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Political Geography and Stock Market Volatility: The Role of Political Alignment Across Sentiment Regimes

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ABSTRACT

We study the nexus between political geography and stock market volatility by examining the interrelation between political geography and the predictive relation between the state- and aggregate-level stock market volatility via recently constructed measures of political alignment. Using data for 1994–2023 and random forests, we show that the importance of the state-level volatilities as drivers of aggregate volatility displays considerable variation in the cross-section and across time. Stronger political alignment of a state with the ruling party is associated with a lower contribution of the state's volatility to aggregate volatility. This negative link is significant during high-sentiment periods.

JEL Classification: C22, C23, C51, C53, G10, D81

1 | Introduction

The effect of presidential politics on the stock market is well documented in the literature. One strand of this literature focuses on the aggregate stock market performance during presidential cycles, i.e., Democratic vs. Republican administrations (e.g., Santa-Clara and Valkanov 2003; Pástor and Veronesi 2013, 2020). Others focus on firm-level risk exposures with respect to presidential politics and examine whether this type of exposure contributes to a systematic risk premium that cannot be diversified away by investors (Chen et al. 2023). A growing number of works in this area, however, highlight the role of political geography, i.e., the effect of a firm's location on the political map and its proximity to political powers on corporate decision making and the real options available to the firm (Kim et al. 2012; Douidar et al. 2023). A common theme that comes out of these works highlights the risk effects of political geography on expected firm returns associated with a firm's exposure to political

uncertainty, although the link to return volatility is largely ignored.¹

Although there is substantial evidence pointing to the impact of political geography on firm valuations and expected returns (e.g., Douidar et al. 2023), the literature has not yet established a direct connection to return volatility. The existing research that connects political geography with stock risk premiums implies an inherent risk effect that influences both corporate decision making and investor preferences. Interestingly, however, although political geography has been linked to the value of real options in corporate decisions using risk-based arguments, a straightforward link to how this dynamic affects return volatility is yet to be firmly established. In this paper, we contribute to the strand of literature that connects stock market dynamics to politics from a novel perspective by examining the role of political geography on the interrelation between stock market volatility dynamics at the state and aggregate market levels via

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recently constructed measures of state-level political alignment indexes. By doing so, our study aims to provide new insight to the risk-based arguments that associate political geography with stock market dynamics.

Our focus on volatility is largely motivated by the fact that volatility is a key component of option pricing, hedging, and portfolio optimization applications (Poon and Granger 2003; Rapach et al. 2008). The wide-ranging applications of volatility in different contexts have eventually led to a large strand of literature that offers a wide array of linear and nonlinear models in univariate and multivariate settings to predict and model stock-market volatility.² In the context of multivariate models, several researchers (Tsuji 2012; Demirer et al. 2019; Lu and Feng 2023; Niu et al. 2023, 2024) have also emphasized the role of industry-level volatility information for aggregate stock-market variability of the United States (US) which could be a manifestation of differential industry exposures to presidential policies and government spending (see, e.g., Belo et al. 2013; Addoum and Kumar 2016).³ Despite the multitude of studies that explore stock market volatility in various contexts, however, the role of political geography in this context is relatively understudied, although the theories that link political geography to asset pricing mainly rely on risk-based arguments.

In order to provide a policy angle to our analysis, building on the argument that stock market volatility serves as a metric for financial stability (Jurado et al. 2015; Ludvigson et al. 2021), we utilize a machine learning technique known as random forests (Breiman 2001). This method allows us to relate the time-varying (recursive-window-based) importance of the volatilities at the state level in explaining aggregate level volatility, using a novel proxy of political geography associated with a state. The motivation for this approach is derived from the general equilibrium models of Pástor and Veronesi (2012, 2013) that associate political uncertainty with volatility in the stochastic discount factor applied to stock valuations, thus contributing to volatility in stock returns. In our application, the measure of local policy-related uncertainty is captured by the political alignment index (PAI), widely used in the so-called “political geography” literature in financial economics (Kim et al. 2012; Gross et al. 2016; Douidar et al. 2023; Magerakis et al. 2023). This line of research tends to suggest relatively better performance of firms, across various dimensions, whose headquarters are located in states with high values of PAI, indicating higher political alignment of state level politics with the ruling (presidential) party. The implications on stock return volatility, however, are yet to be established.

In the political geography literature, the arguments to relate political uncertainty to stock market dynamics rely largely on risk-based explanations in that a high level of political alignment alleviates potential information asymmetries, thus mitigating opaqueness in the information environment related to forthcoming policy changes. Given these points, we hypothesize that states with lower PAIs are likely to be the ones whose volatilities will be contributing more to volatility at the aggregate level due to increased uncertainty inherent in the business operations associated with firms in that environment. In our application, we test this hypothesis using a panel data setting by relating the time-varying importance of the volatilities of the state with the

corresponding PAIs. In this regard, our decision to look at state-level equity markets rather than industries is well-warranted, particularly from a political geography perspective. If indeed, our hypothesis is true, then from a policy perspective, reducing uncertainty about policy decisions becomes of paramount importance to reduce instability of the financial system. Such a result would also indicate that proximity to political power has also second-moment stock market implications by reducing the exposure of firms to policy risks.

Our study contributes to several strands of the literature that relate stock market dynamics to politics. First, it contributes to the discussion on the effect of political cycles on stock market returns (e.g., Santa-Clara and Valkanov 2003) from a risk-based perspective by directly focusing on volatility. It also provides a novel perspective to the growing literature on the effect of a firm's location on the country's political map on its exposure to policy uncertainty (e.g., Douidar et al. 2023) by relating state and aggregate level stock volatility via measures of state level political alignment as a proxy for political uncertainty. To take our insights one step further, as another novelty to the literature on the nexus between political geography and stock market dynamics, we also investigate the role of investor sentiment-regimes as a determinant of the effect of political alignment on the predictive link between the state- and aggregate-level stock market volatility. The motivation to extend the analysis to sentiment emanates from the finding of Montone (2022) that the effect of political alignment on stock market movements is likely nonlinear, contingent on the behavioral mindset of investors – an observation also consistent with results indicating the presence of nonlinear links between the presidential approval ratings and stock market dynamics reported by Gupta et al. (2021, 2023). This, in turn, would imply that the effectiveness of governmental policies to reduce the potential destabilizing effects of policy uncertainty on the stock market could be contingent on the level of investor sentiment, adding an extra layer to policy decisions.

To the best of our knowledge, this is the first paper to use random forests, a machine-learning technique, to model the relative roles of state-level volatilities as a determinant of volatility at the aggregate level and to examine, via panel analysis, the effect of state-level political uncertainty in this context. Looking ahead, our econometric analysis based on monthly data for the period from February 1994 to March 2023 shows that the predictive role of state-level realized stock market volatilities over the aggregate stock market exhibits substantial variation over time along with considerable cross-sectional dispersion across the 50 states included in the sample. While the state of New York is found to play a more dominant role as the driver of aggregate stock market volatility compared to the rest of the states, the findings from our panel analysis show that stronger political alignment of a state is associated with lower importance of the state's realized volatility over volatility at the aggregate level. This finding lends support to the hypothesis that political stability and predictability at the state level reduce economic uncertainty, eventually resulting in a lower contribution to aggregate stock market volatility. Our results are also in line with the recent evidence in Magerakis et al. (2023) that firms in politically aligned states adopt a precautionary strategy against market shocks by increasing their cash holdings, which, in our case, leads to a

smaller contribution of these states to aggregate stock market volatility. Finally, we find that the role of political alignment in a state's contribution to aggregate stock market volatility is largely confined to high-sentiment periods, highlighting the interaction between political uncertainty and investor sentiment as a driver of volatility in financial markets.

We organize the rest of this paper as follows: In Section 2, we present a brief review of the vast literature on the relationship between politics and the stock market with a focus on the recent works on the role of political geography. In Section 3, we describe how random forests can be used to trace out the importance of state-level realized volatilities for aggregate stock market volatility. In Section 4, we present our empirical results, both for random forests and for the panel analysis. In Section 5, we conclude the paper with directions for future research.

2 | Literature Review

The link between politics and stock market dynamics has been examined in several strands of the literature. Generally, these works build on the political business cycle models (Alesina and Stella 2010) that can be classified into two strands. The first strand focuses on the opportunistic behavior of politicians as they adopt expansionary economic policies to increase their chances of reelection. In this setting, budgetary distortions and macroeconomic uncertainty might arise due to the presence of information asymmetries between the government and voters (e.g., Rogoff 1990). The second strand in this literature relates to partisan politics, putting the focus not necessarily on winning an election, but instead catering to the preferences and interests of their political supporters. In this setting, the government's partisan orientation becomes a determining factor in economic dynamics such that orientation towards the left is associated with fiscal and monetary policies that stimulate employment and inflation. Linking these arguments to the stock market, a popular line of works highlights the role of presidential cycles in stock market returns (e.g., Santa-Clara and Valkanov 2003) associating Democratic presidencies in the U.S. with higher stock market returns than Republican administrations. In a later study, Pástor and Veronesi (2020) explain this phenomenon using risk-based arguments such that voters are more likely to elect a Democratic president when risk aversion is high because they demand more social insurance, driving up the risk premia in the stock market. A direct link to stock market volatility, however, is yet to be established.

Another growing strand of the literature focuses on the role political uncertainty plays for corporate decision making and investor behavior in financial markets. Using the arguments of real options theory in corporate finance, studies including Julio and Yook (2012) and Jens (2017) show that firms delay their investments when political uncertainty is high due to the real option value of deferring investments until uncertainty has been resolved. Similarly, Pástor and Veronesi (2012, 2013) argue that political uncertainty drives up the dispersion in investor beliefs regarding economic fundamentals, which induces herd formation among investors during politically uncertain times, particularly for politically sensitive stocks (Gavriilidis et al. 2024). Indeed, this could be one channel that contributes to volatility in

financial markets (Boutchkova et al. 2012) and a risk premium in the cross-section of stock returns associated with uncertainty induced by potential changes in economic policies (Pástor and Veronesi 2013; Brogaard and Detzel 2015; Kelly et al. 2016; Montone 2022).

In an emerging strand of the literature that is more closely related to our focus, a growing number of studies highlight the role of partisan politics on financial market variables. From an investor's perspective, these studies build on the evidence that highlights the role of nonmonetary values in understanding investor behavior, associating party affiliation with stock market participation (Kaustia and Torstila 2011), asset allocation decisions (Hong and Kostovetsky 2012), risk-taking behavior (Bonaparte et al. 2017; Meeuwis et al. 2018) and stock returns (Montone 2022). These studies, in general, argue that investors tend to be more optimistic when their preferred political party is in power, thus inducing risk-taking behavior in asset allocation decisions. Separately, other works take the perspective of the firm and explore the role of political connectedness on firm-level outcomes including firm performance (Aggrawal et al. 2012), ability to secure government funding (Duchin and Sosyura 2012), or a government bailout (Faccio 2006) and preferential treatment when it comes to obtaining loans from state-linked institutions (Li et al. 2008).

