.086	−1.244
	(3.572)	(1.086)	(1.090)	(1.103)	(1.109)	(1.120)	(1.135)	(1.092)	(1.160)
Treat	1.561	−10.039***	−4.727**	−4.618**	−21.510***	−15.831***	−12.312***	−6.303**	−1.655**
	(2.181)	(3.752)	(1.927)	(2.235)	(5.332)	(4.103)	(3.361)	(2.727)	(0.781)
Pre×Treat	−2.929	18.876***	7.549***	5.449**	29.560***	20.697***	15.298***	9.987***	2.498**
	(3.720)	(5.194)	(2.708)	(2.758)	(6.586)	(5.075)	(4.232)	(2.440)	(1.036)
Constant	11.202***	12.565***	12.584***	12.676***	12.978***	13.052***	13.137***	12.614***	12.726***
	(2.614)	(1.450)	(1.452)	(1.468)	(1.507)	(1.519)	(1.534)	(1.456)	(1.484)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	2,801	2,801	2,801	2,801	2,801	2,801	2,801	2,801	2,801
Adjusted R^2	0.005	0.005	0.005	0.005	0.006	0.006	0.006	0.005	0.005

Note: *p<0.1; **p<0.05; ***p<0.01