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Presidential Elections and the Stock Market: Comparing Markov-Switching and Fractionally Integrated GARCH Models of Volatility

David Leblang
*Department of Political Science, University of Colorado,
106 Ketchum Hall, Boulder, CO 80309
e-mail: leblang@colorado.edu*

Bumba Mukherjee
*Department of Political Science, Florida State University,
554 Bellamy Building, Tallahassee, FL 32306
e-mail: smukherj@mailer.fsu.edu*

Existing research on electoral politics and financial markets predicts that when investors expect left parties—Democrats (US), Labor (UK)—to win elections, market volatility increases. In addition, current econometric research on stock market volatility suggests that Markov-switching models provide more accurate volatility forecasts and fit stock price volatility data better than linear or nonlinear GARCH (generalized autoregressive conditional heteroskedasticity) models. Contrary to the existing literature, we argue here that when traders anticipate that the Democratic candidate will win the presidential election, stock market volatility decreases. Using two data sets from the 2000 U.S. presidential election, we test our claim by estimating several GARCH, exponential GARCH (EGARCH), fractionally integrated exponential GARCH (FIEGARCH), and Markov-switching models. We also conduct extensive forecasting tests—including RMSE and MAE statistics as well as realized volatility regressions—to evaluate these competing statistical models. Results from forecasting tests show, in contrast to prevailing claims, that GARCH and EGARCH models provide substantially more accurate forecasts than the Markov-switching models. Estimates from all the statistical models support our key prediction that stock market volatility decreases when traders anticipate a Democratic victory.

1 Introduction

In recent years, political scientists from different subfields have started analyzing how certain exogenous and endogenous variables affect the variance and volatility of the dependent variable. For example, recent work in the study of macropartisanship has

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focused on the degree of persistence and variation of partisanship at the aggregate and the individual level (Mackuen et al. 1989; Stimson et al. 1995; Box-Steffensmeier and Smith 1996; Green et al. 2002). Likewise, numerous studies focus on volatility in presidential approval ratings and public opinion across time (Beck 1991; Brace and Hinckley 1991, 1992; Brehm and Gronke 1994; Jackman 1995). In comparative political economy, political scientists have examined how institutions, elections, and government partisanship affect the volatility of financial markets and economic growth (Freeman et al. 1999, 2000; Herron 2000; Quinn and Woolley 2001).

Although scholars have increasingly focused on how best to statistically model volatility, few have attempted to estimate the generalized autoregressive conditional heteroskedasticity (GARCH) model as a tool for studying volatility.[1] This is surprising because it is well known that the GARCH model—developed by Engle (1982) more than two decades ago—provides a powerful and parsimonious method to examine the variance and volatility of the dependent variable in time-series data. Instead, political scientists who, for example, study how democratic politics affects financial markets use estimation techniques such as nonlinear least squares (Herron 2000) and the Markov-switching model (Freeman et al. 1999, 2000). In other areas, Box-Steffensmeier and Smith (1996) use Sowell's (1992) method to examine heteroskedasticity in individual partisan identification, while the error-correction model has often been used to examine volatility in presidential approval ratings and partisanship (Beck 1991; Stimson et al. 1995).

Given the surprising lack of attention paid to GARCH models not only in political science in general but also in studies of democratic politics and financial markets—our main focus—this paper has two objectives. First, at a broader level, we introduce readers to a detailed formal treatment of various GARCH models such as the standard GARCH, exponential GARCH (EGARCH), and the fractionally integrated exponential GARCH models, which we believe are useful tools for examining the volatility of the dependent variable, especially in time-series data. Second, we focus primarily on comparing the forecasting performance of a variety of GARCH models to the Markov-switching model using two data sets that contain information on the impact of elections, political uncertainty, and partisan expectations on stock market volatility during the 2000 presidential election. We do so because numerous scholars—who statistically examine the impact of political variables on the volatility of financial markets—favor the use of Markov-switching models, claiming that these models are more accurate and provide better forecasts than a variety of linear and nonlinear GARCH models (Turner et al. 1989; Van Norden and Schaller 1997; Sola and Timmerman 1994; Kim et al. 2002). For instance, in their empirical analysis of exchange rate volatility, Freeman et al. (2000, p. 459) find that Markov-switching models fit the data better than GARCH models.[2] Likewise, Sola and Timmerman (1994) compare EGARCH and Markov-switching models and find that the latter fit the data on daily U.S. stock returns better than various EGARCH models that they estimate.

The claims of Freeman et al. (2000) and Sola and Timmerman (1994) are unwarranted. This is because there is almost no work that seriously evaluates the statistical merits—especially the relative forecasting performance—of these two competing sets of models

[1]Leblang and Bernhard (2000) use GARCH models to estimate the impact of partisanship, elections, and public opinion on exchange rate volatility, while Brehm and Gronke (1994) use an ARCH model to examine the volatility of presidential approval. These studies are, however, the exception rather than the norm.

[2]The finding of Freeman et al. (2000) is largely driven by the fact that their exchange-rate series does not contain ARCH effects (see Freeman et al. 2000, p. 459n20). We believe that their finding is interesting but rare, since arguably most financial time-series data are likely to contain ARCH effects.

(GARCH versus Markov-switching).[3] Hence, as noted above, we address here the aforementioned lacuna in the empirical literature on politics and financial markets by examining in some depth whether Markov-switching models provide more accurate forecasts than GARCH models (or vice versa).

