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Abstract

This paper extends the literature on the nexus between political geography and financial markets 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 political alignment. Using monthly data for the period from February 1994 to March 2023 and a machine learning technique called random forests, we 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 substantial variation over time, with the state of New York playing a prominent role. Further analysis shows that stronger political alignment of a state with the ruling party is associated with a lower contribution of the state's realized volatility to aggregate stock market volatility, highlighting the role of risk effects associated with the political geography of firms. Finally, we show that the negative link between the political alignment of a state and the importance of that state's realized volatility over aggregate stock market volatility 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. Our findings presents new insight to the risk-based arguments that associate political geography with stock market dynamics.

JEL Classifications: C22, C23, C51, C53, G10, D81.

Keywords: Stock market volatility; Random forests; Political alignment; Investor sentiment.

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1 Introduction

The effect of presidential politics on the stock market is well documented in the literature. While one strand of this literature focuses on the aggregate stock market performance during presidential cycles, i.e., Democratic vs. Republican administrations, (see, for example, Santa-Clara and Valkanov (2003), Pástor and Veronesi (2013, 2020)), other studies 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 the 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 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 its implications for risk, the literature still lacks a direct connection to stock market 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. However, a straightforward link to how this dynamic affects stock market volatility has yet to be firmly established. 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. By doing so, our study aims to provide new insight to the risk-based

[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)).

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 (Granger and Poon, 2003; Rapach et al., 2008). The wide ranging applications of volatility in different contexts has thus 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 (see, for example, the discussions in Engle and Rangel (2008), Rangel et al. (2011), Engle et al. (2013), Ben Nasr et al. (2012, 2016), Salisu et al. (2022), Segnon et al. (2024)). In the context of multivariate models, several researchers (Tsuji, 2012; Demirer et al., 2019; Lu and Ma, 2023; Niu et al., 2023, 2024) have emphasized the role of industry-level volatility information for aggregate stock-market variability of the United States (US).[2]

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 that portfolios constructed at the state level can also be used to predict volatility at the aggregate level by after 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;

[2] In this regard, Demirer et al. (forthcoming), 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.

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 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.

In our empirical analysis, we use a machine learning technique known as random forests (Breiman, 2001) to explain the realized volatility of aggregate stock market returns. 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 analyze the link between overall and state-level monthly realized volatilities, as measured by the sum of squared daily log-returns over a month. 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 realized volatility 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. Finally, random forests always yield fits of RV that are non-negative, i.e., estimated of observed volatility that are consistent with econometric theory.

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 relate the time-varying (recursive-window-based) importance of the volatilities at the state level, derived from the random forests model, in explaining aggregate level RV, using a proxy for state level uncertainty involving economic policy decisions. The motivation for this approach is derived from the general equilibrium models of Pástor and Veronesi (2012, 2013) which feature uncertainty regarding government policies, to theoretically show that political uncertainty raises the volatility of the stochastic discount factor, raising the risk premia applied to valuations, thus contributing to volatility in stock returns. In this regard, 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 argument put forth in this regard is largely a risk-based one 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 can 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 appliation, 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. To take our insights one step further, as another novelty to the literature on the nexus between political geography and stock markets, we also investigate the role of investor sentiment-regimes as a determinant of the effect of PAI on the predictive link between the state- and aggregate-level stock market volatility. The motivation to extend the analysis sentiment regimes 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 the investors - an observation also made 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 stock market stability 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 reduces economic uncertainty, eventually resulting in a lower contribution to aggregate stock-market volatility. This finding supports the finding 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 describe how random forests can be used to trace out the importance of state-level realized volatilities for aggregate stock-market volatility. In Section 3, we presents our empirical results, both for random forests and for the panel analysis. In Section 4, we conclude the paper with directions for future research.

2 Data & Methodology

2.1 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.[3] Our monthly sample for the aggregate- and state-level RVs cover the period of February 1994 to March 2023, based on data availability at the time of writing this paper.

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

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

of the state, we utilize the monthly state-level political alignment indexes (PAI) originally developed by Kim et al. (2012), and extended in more recent studies by Gross et al. (2016), Douidar et al. (2023), and Magerakis et al. (2023).[4] In essence, PAI is a state-level measure of political alignment with the party of the President, thus capturing the proximity to political power. 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.[5]

2.2 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 the random forest technique. 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, $RV_{s_i,t}, i = 1, 2, ..., 50$. 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

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

[5]Specifically, PAI is constructed as follows: $PAI = (1/4) \times Senators + 1/4 \times Representatives + 1/4 \times Governor + 1/4 \times (1/2 \times Statesenators + 1/2 \times Staterepresantatives]$, 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 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.

model is given by the following equation:

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

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 50 US 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:

$$f(RV_{a,t-1}, RV_{s_1,t}, RV_{s_2,t}, ..., RV_{s_{50},t}) = \sum_k T_k, \quad k = 1, 2, ...m, \quad j \neq i. \tag{2}$$

Estimating the function f, by means of a 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. (1983)).