The stock market-political nexus has also been examined in the context of political geography as another growing strand of this vast literature. Arguing that a firm's political geography determines proximity to political power, this line of work associates political geography with the firm's exposure to uncertainty regarding the administration's policies. The evidence in this literature suggests that political geography can have a significant effect on firm performance (Kim et al. 2012; Pantzalis and Park 2014), its political strategies (Antia et al. 2013), investment (Kim et al. 2012) and financing decisions (Colak et al. 2021), corporate earnings disclosures (Gross et al. 2016), audit pricing (Truong et al. 2020) as well as their informational advantage (Aabo et al. 2020). In a recent study, Magerakis et al. (2023) establish a link between the political geography of the firm and its earnings management practices such that firms in politically aligned states try to improve their flexibility to adapt to market shocks by increasing their cash holdings.

Interestingly, however, although the role of political geography on a firm's economic environment is largely explained via risk-based arguments, the literature has not yet established a direct link with stock return volatility. For example, studies including Bradley et al. (2016) and Gross et al. (2016) show that politically connected firms are less exposed to the effects of policy uncertainty compared to firms lacking direct political connections. Similarly, Kim et al. (2019) show that political strategies drive firm idiosyncratic risk in politically uncertain environments. In a recent study, Douidar et al. (2023) link the political geography of a firm to the value of real options as proximity to political power can trigger greater exposure to uncertainty and/or more growth opportunities. Supporting this evidence, Chen et al. (2023) show that stocks with high exposure to presidential approval ratings significantly underperform, arguing that a firm's perceived alignment to the incumbent president's economic policies is mispriced by

investors. Accordingly, the existing evidence clearly establishes risk spillover effects of political geography to stock market dynamics, and our study provides a novel perspective by establishing a direct link to volatility. Therefore, while the effects of political geography have received increasing attention in the finance literature over the last decade, our study is the first to directly link it to volatility.

Considering the established evidence that exposure to presidential policies results in predictable patterns in industry returns (Belo et al. 2013) and industry return volatility can be used to predict volatility at the aggregate stock market level (Niu et al. 2024), one can argue, in the context of our application, that portfolios constructed at the state level can also be used to predict volatility at the aggregate level by considering state exposures to presidential politics. In that regard, the political alignment indexes of Kim et al. (2012) which are available at the state level, provide an interesting opening to link political geography to stock market volatility in a novel context. The focus on state-level politics is, in fact, supported by a well-established literature that suggests that core business activities of firms often occur close to their headquarters (Pirinsky and Wang 2006; Chaney et al. 2012) and, hence, equity prices should contain a non-negligible regional component, so that investors overweight local firms in their portfolios (Coval and Moskowitz 1999, 2001; Korniotis and Kumar 2013). Given this, our objective in this research is to determine the relative role of the stock return volatilities at the state level (50 states in all), involving a capitalization-weighted index of equities domiciled in a given state, in shaping volatility at the aggregate level. Understandably, the econometric exercise that we undertake in this research should be of immense value to investors from the perspective of portfolio decisions.

3 | Data and Methodology

3.1 | Data

State-level stock returns are computed using data for the state-level stock market indexes obtained from the Bloomberg terminal. These indexes represent the capitalization-weighted portfolios of equities domiciled in a given state. Following Andersen and Bollerslev (1998), we use the daily log-returns for each state-level index to compute the monthly realized volatility estimates RV_i for state i as the sum of daily squared log-returns over a month. Similarly, we utilize the Center for Research in Security Prices (CRSP) composite index, obtained from the data library of Professor Kenneth French to compute the aggregate stock market realized volatility estimates.⁴ Our monthly sample for the aggregate- and state-level RV series covers the period of February 1994 to March 2023, based on data availability at the time of writing this paper.⁵

Since we examine in our subsequent analysis the predictive relationship between the state- and aggregate-level stock market volatilities with respect to the political geography of the state, we utilize the annual state-level political alignment indexes (PAI) originally developed by Kim et al. (2012), and extended in more recent studies by Gross et al. (2016), Doudar et al. (2023), and Magerakis et al. (2023).⁶ In essence, PAI is a state-level measure

of political alignment with the party of the President, thus capturing the proximity to political power.⁷

In technical terms, Kim et al. (2012) construct this index by assigning equal weights to the degree of the control of the presidential party of political institutions (i.e., mansions of governors and state legislatures) of a particular state and to the percentage of the representatives of a state in the Senate and House (i.e., Congress) that belong to the party of the President.⁸

3.2 | Methodology

In this section, we explain the methodology used to trace out the importance of state-level realized volatilities over the aggregate stock market volatility via a machine learning technique known as random forests (Breiman 2001). At this stage, we must point out two critical issues: First, instead of relying on conditional volatility models from the generalized autoregressive conditional heteroskedasticity (GARCH)-family, we follow Andersen and Bollerslev (1998) and use realized volatilities as measured by the sum of squared daily log-returns over a month to analyze the link between overall and state-level monthly. The use of realized volatility (RV) in our analysis provides an observable measure of the latent process of volatility that is model-free, unlike the conditional estimates of the same. Second, our econometric model incorporates a substantial number of control variables, totaling up to 51. As a result, we turn to a machine learning method for analysis. Specifically, the use of random forests enables us to comprehensively investigate how state-level stock market RV affects overall market RV, employing a thoroughly data-driven approach. In addition, random forests automatically capture potential nonlinear associations between realized volatility at the aggregate and state levels with the state-level RV acting as a predictor, while possible interaction effects among these impact variables are also considered.

We begin the procedure by modeling aggregate realized stock market volatility, $RV_{a,t}$, in period t , by means of an autoregressive process, extended to include the various state-level stock market realized volatilities, $RV_{s_i,t}$, $i = 1, 2, \dots, 50$. Hence, the state-level stock market realized volatilities capture any new information and innovations affecting aggregate stock market volatility not already embedded in lagged aggregate stock market volatility, which can be viewed as a simple proxy for the various types of autoregressive models studied in the literature on realized volatility. In formal terms, the empirical model is given by the following equation:

$$RV_{a,t} = f(RV_{a,t-1}, RV_{s_1,t}, RV_{s_2,t}, \dots, RV_{s_{50},t}) \quad (1)$$

where f denotes a function to be estimated. In order to bring the data closer to normality, we consider the natural logarithm of realized (aggregate, state-level) stock market volatility.

Given that our empirical model features a large number of explanatory variables, i.e., the lagged aggregate RV and the same for the 50US states, we use the random forest technique (Breiman 2001) to estimate the function, f , and assess the role played by the state-level realized volatilities to explain

aggregate stock market realized volatility. Random forests, recognized as a robust data-driven approach in machine learning, are particularly effective for estimation tasks involving a large number of predictors. In addition, random forests have the advantage that they automatically capture any interactions among the explanatory variables and potential nonlinearities in the data (see, for example, Hastie et al. (2009) for a comprehensive textbook exposition). A key advantage of random forests is their ability to let the data define the optimal form of the function f , without imposing any predetermined structure, such as a linear form, on it.

Random forest belong to the class of ensemble machine-learning models as a forest combines a large number of individual regression trees, T , in an additive way. In other words, a random forest that consists of m individual regression trees approximates the function, f , given in Equation (1) as follows:

$$f(\text{RV}_{a,t-1}, \text{RV}_{s_1,t}, \text{RV}_{s_2,t}, \dots, \text{RV}_{s_{50},t}) = \sum_k T_k, \quad k = 1, 2, \dots, m, \quad j \neq i \quad (2)$$

Estimating the function f , by means of a large number of individual regression trees is advantageous because an individual regression tree, given the way it is constructed, is a data-sensitive predictor of aggregate stock market volatility. In order to see this more clearly, we next describe briefly how an individual regression tree, T_k , is grown by combining a root and several nodes and branches (see, Breiman et al. (1984)).

The nodes and branches of a regression tree subdivide the space of the explanatory variables into l non-overlapping regions, R_l . These regions, in turn, are constructed by applying a search-and-split algorithm in a recursive top-down way. While this recursive top-down algorithm sounds abstract on first reading, its details can easily be explained by starting at the root of a regression tree. At the root, we subdivide the space of predictors into a left region (i.e., a branch), R_1 , and a right region, R_2 . In order to identify these two regions in an optimal way, we iterate over the entire array of predictors using (in the simplest case) every realization of a predictor as a candidate splitting point. For every pair of a predictor and a splitting point, $\{s, p\}$, we construct the left and right regions, $R_1(s, p) = \{x_s | x_s \leq p\}$ and $R_2(s, p) = \{x_s | x_s > p\}$, where $x = \text{RV}_{a,t-1}, \text{RV}_{s_1,t}, \text{RV}_{s_2,t}, \dots, \text{RV}_{s_{50},t}$. The optimal pair, $\{s^*, p^*\}$, solves the following minimization problem:

$$\min_{s,p} \left\{ \bar{y}_1 \min_{x_s \in R_1(s,p)} \sum (RV_a - \overline{RV}_{a1})^2 + \overline{RV}_{a2} \min_{x_s \in R_2(s,p)} \sum (RV_a - \overline{RV}_{a2})^2 \right\} \rightarrow \{s^*, p^*\} \quad (3)$$

where z identifies those realizations of aggregate stock market volatility that belong to a region, and $\overline{RV}_{ak}, k = 1, 2$ denote the region-specific means of aggregate stock market volatility (note that we have dropped the time index to simplify the notation).

The two regions we have identified by solving the minimization problem stated in Equation (3) already form a rudimentary regression tree, which we already can use, however, to predict aggregate stock market volatility in terms of the region-specific

means, $\overline{RV}_{ak}, k = 1, 2$. It is clear though that such a prediction does not really fully exploit the rich information embedded in the large array of predictors. Therefore, we expand our regression tree further by reapplying the search-and-split algorithm to both the left and right top-level regions. This second iteration provides us with two sets of second-level optimal splitting predictors and their corresponding split points, as well as four region-specific second-level means for aggregate stock market volatility. By continuing this process, we progressively develop a more intricate regression tree, yielding increasingly detailed predictions of aggregate stock market volatility. To control the growth of this tree, we can set a predefined maximum number of terminal nodes, or ensure that each terminal region contains a minimum number of observations. After collecting information on the various terminal-node region-specific means of aggregate stock market volatility, which we determine by halting the search-and-split algorithm, we are able to predict overall stock market volatility in the following manner:

$$T(\mathbf{x}_i, \{R_l\}_1^L) = \sum_{l=1}^L \overline{RV}_{al} \mathbf{1}(\mathbf{x}_i \in R_l) \quad (4)$$

where L denotes the number of regions and $\mathbf{1}$ denotes the indicator function.

While it should be clear by now that growing a complex regression tree produces a granular prediction of aggregate stock market volatility, a problem with such an overly complex tree is that its complicated hierarchical structure results in an overfitting and data-sensitivity problem. Pruning a complex regression tree is an obvious solution to this problem, but pruning also implies that the predictions of aggregate stock market volatility become less precise.