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 $x = RV_{a,t-1}, RV_{s_1,t}, RV_{s_2,t}, ..., RV_{s_50,t}$. The optimal pair, $\{s^*, p^*\}$, solves the following minimization problem:

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

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:

$$T\left(\mathbf{x}_i, \{R_l\}_1^L\right) = \sum_{l=1}^{L} \overline{RV_{al}} \mathbf{1}(\mathbf{x}_i \in R_l), \tag{4}$$

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 upon 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 2,000 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 tune 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.

3 Empirical Results

3.1 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.

– Figure 1 about here. –

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 about here. –

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 fifty 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.

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 up 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.

3.2 The Role of Political Alignment across Investor Sentiment Regimes

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 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 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 about here. –

Figure 3 summarizes the correlation of the importance of the fifty 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. 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 dynamics.[6] The panel regression model can be formally represented as follows:

$$VIMP_{it} = \alpha_i + \beta PAI_{it} + \delta Z_{it} + \varepsilon_{it}, \tag{5}$$

where $VIMP_{it}$ is the variable importance of state i at time t, PAI_{it} is the political alignment index and Z_{it} stands for the control variables, which involves the state-level coincident indicator (CI), sourced from the FRED database of the Federal Reserve Bank of St. Louis (originally created by the Federal Reserve Bank of Philadelphia), and a well-established regional leading indicator, i.e., the log-returns (Emirmahmutoglu et al., 2016) of the Federal Housing Finance Agency (FHFA) All Transactions Index of house prices (HR).[7] Note that in this formulation, α_i captures state-specific effects and ε_{it} is

[6]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).

[7]The 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:

the error term.

– Table 1 about here. –

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 on 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. 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.[8]

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 co-

https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

[8]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.

efficients 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.

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 the political alignment and stock market volatility. It can be argued that investor sentiment, a crucial factor that drives trading behavior of investors, can considerably alter the influence of political elements on financial markets.[9] 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

[9]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.

sentiment periods.[10] 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 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 than during high-sentiment periods. 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. 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. Nevertheless, our findings 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 highlights the multifaceted nature of factors influencing stock market dynamics and the need to consider them in conjunction with one another for a more comprehensive understanding.

[10]The data can be downloaded from: https://www.aaii.com/sentimentsurvey/sent_results.

4 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, leads 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.[11]

[11] 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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Table 1: Results of panel regressions

	(1)	(2)	(3)
	All Sample	High Sentiment	Low Sentiment
Variables	VIMP	VIMP	VIMP
PAI	-0.00318**	-0.00415**	-0.000673
	(0.00129)	(0.00164)	(0.00199)
CI	0.000334	0.000662	0.000197
	(0.00395)	(0.0326)	(0.00364)
HR	-0.00188	0.00181	-0.00416
	(0.00687)	(0.0117)	(0.00818)
State Fixed Effects	Yes	Yes	Yes
Observations	1,250	950	300
Adj. R^2	0.852	0.827	0.935