The idea behind growing a random forest is to solve the overfitting problem by growing not only one but many regression trees, that is, an ensemble of regression trees. Such an ensemble of regression trees can be constructed by following the following three instructions:

1. Start by computing a large number of bootstrap samples by resampling from the data.
2. Grow a *random* regression tree on every single bootstrap sample. For growing a *random* regression tree, use for the

search-and-splitting algorithm only a random subset of the predictors so as to mitigate the effect of influential predictors on tree building.

3. Combines the large number of random regression trees to form a random forest. The prediction of aggregate stock market volatility is the average prediction obtained from the individual random regression trees. Averaging stabilizes the resulting prediction.

In this application, our focus is not on the predictions of aggregate stock market volatility, but rather to explore how much the state-level variables contribute to the formation of a random forest, that is, the importance of the explanatory variables (VIMP). A natural way to quantify the importance of the explanatory variables is to compute a weighted sum of how many times an explanatory variable was split on at each depth in the forest. Moreover, given that the importance of the explanatory variables most likely changed over the sample period that we consider in our empirical analysis, we estimate a sequence of random forests on a recursively expanding estimation window adding data on a yearly basis, and then compute the corresponding time-series of the importance of all explanatory variables in our empirical model. We start the recursively expanding estimation window in 1999.

Finally, the estimations are performed using the environment for statistical computing (R Core Team 2023) and the R add-on package “grf” (Tibshirani et al. 2022). We use 2000 individual regression trees to grow a random forest, setting the minimum node size, the number of variables tried for each split, and the maximum imbalance of a split as tuning parameters. Because random forests inherently incorporate randomness into their estimation procedure, we perform the random forest estimations ten times over an expanding estimation window. For each year in our sample, we then calculate the average importance of each explanatory variable. To determine the importance of the state-level variables, we use the default settings from the “grf” package. These defaults are designed to assign a lower weight to splits involving an explanatory variable at later stages of tree construction, meaning that splits occurring at the top level are given greater weight. The decay exponent in this calculation is set at two, and the maximum tree depth considered for evaluating the importance of explanatory variables is capped at four.

4 | Empirical Results

4.1 | Importance of State-Level Realized Volatilities

Figure 1 presents the time-series plots for the variable importance (VIMP) estimates that measure the relative importance of each state-level realized volatility in explaining aggregate stock market volatility. To enhance readability, each state's data is displayed using a different vertical axis scale.

The figure clearly shows significant variation over the years in the importance of state-level volatilities. For instance, several states including Colorado, Delaware, Georgia, Indiana, Maine, Massachusetts, and Mississippi have seen a decline in their relative importance over time. On the other hand, states such as Maryland, Minnesota, and New York exhibit a marked increase in their relative importance to explain aggregate stock market volatility. This indicates a notable shift over time in the relative impact of state-level volatilities. Additionally, by examining the scales of the vertical axes, we can observe considerable differences across states in the magnitude of their impact on aggregate stock market volatility.

Figure 2 sheds more light from a different angle on the time variation and the cross-sectional dimension of the relative importance of the state-level realized volatilities. Panel A displays the time series of the relative importance of the top three states (New York, Pennsylvania, and Minnesota), as measured by the mean (or median) of the importance of the state-level realized volatility computed over the estimation period. In addition, we plot a shaded area whose boundaries inform about the maximum and minimum of the state-level realized volatility across all 50 states for each year. The comparison of the three states in the figure clearly identifies New York state as the dominant driver of aggregate stock market volatility, consistently for each year during the estimation period. This is not unexpected considering that New York is a global financial center (perhaps the most important one) with some of the largest corporations included in broad stock market indexes domiciled in this state. Furthermore, firms incorporated in this state include some of the mega firms listed on the U.S. stock exchanges, which in turn, might contribute to this state's dominance over the aggregate market volatility patterns. From a different perspective, Faccio et al. (2006) argue that corporate bailouts tend to happen to mega firms or firms in the finance sector. Such an insurance offered by the government could then induce greater risk-taking behavior by these firms, which in turn, contributes to a possible volatility spillover effect emanating from firms associated with this state.

Panel B of Figure 2 displays the evolution of the cross-sectional standard deviation of the importance of the state-level realized volatilities over time. Essentially, the plot offers a visual representation of the dispersion in the relative importance of state-level volatilities to explain aggregate market fluctuations. While the cross-sectional standard deviation exhibits some marked ups and downs, it is evident that, on balance, a slight upward trend is a characteristic feature of the dispersion in the relative importance of state-level volatilities, suggesting that some states have assumed a more important role over time, while others have lost explanatory power. The upward trend in the dispersion of relative importance estimates is, in fact, in line with the state-level results presented in Figure 1 wherein the realized volatilities of several states have played a less important role as drivers of aggregate stock market volatility, while the importance of certain states such as New York, a major global financial center, substantially increased over time.

4.2 | The Role of Political Alignment Across Investor Sentiment Regimes

4.2.1 | Political Alignment and State-Level Volatility Contribution

Clearly, the time variation in the relative importance of state-level stock market fluctuations over the aggregate market can be driven by a number of factors such as the economic contribution of each state or business uncertainty emanating from corporate decisions domiciled in that state, which can eventually trickle down to the aggregate economy. In this study, motivated by the literature on the nexus between financial markets and political geography, we focus on the role of state-level political

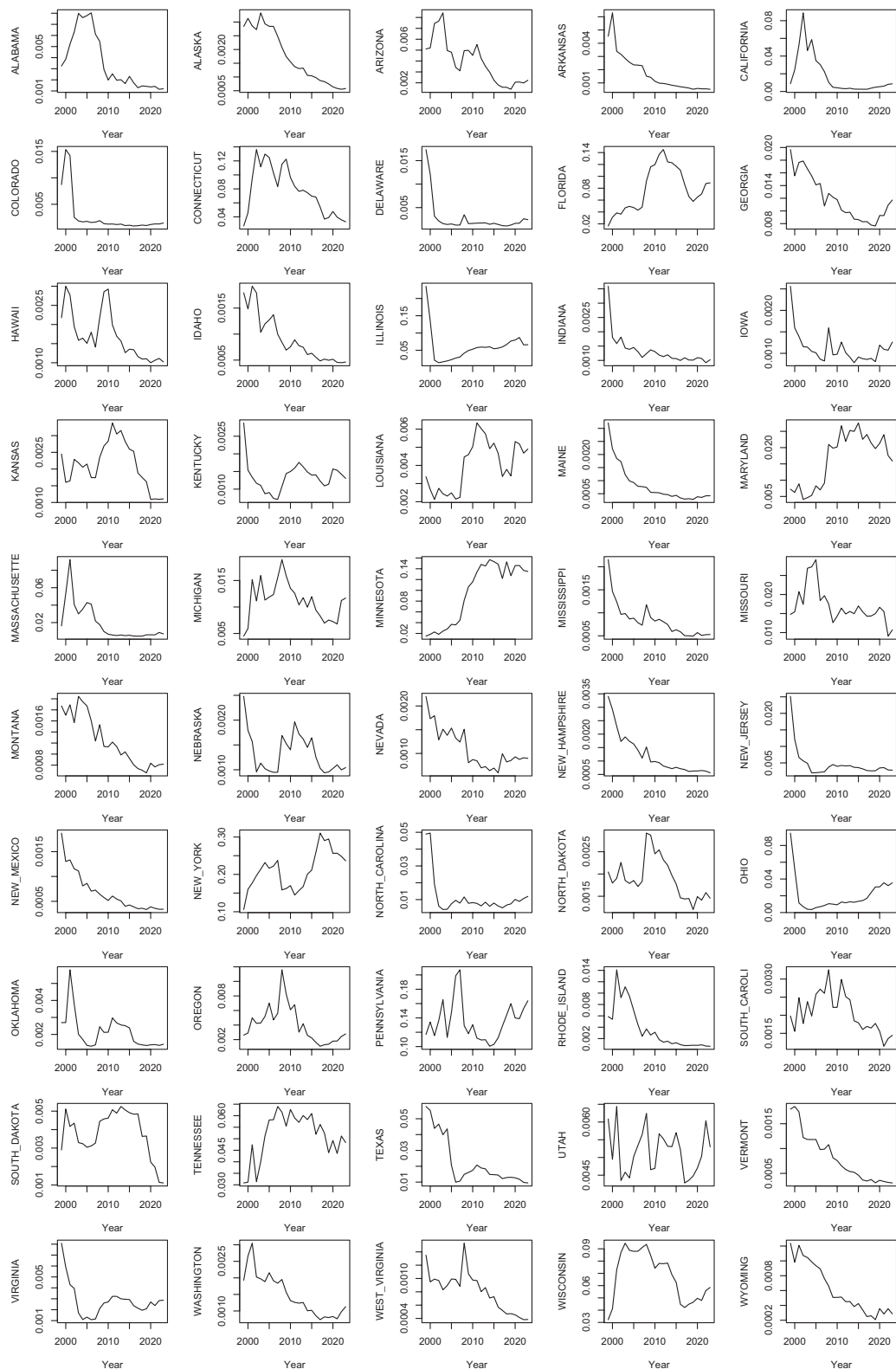


FIGURE 1 | Estimated importance of state-level realized volatilities.

uncertainty in the interaction between state- and aggregate-level stock market volatility. To that end, having derived the relative importance of the state-level realized volatilities, we next utilize the state-level political alignment index (PAI) series described earlier and relate the estimated state-level relative importance estimates (VIMP) to PAI.

Our focus on the role of political geography, particularly state-level political alignment, in this context stems from the hypothesis that firms domiciled in states that are more aligned with the ruling party, i.e., higher PAI, will benefit from the closer alignment between state- and federal-level politics, which will eventually help reduce these firm's exposure