Figure 1: Estimated importance of state-level realized volatilities

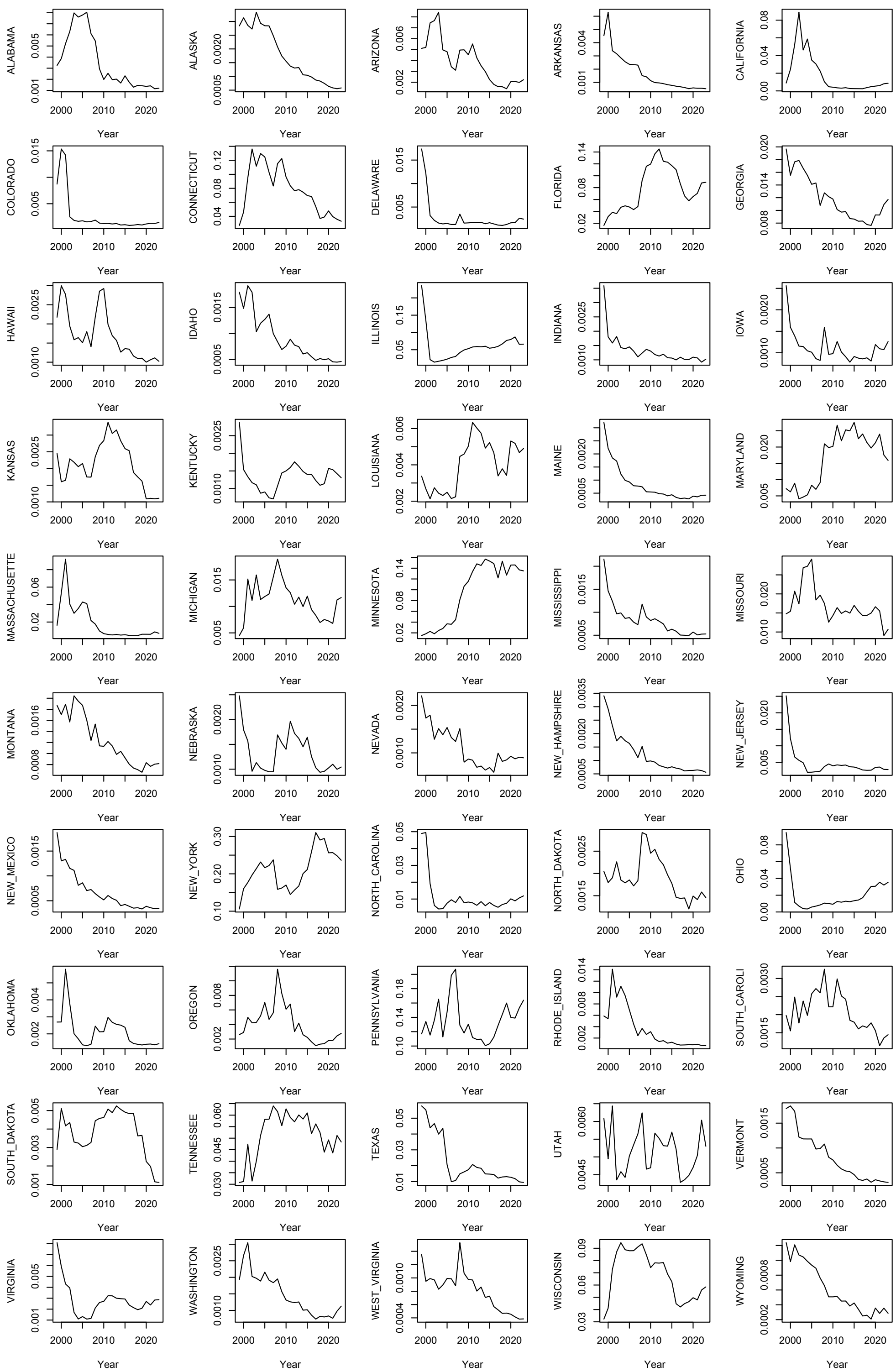
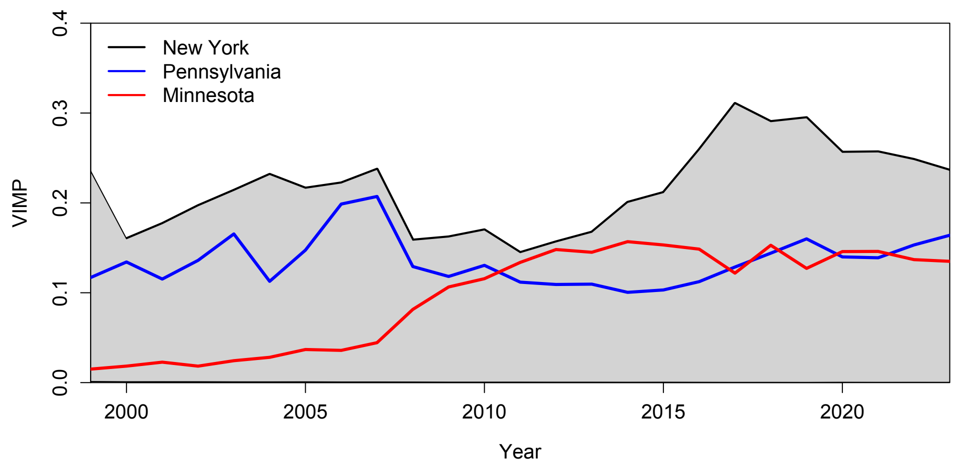


Figure 2: Cross-sectional dispersion of the importance of state-level realized volatilities

Panel A: Top three states



Panel B: Cross-sectional standard deviation

Figure 3: Correlation of importance of state-level realized volatilities with PAI