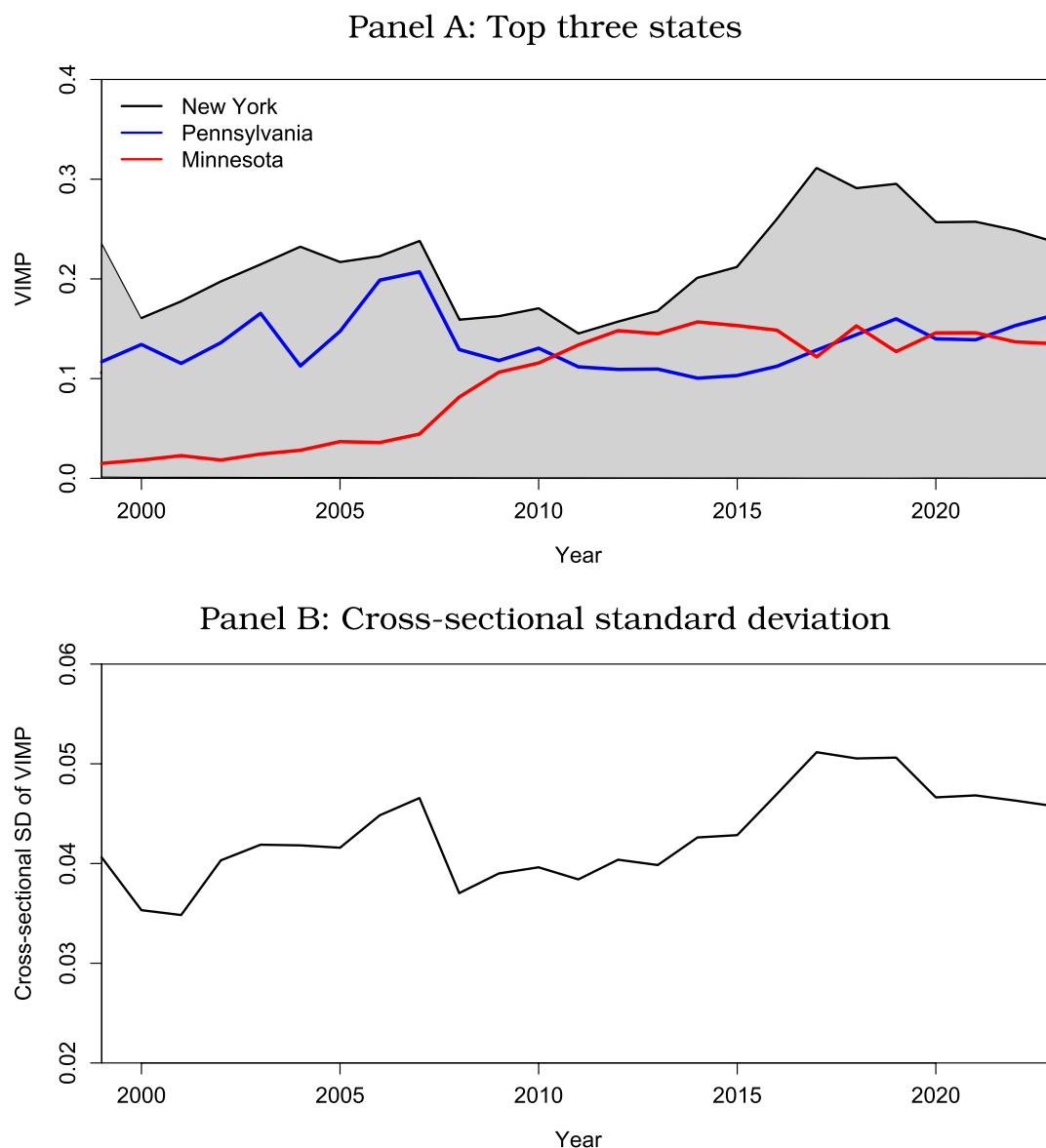


FIGURE 2 | Cross-sectional dispersion of the importance of state-level realized volatilities. Panel A: Top three states. Panel B: Cross-sectional standard deviation.

with respect to economic uncertainty associated with policy changes. This, in turn, would help mitigate possible information asymmetries that might arise between investors and corporate managers, thus resulting in these firm returns to contribute relatively less to aggregate market fluctuations. Accordingly, we hypothesize a negative relationship between political alignment of a state captured by PAI and the volatility contribution of the state-level volatility to that of the aggregate market as political stability and predictability in a state's policy environment reduces economic uncertainty, thus resulting in a more stable financial environment and, eventually, to a lower contribution to aggregate stock market volatility. Hence, it is plausible to hypothesize that states with a high PAI, signifying a stable political climate, would exhibit a lower contribution of their state-level stock market volatilities to aggregate stock market volatility.

Figure 3 summarizes the correlation of the importance of the 50 state-level realized volatilities with their respective political

alignment series. We observe that the correlations cover a wide range of positive and negative values with the mean (median) correlation of the state-level realized volatilities with the with their respective PAI series is -0.06 (-0.04). While the generally negative correlations are informative in terms of our hypothesis, we formally examine the link between political alignment and state-level contribution to aggregate market fluctuations via panel regression analysis.

4.2.2 | Panel Regression Setup and Control Variables

Specifically, we estimate panel regressions across the 50 U.S. states in the sample by setting VIMP as the dependent variable and PAI as the independent variable. In order to control for the other state-level factors in the model, we also include several control variables such as the state-level coincident index (CI) and state-level housing returns (HP) as possible indicators of economic activity that might have an impact on financial market

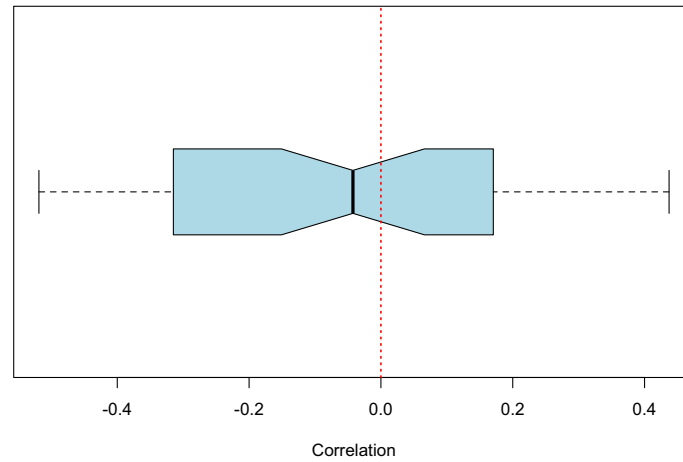


FIGURE 3 | Correlation of importance of state-level realized volatilities with PAI.

dynamics.⁹ The panel regression model can be formally represented as follows:

$$\text{VIMP}_{it} = \alpha_i + \beta \text{PAI}_{it} + \delta Z_{it} + \varepsilon_{it} \quad (5)$$

where VIMP_{it} is variable of importance of state i at time t , PAI is the political alignment index and Z_{it} stands for the control variables, which include the state-level coincident indicator (CI) and a well-established regional leading indicator (e.g., Emirmahmutoglu et al. 2016), namely the log-returns of the Federal Housing Finance Agency (FHFA) All Transactions Index of house prices (HR).¹⁰ Finally, α_i captures state-specific effects and ε_{it} is the error term.

The inclusion of CI is motivated by the large and significant research on the link between the real economy and financial markets (for an early contribution, see Schwert 1989). While a strong state economy (higher CI) might stabilize firm fundamentals and reduce idiosyncratic volatility, it can also lead to increased investment, leverage, sectoral concentration in cyclical industries, asset bubbles, speculation, and greater inter-state economic linkages. These factors could amplify a state's stock market volatility and its correlation with the aggregate market dynamics, potentially leading to a positive relationship between CI and a state's contribution to overall market volatility. In that regard, controlling for CI helps isolate the impact of political alignment.

Similarly, housing is a significant component of household wealth and a key driver of regional economic activity. Fluctuations in house prices can have substantial spillover effects on consumer spending, confidence, and overall economic sentiment (e.g., Case and Shiller 2003; Iacoviello 2005). Higher housing returns (HR) in a state might indicate increased wealth and economic optimism, potentially leading to more stable financial markets within that state and a lower contribution to aggregate volatility due to reduced local uncertainty. Including HR as a control helps to account for these regional wealth effects and their potential influence on the relationship between political alignment and volatility contribution. Higher housing returns could translate to more stable investor sentiment within the state and potentially lower financial market volatility, leading to a reduced contribution

to aggregate volatility. In this case, the coefficient of HR is expected to be negative.¹¹

4.2.3 | Panel Regression Results: Political Alignment and Volatility Contribution

Table 1 presents the results of the panel regressions applied to state-month observations. The estimates for the whole sample is reported in Column 1, while the results for high and low sentiment subsamples are reported in Columns 2 and 3. In Column 1, we observe that the coefficient of the political alignment index is significant and negative, suggesting that greater alignment of a state with federal politics is associated with a lower contribution of that state to aggregate market fluctuations.¹² This result supports our hypothesis of a negative relationship between state-level political alignment and the contribution of state-level realized volatilities to aggregate stock market volatility. Considering the finding by Magerakis et al. (2023) that firms in politically aligned states increase their cash holdings, thus providing them the flexibility to adapt to shocks associated with policy changes, our finding of a negative relationship between VIMP and PAI could be a manifestation of increased stability in firm operations thanks to corporate actions in response to political uncertainties, which in turn, determines the extent to which firm-level volatility is transmitted to the aggregate financial market.¹³

Interestingly, however, although one would expect some degree of association between the economic variables used as control variables in the model and the state's contribution to aggregate stock market fluctuations, we observe largely insignificant coefficients for CI and HR, suggesting that, once PAI is accounted for, the effect of coincident and leading indexes are not influential in determining the contribution of the state to the overall stock market volatility. In summary, the regression analysis reinforces the role of political geography in financial markets by providing empirical evidence that political alignment plays a noteworthy role in influencing the extent of a state's contribution to aggregate stock market volatility. This finding adds an important dimension to our understanding of the determinants of stock market volatility and highlights the relevance of political factors in financial market analysis.

TABLE 1 | Results of panel regressions.

Variables	(1)	(2)	(3)
	All sample	High sentiment	Low sentiment
	VIMP	VIMP	VIMP
PAI	−0.00318** (0.00129)	−0.00415** (0.00164)	−0.000673 (0.00199)
CI	0.000334 (0.00395)	0.000662 (0.0326)	0.000197 (0.00364)
HR	−0.00188 (0.00687)	0.00181 (0.0117)	−0.00416 (0.00818)
State fixed effects	Yes	Yes	Yes
Observations	1250	950	300
Adj. R^2	0.852	0.827	0.935

**Denotes significance at the 5% level.

4.2.4 | The Role of Investor Sentiment

In a related study, Montone (2022) investigates the impact of nonpartisan political views, particularly presidential approval ratings, on stock market trends. The study reveals that significant disapproval of the US president, especially during periods of political uncertainty and low overall market sentiment, correlates with diminished stock returns. This finding offers a fresh perspective on how nonpartisan political attitudes can profoundly influence stock prices, distinct from the effects of political affiliation. In light of this perspective, as well as findings by Gupta et al. (2021, 2023), that the impact of presidential approval ratings on stock market fluctuations is contingent on the underlying behavioral patterns of investors, we delve into how investor sentiment affects the relationship between political alignment and stock market volatility. It can be argued that investor sentiment, a crucial factor that drives the trading behavior of investors, can considerably alter the influence of political elements on financial markets.¹⁴ Therefore, analyzing the interplay between high and low sentiment regimes and political alignment enables a more nuanced understanding of the factors driving stock market volatility.

To that end, we utilize the American Association of Individual Investors (AAII) US Investor Sentiment Bullish and Bearish Readings indexes to differentiate high and low sentiment periods.¹⁵ These indexes reflect the short-term outlook of individual investors towards the stock market. A positive difference between bullish and bearish readings denotes a high sentiment period, signaling general market optimism, while a negative difference indicates a low sentiment period, reflecting prevailing market pessimism. In order to examine the role of investor sentiment over the relationship between PAI and VIMP, we conduct panel regression analysis separately for high and low sentiment periods by estimating the regression model given in Equation (5) for sub-samples based on sentiment states.

The results reported in Columns 2 and 3 of Table 1 indicate that the negative relationship between political alignment

and VIMP is more pronounced during high sentiment periods, while political alignment loses its significance when sentiment is low. This is indeed in line with the recent evidence in Gavrilidis et al. (2024) of significant herding by institutional investors due to political uncertainty particularly during periods of low sentiment, implying that behavioral factors dominate market dynamics during low sentiment periods. During high sentiment periods, however, political alignment may reduce volatility as confidence in political stability is greater.¹⁶ Hence, in periods of optimistic market conditions, more politically aligned states are considered as contributing less to aggregate market volatility. One can argue that, in periods of positive sentiment, investors perceive firms operating in politically stable states as safer bets, thus reducing their perceived risk and contribution to overall market volatility further. In essence, this observation suggests that political stability becomes a more valued asset in times of general market optimism. Conversely, we observe that during low-sentiment periods the relationship between PAI and VIMP is not statistically significant.¹⁷ This observation could imply that in periods of market pessimism, investors' concerns are likely dominated by broader national or global economic factors, overshadowing the influence of state-specific political stability or alignment on market volatility.¹⁸

These findings are in line with the theoretical model developed by Pástor and Veronesi (2012) which shows how uncertainty about government policy can have a substantial impact on stock prices and volatility. In their framework, policy uncertainty raises the volatility of the stochastic discount factor, which leads to a higher risk premium and increased volatility in stock prices. During periods of high uncertainty, often associated with low investor sentiment, the stabilizing effects of political alignment may be overwhelmed by larger concerns about potential policy changes at the national level, increasing overall volatility. Conversely, in times of high sentiment, when investors are more confident in the political environment, the proximity of state-level political alignment to the ruling party can enhance perceived stability, thus reducing volatility.

Furthermore, we conduct an additional analysis by excluding New York, Pennsylvania, and Minnesota from the sample to ensure the robustness of our findings. As reflected in Table A4 (Appendix), our results remain consistent with those presented in the original analysis. Notably, PAI continues to exhibit a statistically significant negative coefficient in both the full sample and the high sentiment subsample, reinforcing the robustness of our main hypothesis. Dropping these states, which are among the largest contributors to aggregate stock market volatility, does not alter the central finding that higher political alignment reduces the importance of state-level stock market volatility in explaining aggregate market fluctuations. This outcome underscores that the observed relationship is not disproportionately driven by firms headquartered in these states, but rather reflects a broader pattern across the remaining states in the sample.¹⁹

Our results indicate that proximity to political power has also second-moment stock market implications potentially channeled by its impact on the exposure of firms to policy uncertainty. This is an important consideration given the evidence that exposure to policy uncertainty carries a significant risk premium in the cross-section of stock returns, and our findings imply that a firm's proximity to political power could be the channel that drives the risk premium. Considering the evidence that political risk can fuel investor disagreement by introducing uncertainty in firm valuations (Pástor and Veronesi 2012, 2013) and intensify information asymmetry (Nagar et al. 2019), thus contributing to crash risks in stock prices (Makrychoriti and Pyrgiotakis 2024), our findings imply that a high level of political alignment can help alleviate potential information asymmetries, thus mitigating price distortions and excess fluctuation in stock prices.

At the same time, our findings also underscore the importance of considering investor sentiment when analyzing the nexus between political geography and financial market dynamics, as the influence of political stability on market volatility is context-dependent, varying with the prevailing market sentiment. This is indeed in line with the evidence in Montone (2022) that the effect of political alignment on stock market movements is contingent on the behavioral mindset of investors. Thus, our results imply that the effectiveness of governmental policies to reduce the potential destabilizing effects of policy uncertainty on the stock market could be contingent on the level of investor sentiment. Overall, our findings present a novel angle to the channels in which politics impact stock market dynamics in that the level of political alignment can help alleviate potential information asymmetries from the perspective of investors, which in turn affects volatility in price changes. From a forecasting perspective, our findings also show that portfolios constructed at the state level can be used to predict volatility at the aggregate market level by considering state-level exposures to presidential politics.

5 | Concluding Remarks and Discussion

There is a well-established literature on the role of political geography on corporate decisions and firm valuations. The literature, however, has not yet established a direct link to stock market volatility although the documented evidence that links

political geography to stock risk premia assumes an underlying risk effect. In our application, we extend this literature to the stock market volatility context by examining the interrelation between political geography and the predictive relation between the state- and aggregate-level stock market volatility via recently constructed measures of state-level political alignment indexes.

Our empirical investigation is structured into two steps. In the first step, we trace out the contribution over time of state-level realized stock market volatility to aggregate US stock market volatility by means of a machine-learning technique known as random forests. Our results show that the importance of the state-level realized stock market volatilities as a driver of aggregate stock market volatility displays considerable cross-sectional dispersion as well as a substantial variation over time. While our empirical results indicate that the importance of the realized volatilities of several states as drivers of aggregate stock market volatility decreased over time, the state of New York, being a major global financial hub, assumed a more dominant role as a driver of aggregate volatility over time. In the second step, we employ panel regressions to measure whether the importance of the state-level realized volatilities for aggregate stock market volatility is linked to a state's political alignment as well as measures of market sentiment.

The first key finding from the panel regressions is that political alignment plays a statistically significant role in influencing the extent of a state's contribution to aggregate stock market volatility. Specifically, our results show that stronger political alignment of a state with the ruling party is associated with a lower importance of a state's realized volatility to aggregate stock market volatility, a finding which is in line with the hypothesis that political stability and predictability at the level of individual states help reduce economic uncertainties and, thereby, lead to a more stable financial environment, as reflected in a lower contribution of that state to aggregate stock market volatility. A second key finding of the panel analysis is that the negative link between the importance of a state's realized volatility over aggregate stock market volatility and political alignment is statistically significant during high-sentiment periods, but weak and statistically insignificant during low-sentiment periods, underscoring the role of investor sentiment for the nexus between political geography and financial markets.

From an investment perspective, our findings imply that volatility of the stock markets at the state level is likely to carry important information for the aggregate equity market fluctuations especially when there is increased uncertainty regarding government policy changes. Given that volatility is a key input used in portfolio allocation and risk management strategies, our findings imply that investors can improve volatility models by considering the role of political geography, particularly during high sentiment regimes. Likewise, from a policy making perspective, our findings suggest that greater monitoring of corporate policies in states that are less aligned with the ruling party can help mitigate possible information asymmetries and excessive market fluctuations, eventually ensuring financial stability. Although the main objective of this paper was to shed light on the possible interactions between the state- and aggregate-level stock market fluctuations from the perspective of political geography of firms, future research could be devoted to a full-fledged

forecasting analysis in a machine learning set-up, involving regime-specific future predictions of equity market volatility using corresponding information of regional stock market volatilities.²⁰

Looking ahead, several avenues for future research emerge from our analysis, especially considering the limitations of the current study. While we have focused on political alignment as a key measure of political geography, other political factors, such as state-level policy uncertainty, partisan control shifts, or gubernatorial elections, may offer additional insights into the dynamics of stock market volatility. Incorporating such political factors, thus, could provide a more nuanced understanding of how local politics interact with financial markets. Moreover, further exploration into fiscal policies enacted at the state level and their influence on investor sentiment could deepen the type of analysis we have undertaken in our research. Methodologically, while random forests have proved effective in modeling complex relationships, future research could enhance interpretability by comparing results with other machine learning techniques, such as boosting or deep learning, or by utilizing regime-switching models to capture time-varying effects more dynamically. Additionally, expanding the framework of this research to other financial markets could yield broader insights into the influence of political geography. The interconnectedness of financial systems suggests that political factors likely affect not only stock markets but also bond markets, corporate debt instruments, and real estate markets. Investigating these areas could reveal how political geography shapes risk premiums and market volatility across a wider range of financial instruments. Furthermore, refining the data by integrating more granular measures of political uncertainty or regional economic indicators would enhance the robustness of the analysis and offer more precise predictions in future research.

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Endnotes

¹ A similar argument applies to industries with respect to their exposures to presidential policies and public spending, manifested by predictability in industry returns during political cycles (as in, for example, Belo et al. 2013).

² See, for example, the discussions in Engle and Rangel (2008), Rangel and Engle (2011), Engle et al. (2013), Ben Nasr et al. (2014, 2016), Salisu et al. (2022), Segnon et al. (2023), among others.

³ In this regard, Demirer et al. (2024), show that industry-level stock returns can also carry substantial predictive content for the overall volatility of the US equity market. In light of the well-established “leverage-effect” (Black 1976), it would also imply a possible indirect effect on the aggregate stock market volatility, with industry returns impacting corresponding sectoral volatilities.

⁴ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

⁵ We plot the aggregate realized volatility in Figure A1 and the state-level realized volatilities in Figure A2 in the Appendix.

⁶ We would like to thank Professor Jung Chul Park for kindly providing us with the PAI data.

⁷ Table A1 in the Appendix provides the descriptions of the variables used in the analysis.

⁸ Specifically, PAI is constructed as follows: $PAI = (1/4) \times \text{Senators} + 1/4 \times \text{Representatives} + 1/4 \times \text{Governor} + 1/4 \times (1/2 \times \text{Statesenators} + 1/2 \times \text{Staterepresentatives})$, where Senators equals the percentage of two members of the Senate in Washington, D.C. who are part of the Presidential party; Representatives equals the percentage of the house representatives in Washington, D.C. who are part of the Presidential party; Governor is an indicator that equals 1 if the Governor and President are in the same party, and 0 otherwise; State senators is an indicator that equals to 1 if the fraction of members of the state that belong to the party of the President is $> 50\%$ and 0 otherwise, and $\text{State representatives}$ is an indicator that equals 1 if the percent of representatives of the state in the house that belongs to the party of the President is $> 50\%$, and 0 otherwise. See Kim et al. (2012) for further details.

⁹ The CI includes four indicators: nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries. The trend for the index of each state is set to match the trend for gross state product (GSP).

¹⁰ We sourced the state-level coincident indicator (CI) from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis (originally created by the Federal Reserve Bank of Philadelphia). The Federal Housing Finance Agency (FHFA) All Transactions Index of house prices (HR) index incorporates tens of millions of single-family home sales based upon a weighted, repeat-sales statistical technique to analyze house price transaction data. The data is available for download from: <https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx>.

¹¹ We report state-level summary statistics of VIMP and PAI in Table A2 (Appendix). The summary statistics clearly demonstrate the importance of New York in terms of VIMP. When inspecting the summary statistics, it should be kept in mind that the statistics like the mean or the median cloud important variation (and comovement) of VIMP and PAI over time. We report the corresponding state-level summary statistics of CI and HR in Table A3.

¹² In the “All Sample” (column 1), the coefficient of PAI is -0.00318 , which means that a 1-unit increase in the PAI (indicating stronger political alignment with the ruling party) leads to a 0.318% decrease in the variable importance (VIMP) of state-level realized volatility in predicting aggregate market volatility. This implies that states with higher political alignment contribute less to market fluctuations. The negative and significant coefficient suggests that political stability at the state level reduces uncertainty and market volatility at the aggregate level, as firms in these states face fewer political risks and uncertainties.

¹³ Interestingly, when we use the state-level economic policy uncertainty (EPU) indexes of Baker et al. (2022), available at: https://policyuncertainty.com/state_epu.html, the effect on VIMP was found to be insignificant. At the same time, keeping in mind the so-called “Presidential-Puzzle” (Santa-Clara and Valkanov 2003), that Democratic governments are relatively more risk-averse than Republican ones (see, Demirer and Gupta (2018), and Pástor and Veronesi (2020) for detailed discussions of this literature), we related the Democratic-Republican index (DRI), also provided to us by Professor Jung Chul Park, to VIMP. Note that, the DRI ranges from 0 (indicating all politicians are Republican) to 1 (indicating all politicians are Democratic), i.e., it represents the political color of the state based on the party affiliation of the local politicians, given the same weighting scheme as used in the PAI. The expectation in line with the Presidential-Puzzle was that states with higher DRI should reduce the VIMP, just like in the case of PAI. However, as with EPU, the effect for DRI on VIMP was statistically insignificant. Complete details of these results are available upon request from the authors.

- ¹⁴ As mentioned earlier, the established literature on the “Presidential-Puzzle” (Santa-Clara and Valkanov 2003) attribute the relatively higher excess returns observed during Democratic governments to greater risk aversion by investors during these periods.
- ¹⁵ The data can be downloaded from: https://www.aaii.com/sentimentsurvey/sent_results.
- ¹⁶ During high-sentiment periods, politically aligned states contribute 0.415% less to market volatility with each unit increase in political alignment, indicating that political stability is particularly valued in optimistic market conditions. However, during low-sentiment periods, political alignment has no significant effect on reducing volatility, suggesting that broader macroeconomic concerns overshadow its impact in pessimistic environments.
- ¹⁷ Additionally, we consider an analysis on the full sample by including an interaction term between PAI and a dummy variable that takes on the value one for the high-sentiment regime, and zero otherwise. The estimated coefficient of this dummy variable takes on the value -0.0014 and has the expected sign, though the coefficient, given that most years in our sample period are high-sentiment years, is not statistically significant with a 95% confidence interval of $(-0.0045, 0.0018)$, based on robust standard errors. The PAI coefficient, in contrast, remains negative and statistically significant at the 1% level. In any case, our primary focus in the sub-sample analysis is to examine the presence and direction of the relationship between political alignment and a state's contribution to aggregate volatility within distinct investor sentiment environments. The statistically significant coefficient for PAI in the high-sentiment regime, contrasted with the insignificant coefficient in the low-sentiment regime, suggests that the influence of political alignment on volatility dynamics is indeed conditional on investor sentiment.
- ¹⁸ We plot sentiment and also provide a graphical exposition of the evolution across time of the cross-sectional correlation between VIMP and PAI in Figure A3 at the end of the paper (Appendix), where we also show low-sentiment years. The graph shows that the cross-sectional correlation was negative until 2008 and again from 2017 to 2020. The correlation turned positive in the years after the Great Financial Crisis and during the years of the Covid-19 years. Importantly, the correlation was positive in two-thirds of the low-sentiment years.
- ¹⁹ Interestingly, the estimated coefficient for the HR predictor turns out to be significant in the low-sentiment regime in Table A4. Moreover, the coefficient has the expected negative sign, suggesting that investors view housing as a potential safe-haven asset which becomes more important for investors during the low-sentiment regime. This finding, however, must be interpreted cautiously as the coefficient, although negative during the low-sentiment regime, is statistically insignificant in Table 1. While the significance of the estimated coefficient depends on the specification of the panel-data model, the results in both tables are economically meaningful.
- ²⁰ The focus will continue to be on state-level RVs, since, interestingly, Granger causality on CRSP stock returns from both PAI and DRI over the longest possible annual sample period of 1967–2023 (based on the data availability of the independent variables), produced very weak predictive impacts. In fact, significant causal impact was derived under PAI from only 3 states (Georgia, Mississippi, and South Carolina), with DRI showing relatively more cases of prediction due to 11 states (Florida, Georgia, Kansas, Louisiana, Maine, Michigan, Nevada, New Hampshire, Oklahoma, Texas, and Vermont). Complete details of these results are available upon request from the authors.

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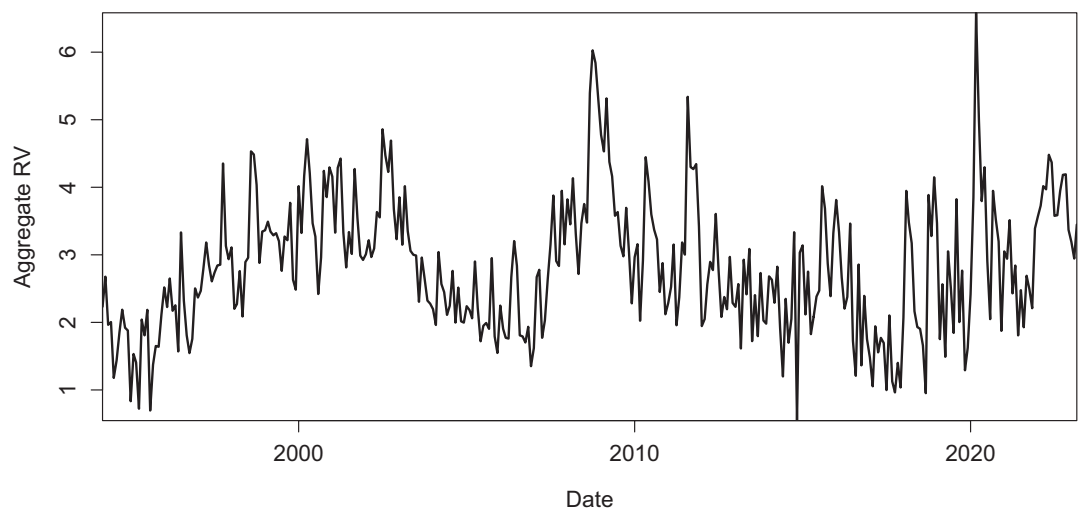


FIGURE A1 | Aggregate RV (natural log).

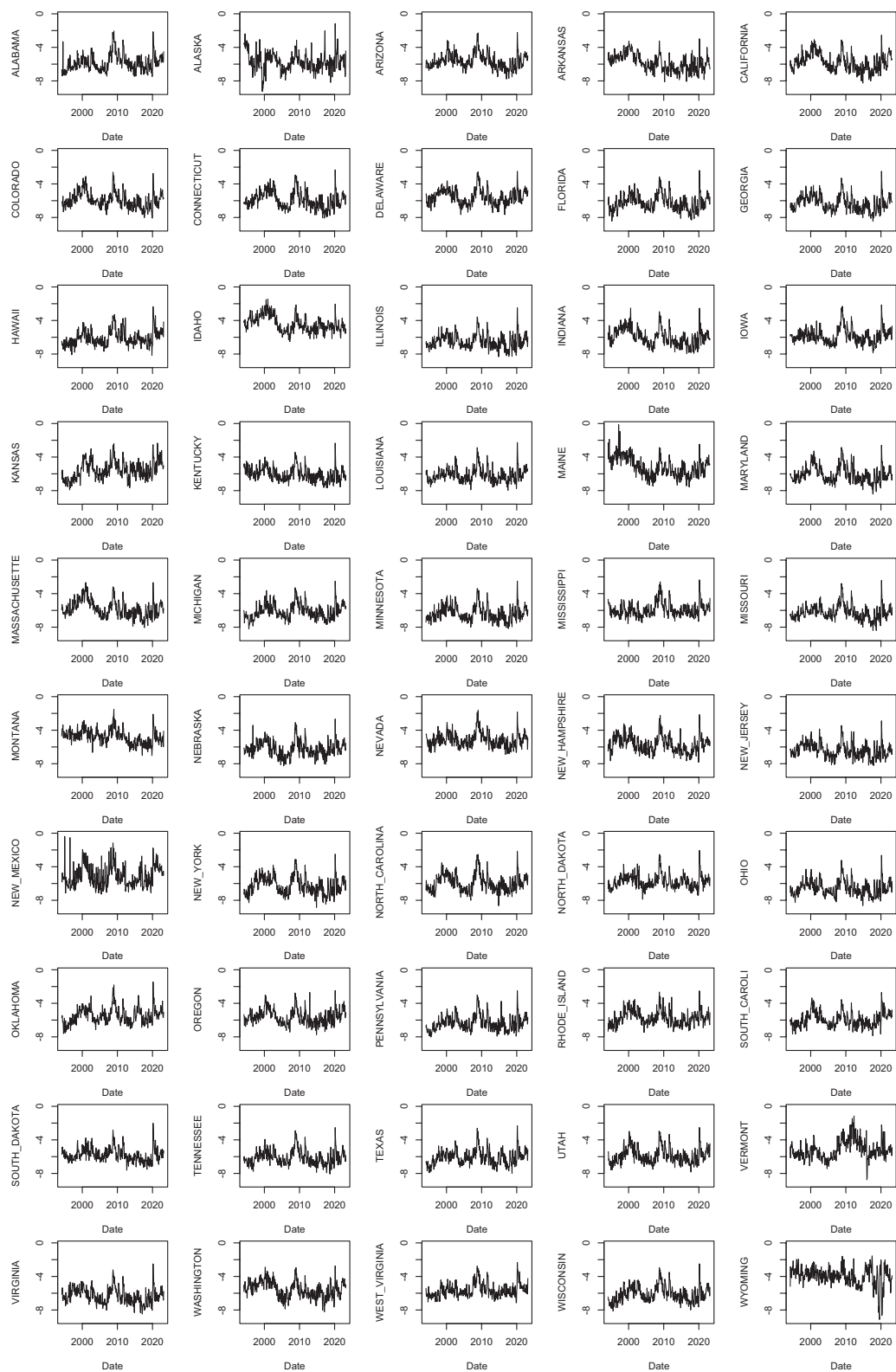
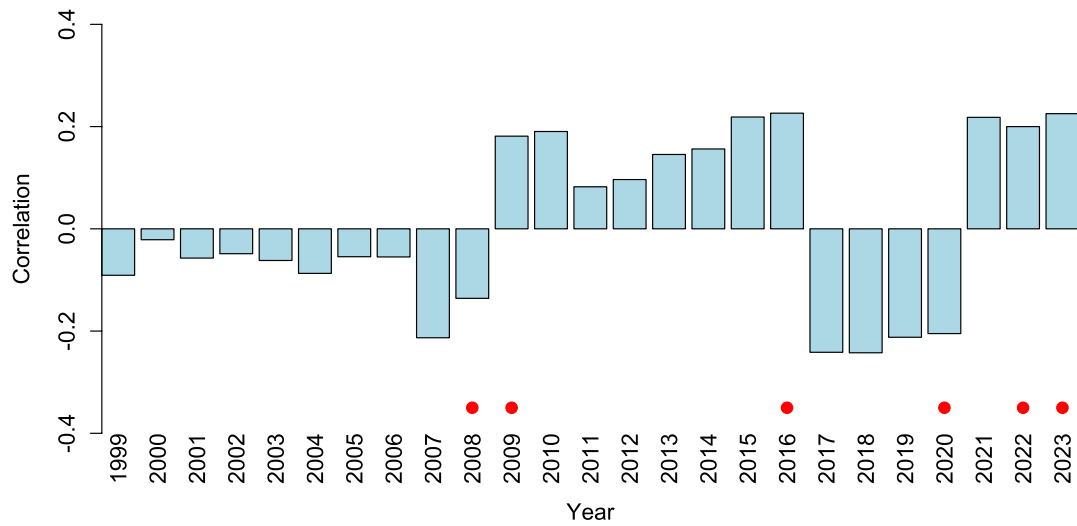


FIGURE A2 | State-level RV (natural log).

Panel A: Cross-sectional correlation



Panel B: Sentiment

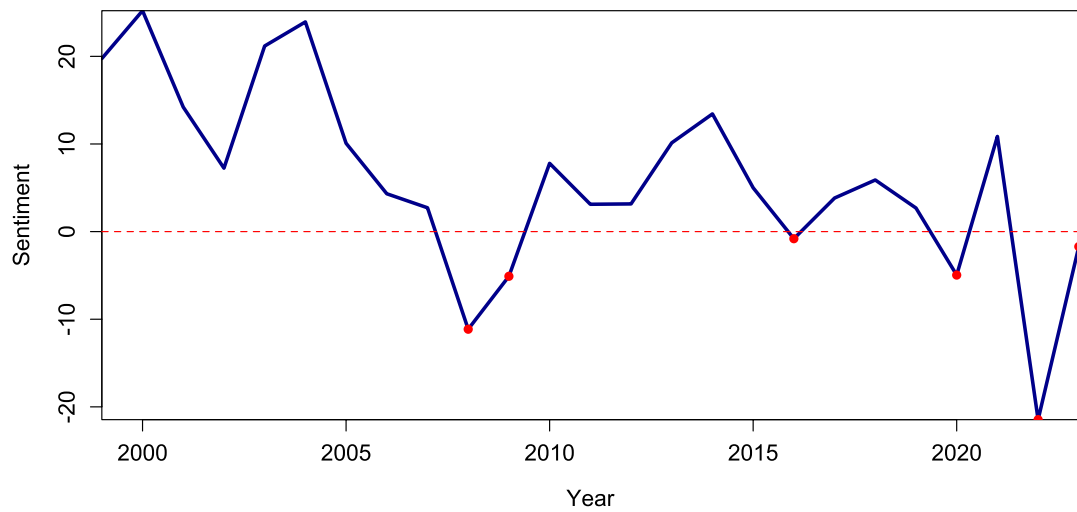


FIGURE A3 | Cross-Ssectional correlation of VIMP and PAI and sentiment over time. Panel A: Cross-sectional correlation. Panel B: Sentiment. The cross-sectional correlation is computed for every year across states. The red dots indicate years of low sentiment.

TABLE A1 | Definitions, construction, and data sources.

Variable	Symbol	Definition/Construction	Primary source
Aggregate realizedz volatility	$RV_{a,t}$	Monthly sum of squared daily log—returns of the CRSP value—weighted composite index.	CRSP via Kenneth French data library
State realizedz volatility	$RV_{s,t}$	For state i , monthly sum of squared daily log—returns of Bloomberg's cap—weighted equity index of firms headquartered in state i .	Bloomberg
Political alignment index	$PAI_{i,t}$	Measure (0–1) of a state's alignment with the incumbent presidential party: equal—weight average of governor party, state—legislature majorities, and share of federal delegation that matches the president.	Kim et al. (2012); Gross et al. (2016)
Variable importance	$VIMP_{i,t}$	Relative importance of $RV_{s,t}$ in predicting $RV_{a,t}$ from a 2000—tree random forest.	Authors' calculations
Coincident index	$CI_{i,t}$	Composite of non—farm payrolls, unemployment rate, average hours worked, and real wage income; normalizedz to track state GDP growth.	Federal Reserve Bank of Philadelphia (FRED)
House price return	$HR_{i,t}$	Log—return of the FHFA All—Transactions House—Price Index for state i (quarterly series interpolated to months).	FHFA house—price index database
Investor sentiment	$SENT_t$	Difference (Bullish—Bearish) in AAI Sentiment Survey; positive (negative) denotes high (low) sentiment regime.	AAII sentiment survey
Democrat—Republican Index	$DRI_{i,t}$	Share (0–1) of state institutional seats held by Democrats; constructed analogously to PAI to capture political color.	Kim et al. (2012) dataset
State policy uncertainty	$EPU_{i,t}$	News—based index of state—level economic—policy uncertainty; scaled to mean = 100 over 1987–2023.	Baker et al. (2022) state—EPU database

TABLE A2 | Descriptive statistics of VIMP and PAI.

Variable statistic	VIMP mean	VIMP median	VIMP sd	VIMP skew	VIMP max	VIMP min	PAI mean	PAI median	PAI sd	PAI skew	PAI max	PAI min
Alabama	0.0035	0.0023	0.0025	0.7330	0.0080	0.0011	0.4171	0.4286	0.3223	-0.1016	0.8393	0.0357
Alaska	0.0017	0.0014	0.0010	0.2731	0.0033	0.0006	0.5100	0.2500	0.4129	0.1056	1.0000	0.0000
Arizona	0.0039	0.0035	0.0020	0.5940	0.0084	0.0014	0.4282	0.3889	0.3167	0.0707	0.8889	0.0417
Arkansas	0.0017	0.0010	0.0015	1.4628	0.0063	0.0005	0.4600	0.3750	0.3576	0.2663	1.0000	0.0000
California	0.0178	0.0060	0.0225	1.6288	0.0889	0.0025	0.5459	0.6604	0.3758	-0.1657	0.9481	0.0283
Colorado	0.0027	0.0013	0.0039	2.4130	0.0154	0.0009	0.6170	0.7321	0.2952	-0.5239	0.9286	0.0833
Connecticut	0.0771	0.0765	0.0340	0.1605	0.1362	0.0270	0.6013	0.6667	0.3683	-0.2875	1.0000	0.0000
Delaware	0.0028	0.0016	0.0037	2.9935	0.0174	0.0011	0.5750	0.5000	0.3767	-0.1122	1.0000	0.0000
Florida	0.0786	0.0703	0.0372	0.1795	0.1451	0.0164	0.4521	0.2269	0.2966	0.1576	0.8796	0.0714
Georgia	0.0120	0.0109	0.0035	0.6109	0.0197	0.0076	0.4793	0.3571	0.3481	0.0942	0.9286	0.0893
Hawaii	0.0017	0.0016	0.0006	0.8067	0.0030	0.0010	0.5550	0.6250	0.4391	-0.1034	1.0000	0.0000
Idaho	0.0009	0.0008	0.0005	0.8722	0.0019	0.0004	0.4900	0.1250	0.5012	0.0637	1.0000	0.0000
Illinois	0.0606	0.0579	0.0451	2.3216	0.2353	0.0141	0.5107	0.5139	0.3136	-0.0292	0.9559	0.0694
Indiana	0.0013	0.0012	0.0005	3.1166	0.0036	0.0009	0.4422	0.4000	0.3007	0.2168	0.9444	0.0556
Iowa	0.0011	0.0010	0.0004	2.3094	0.0026	0.0008	0.4640	0.4250	0.2713	0.1234	0.9375	0.0000
Kansas	0.0021	0.0021	0.0007	0.0451	0.0034	0.0011	0.4275	0.3125	0.3566	0.1587	1.0000	0.0000
Kentucky	0.0014	0.0014	0.0004	1.5077	0.0029	0.0007	0.5483	0.4583	0.2099	0.2644	0.9583	0.1667
Louisiana	0.0040	0.0045	0.0013	-0.0152	0.0063	0.0021	0.3907	0.3929	0.1982	0.2175	0.7083	0.0417
Maine	0.0008	0.0005	0.0007	1.8340	0.0032	0.0003	0.4100	0.2500	0.2210	0.4588	0.7500	0.1250
Maryland	0.0166	0.0198	0.0080	-0.3224	0.0276	0.0041	0.5538	0.7188	0.3358	-0.0467	0.9688	0.0625
Massachusetts	0.0193	0.0071	0.0214	1.7487	0.0921	0.0045	0.5500	0.7500	0.3733	-0.0667	1.0000	0.0000
Michigan	0.0111	0.0113	0.0035	0.1430	0.0189	0.0045	0.4684	0.4000	0.1802	0.7249	0.8846	0.2750
Minnesota	0.0960	0.1218	0.0553	-0.3790	0.1569	0.0150	0.5675	0.6250	0.2196	-0.2164	0.9063	0.2188
Mississippi	0.0008	0.0008	0.0004	1.8506	0.0022	0.0005	0.4508	0.4000	0.3420	0.1533	0.9375	0.0625
Missouri	0.0170	0.0155	0.0048	1.1228	0.0291	0.0091	0.5536	0.5139	0.2551	-0.3217	0.9375	0.0625
Montana	0.0012	0.0011	0.0005	0.3965	0.0020	0.0007	0.4650	0.5000	0.2487	0.1898	0.8750	0.1250
Nebraska	0.0013	0.0011	0.0004	0.9647	0.0025	0.0009	0.3533	0.1250	0.3132	0.0706	0.7500	0.0000

(Continues)

TABLE A2 | (Continued)

Variable statistic	VIMP mean	VIMP median	VIMP sd	VIMP skew	VIMP max	VIMP min	PAI mean	PAI median	PAI sd	PAI skew	PAI max	PAI min
Nevada	0.0011	0.0009	0.0004	0.8389	0.0022	0.0006	0.5425	0.6250	0.2049	-0.8985	0.9375	0.0625
New Hampshire	0.0012	0.0009	0.0008	1.3564	0.0034	0.0006	0.5750	0.5000	0.2447	0.1279	1.0000	0.2500
New Jersey	0.0047	0.0036	0.0047	3.3433	0.0251	0.0020	0.4462	0.3846	0.3149	0.1720	0.9583	0.0208
New Mexico	0.0007	0.0005	0.0004	1.3566	0.0019	0.0003	0.5400	0.5417	0.2814	0.0239	1.0000	0.0000
New York	0.2114	0.2139	0.0517	0.0560	0.3106	0.1059	0.5595	0.5282	0.3164	-0.2793	0.9741	0.0556
North Carolina	0.0115	0.0079	0.0117	2.6053	0.0495	0.0041	0.4481	0.3750	0.2139	0.2238	0.7788	0.0577
North Dakota	0.0019	0.0018	0.0005	0.6655	0.0029	0.0012	0.4200	0.5000	0.3038	0.2974	1.0000	0.0000
Ohio	0.0202	0.0125	0.0198	2.2415	0.0948	0.0036	0.5189	0.5278	0.3290	0.0051	0.9167	0.1053
Oklahoma	0.0022	0.0020	0.0010	1.9000	0.0058	0.0013	0.3887	0.3000	0.3576	0.3559	1.0000	0.0000
Oregon	0.0040	0.0030	0.0025	1.1209	0.0116	0.0011	0.5567	0.5750	0.3610	-0.1118	0.9500	0.0500
Pennsylvania	0.1355	0.1305	0.0277	0.9849	0.2072	0.1005	0.4949	0.5000	0.2270	-0.0557	0.8810	0.1310
Rhode Island	0.0037	0.0018	0.0038	1.2667	0.0141	0.0007	0.5550	0.6250	0.3574	-0.1610	1.0000	0.0000
South Carolina	0.0021	0.0020	0.0005	0.3654	0.0033	0.0011	0.4714	0.5417	0.4050	-0.0012	0.9643	0.0357
South Dakota	0.0038	0.0042	0.0012	-0.7040	0.0053	0.0011	0.4500	0.3750	0.3662	0.1508	1.0000	0.0000
Tennessee	0.0514	0.0525	0.0099	-0.8151	0.0640	0.0308	0.3778	0.3611	0.3162	0.5764	0.9444	0.0278
Texas	0.0224	0.0148	0.0152	1.1677	0.0577	0.0095	0.4770	0.2667	0.3949	0.0715	0.9236	0.0703
Utah	0.0052	0.0052	0.0006	0.3004	0.0064	0.0043	0.4667	0.0833	0.4597	0.0710	1.0000	0.0000
Vermont	0.0008	0.0007	0.0005	0.7476	0.0018	0.0003	0.4850	0.6250	0.2916	0.0821	0.8750	0.0000
Virginia	0.0028	0.0027	0.0015	1.7627	0.0081	0.0011	0.5268	0.5568	0.2001	-0.0765	0.9091	0.0909
Washington	0.0015	0.0013	0.0006	0.6761	0.0030	0.0007	0.5072	0.6389	0.3561	-0.0301	0.9500	0.0750
West Virginia	0.0008	0.0009	0.0003	0.3433	0.0015	0.0004	0.4683	0.3750	0.3635	0.0379	0.9167	0.0833
Wisconsin	0.0677	0.0728	0.0197	-0.1977	0.0946	0.0322	0.4475	0.4375	0.2110	0.7790	0.9063	0.2188
Wyoming	0.0006	0.0005	0.0003	0.5152	0.0012	0.0002	0.4400	0.2500	0.4406	0.1317	1.0000	0.0000

TABLE A3 | Descriptive statistics of CI and HR.

Variable statistic	CI mean	CI median	CI sd	CI skew	CI max	CI min	HR mean	HR median	HR sd	HR skew	HR max	HR min
Alabama	0.0035	0.0023	0.0025	0.7330	0.0080	0.0011	0.4171	0.4286	0.3223	-0.1016	0.8393	0.0357
Alaska	0.0017	0.0014	0.0010	0.2731	0.0033	0.0006	0.5100	0.2500	0.4129	0.1056	1.0000	0.0000
Arizona	0.0039	0.0035	0.0020	0.5940	0.0084	0.0014	0.4282	0.3889	0.3167	0.0707	0.8889	0.0417
Arkansas	0.0017	0.0010	0.0015	1.4628	0.0063	0.0005	0.4600	0.3750	0.3576	0.2663	1.0000	0.0000
California	0.0178	0.0060	0.0225	1.6288	0.0889	0.0025	0.5459	0.6604	0.3758	-0.1657	0.9481	0.0283
Colorado	0.0027	0.0013	0.0039	2.4130	0.0154	0.0009	0.6170	0.7321	0.2952	-0.5239	0.9286	0.0833
Connecticut	0.0771	0.0765	0.0340	0.1605	0.1362	0.0270	0.6013	0.6667	0.3683	-0.2875	1.0000	0.0000
Delaware	0.0028	0.0016	0.0037	2.9935	0.0174	0.0011	0.5750	0.5000	0.3767	-0.1122	1.0000	0.0000
Florida	0.0786	0.0703	0.0372	0.1795	0.1451	0.0164	0.4521	0.2269	0.2966	0.1576	0.8796	0.0714
Georgia	0.0120	0.0109	0.0035	0.6109	0.0197	0.0076	0.4793	0.3571	0.3481	0.0942	0.9286	0.0893
Hawaii	0.0017	0.0016	0.0006	0.8067	0.0030	0.0010	0.5550	0.6250	0.4391	-0.1034	1.0000	0.0000
Idaho	0.0009	0.0008	0.0005	0.8722	0.0019	0.0004	0.4900	0.1250	0.5012	0.0637	1.0000	0.0000
Illinois	0.0606	0.0579	0.0451	2.3216	0.2353	0.0141	0.5107	0.5139	0.3136	-0.0292	0.9559	0.0694
Indiana	0.0013	0.0012	0.0005	3.1166	0.0036	0.0009	0.4422	0.4000	0.3007	0.2168	0.9444	0.0556
Iowa	0.0011	0.0010	0.0004	2.3094	0.0026	0.0008	0.4640	0.4250	0.2713	0.1234	0.9375	0.0000
Kansas	0.0021	0.0021	0.0007	0.0451	0.0034	0.0011	0.4275	0.3125	0.3566	0.1587	1.0000	0.0000
Kentucky	0.0014	0.0014	0.0004	1.5077	0.0029	0.0007	0.5483	0.4583	0.2099	0.2644	0.9583	0.1667
Louisiana	0.0040	0.0045	0.0013	-0.0152	0.0063	0.0021	0.3907	0.3929	0.1982	0.2175	0.7083	0.0417
Maine	0.0008	0.0005	0.0007	1.8340	0.0032	0.0003	0.4100	0.2500	0.2210	0.4588	0.7500	0.1250
Maryland	0.0166	0.0198	0.0080	-0.3224	0.0276	0.0041	0.5538	0.7188	0.3358	-0.0467	0.9688	0.0625
Massachusetts	0.0193	0.0071	0.0214	1.7487	0.0921	0.0045	0.5500	0.7500	0.3733	-0.0667	1.0000	0.0000
Michigan	0.0111	0.0113	0.0035	0.1430	0.0189	0.0045	0.4684	0.4000	0.1802	0.7249	0.8846	0.2750
Minnesota	0.0960	0.1218	0.0553	-0.3790	0.1569	0.0150	0.5675	0.6250	0.2196	-0.2164	0.9063	0.2188
Mississippi	0.0008	0.0008	0.0004	1.8506	0.0022	0.0005	0.4508	0.4000	0.3420	0.1533	0.9375	0.0625
Missouri	0.0170	0.0155	0.0048	1.1228	0.0291	0.0091	0.5536	0.5139	0.2551	-0.3217	0.9375	0.0625
Montana	0.0012	0.0011	0.0005	0.3965	0.0020	0.0007	0.4650	0.5000	0.2487	0.1898	0.8750	0.1250
Nebraska	0.0013	0.0011	0.0004	0.9647	0.0025	0.0009	0.3533	0.1250	0.3132	0.0706	0.7500	0.0000
Nevada	0.0011	0.0009	0.0004	0.8389	0.0022	0.0006	0.5425	0.6250	0.2049	-0.8985	0.9375	0.0625

(Continues)

TABLE A3 | (Continued)

Variable statistic	CI mean	CI median	CI sd	CI skew	CI max	CI min	HR mean	HR median	HR sd	HR skew	HR max	HR min
New Hampshire	0.0012	0.0009	0.0008	1.3564	0.0034	0.0006	0.5750	0.5000	0.2447	0.1279	1.0000	0.2500
New Jersey	0.0047	0.0036	0.0047	3.3433	0.0251	0.0020	0.4462	0.3846	0.3149	0.1720	0.9583	0.0208
New Mexico	0.0007	0.0005	0.0004	1.3566	0.0019	0.0003	0.5400	0.5417	0.2814	0.0239	1.0000	0.0000
New York	0.2114	0.2139	0.0517	0.0560	0.3106	0.1059	0.5595	0.5282	0.3164	-0.2793	0.9741	0.0556
North Carolina	0.0115	0.0079	0.0117	2.6053	0.0495	0.0041	0.4481	0.3750	0.2139	0.2238	0.7788	0.0577
North Dakota	0.0019	0.0018	0.0005	0.6655	0.0029	0.0012	0.4200	0.5000	0.3038	0.2974	1.0000	0.0000
Ohio	0.0202	0.0125	0.0198	2.2415	0.0948	0.0036	0.5189	0.5278	0.3290	0.0051	0.9167	0.1053
Oklahoma	0.0022	0.0020	0.0010	1.9000	0.0058	0.0013	0.3887	0.3000	0.3576	0.3559	1.0000	0.0000
Oregon	0.0040	0.0030	0.0025	1.1209	0.0116	0.0011	0.5567	0.5750	0.3610	-0.1118	0.9500	0.0500
Pennsylvania	0.1355	0.1305	0.0277	0.9849	0.2072	0.1005	0.4949	0.5000	0.2270	-0.0557	0.8810	0.1310
Rhode Island	0.0037	0.0018	0.0038	1.2667	0.0141	0.0007	0.5550	0.6250	0.3574	-0.1610	1.0000	0.0000
South Caroli	0.0021	0.0020	0.0005	0.3654	0.0033	0.0011	0.4714	0.5417	0.4050	-0.0012	0.9643	0.0357
South Dakota	0.0038	0.0042	0.0012	-0.7040	0.0053	0.0011	0.4500	0.3750	0.3662	0.1508	1.0000	0.0000
Tennessee	0.0514	0.0525	0.0099	-0.8151	0.0640	0.0308	0.3778	0.3611	0.3162	0.5764	0.9444	0.0278
Texas	0.0224	0.0148	0.0152	1.1677	0.0577	0.0095	0.4770	0.2667	0.3949	0.0715	0.9236	0.0703
Utah	0.0052	0.0052	0.0006	0.3003	0.0064	0.0043	0.4667	0.0833	0.4597	0.0710	1.0000	0.0000
Vermont	0.0008	0.0007	0.0005	0.7476	0.0018	0.0003	0.4850	0.6250	0.2916	0.0821	0.8750	0.0000
Virginia	0.0028	0.0027	0.0015	1.7627	0.0081	0.0011	0.5268	0.5568	0.2001	-0.0765	0.9091	0.0909
Washington	0.0015	0.0013	0.0006	0.6762	0.0030	0.0007	0.5072	0.6389	0.3561	-0.0301	0.9500	0.0750
West Virginia	0.0008	0.0009	0.0003	0.3433	0.0015	0.0004	0.4683	0.3750	0.3635	0.0379	0.9167	0.0833
Wisconsin	0.0677	0.0728	0.0197	-0.1977	0.0946	0.0322	0.4475	0.4375	0.2110	0.7790	0.9063	0.2188
Wyoming	0.0006	0.0005	0.0003	0.5152	0.0012	0.0002	0.4400	0.2500	0.4406	0.1317	1.0000	0.0000

TABLE A4 | Results of panel regressions after dropping New York, Minnesota, and Pennsylvania.

Variables	(1)	(2)	(3)
	All sample	High sentiment	Low sentiment
	VIMP	VIMP	VIMP
PAI	−0.00324*** (0.00096)	−0.00388*** (0.00122)	−0.00136 (0.00132)
CI	0.00360 (0.00279)	−0.06071** (0.02623)	0.00371 (0.00278)
HR	−0.00616 (0.00588)	0.00939 (0.00995)	−0.01930*** (0.00636)
State Fixed Effects	Yes	Yes	Yes
Observations	1175	893	282
Adj. R^2	0.732	0.697	0.884

Note: ** (***) Denotes significance at the 5% (1%) level.