More specifically, we use several GARCH, EGARCH, FIEGARCH, and Markov-switching models to analyze the impact of electoral information, uncertainty, and partisanship on stock price volatility during the 2000 U.S. presidential election. We find, using two different data sets, that GARCH-type models outperform Markov-switching models in a number of important ways. Results from forecasting tests—which included root mean square error (RMSE) and mean absolute error (MAE) statistics as well as realized volatility regressions—conducted on a set of out-of-sample observations and on the entire sample (for both data sets) show that the GARCH and especially the EGARCH models more accurately forecast volatility than Markov-switching models. We will discuss later why the GARCH models provide more accurate forecasts than the Markov-switching models in our case and why this finding may be generalizable.

In addition, a central claim (and empirical finding) in the literature on politics and financial markets is that the prices of various financial assets—exchange rates, stock indices, bond prices—decrease, but become increasingly volatile when traders anticipate electoral victory by a "left" party, i.e., Democrats in the United States or Labor in Britain (Alesina et al. 1997; Freeman et al. 2000; Herron 2000). We take issue with this claim and argue that stock price volatility decreases when traders anticipate that the Democratic candidate will win the presidential election. Interestingly, estimates from our Markov-switching and various GARCH models statistically support our theoretical claim.

This article is organized as follows. In the next section, we briefly present a literature review and the theoretical rationale underlying the hypotheses that we test here. This is followed by a discussion of the substantive and econometric reasons that motivated our choice of estimating GARCH and Markov-switching models. In Section 4, we describe the data, variables, statistical models—GARCH, EGARCH, FIEGARCH, and Markov switching—and results obtained from estimating these models. We report and compare the forecasts from all the estimated models in Section 5 and discuss why the Markov-switching model provides poor forecasts. We end with a brief conclusion.

2 Literature Review and Testable Hypotheses

The causal logic underlying the central claim in the Democratic politics and financial markets literature—that the value of financial assets (stocks, bonds, and exchange rates) decreases but becomes increasingly volatile under left-wing governments—is rooted in the vast literature on the effects of partisanship on the economy (Alesina and Rosenthal 1995; Franzese 2002). Specifically, Herron (2000) and Freeman et al. (2000) assume that inflation under left-wing administrations is consistently higher than under right-wing administrations.[4] Based on this assumption, they argue that forward-looking traders in the

[3]To the best of our knowledge, only Pagan and Schwert (1990) have compared the forecasting performance of GARCH, EGARCH, and Markov-switching models by using prewar U.S. stock return data. Our article, however, differs from their work because our Markov-switching model is estimated with time-varying, not constant, transition probabilities. Pagan and Schwert (1990) also do not compare forecasts between FIEGARCH and Markov-switching models as we do here.

[4]For the United States, Alesina and Rosenthal (1995, p. 184) find that "the negative coefficient on the variable R implies that inflation has been lower with Republican administrations than with Democratic administrations."

United States (Britain) rationally expect Democrats (Labor) to implement policies that engender higher inflation and that are detrimental for the stock market.

Since traders typically "lock in" expectations of higher inflation under a Democratic (Labor) administration and when they anticipate a Democratic (Labor) victory, they are also likely to rationally expect a decline in the real returns of stocks. This decreases the demand for stocks and causes prices to fall. Ex ante expectations of lower stock returns under left-wing administrations engender frantic stock selling by traders that can lead to higher stock market volatility.[5] In contrast, traders expect stock returns to increase under right-wing administrations and when they anticipate a Republican (Conservative) victory. This is because right-wing governments are associated with lower inflation and taxes, which benefit the stock market. Expectation of higher stock returns under right-wing governments reduces uncertainty and helps to stabilize stock prices.

There are two main flaws in the arguments posited above. First, if traders anticipate stock returns to decline under a Democratic (Labor) government, they have rational incentives to reduce their level/volume of trading in order to decrease their average (and marginal) trading costs to minimize ex post losses. If the volume of trading declines, stock price volatility will logically decrease (and not increase), since it is well known from existing empirical studies that a decline in trading volume leads to lower market volatility (Gallant et al. 1992; Foster and Vishwanathan 1995). Second, if traders expect higher stock returns under a Republican administration, it is likely that this will lead to a surge in the inflow of capital and investment into the stock market. As shown empirically by many financial economists, a sudden inflow of capital into the stock market leads to rapid adjustment of prices of financial assets and higher trading volume, which consequently increases stock market volatility.[6]

Building on the criticisms discussed above, we have constructed a model of speculative trading between a group of risk-neutral traders and a market maker. The setup of the formal model and its equilibrium results can be found at the *Political Analysis* Web site. We provide a brief intuition of the model's key predictions and causal logic here. Specifically, in the model, traders and the market maker observe exogenous public signals of electoral information, i.e., signals that convey information about which candidate will win the election and the policies that the victorious candidate will implement ex post. Results from the model provide the following insights.

First, we claim that when traders and the market maker expect the Democratic candidate to win the presidential election, stock price volatility decreases. The intuition here is that ex ante, traders expect the Democratic presidential candidate to implement left-of-center policies—i.e., policies that lead to higher inflation—once she or he wins the election. Since higher inflation decreases the real returns from stocks, the expected value of the sum of discounted future dividends declines. We prove in our model that when traders expect future dividends to decline under a Democratic administration, they have incentives to reduce their volume of trading in order to stabilize their profits and reduce their transaction costs of trading. Moreover, they have incentives to "hedge their bets" and reduce their demand for stocks in this case. We find that the volatility of stock prices declines in equilibrium when traders rationally seek to reduce their transaction costs and their volume of trading.

[5]A rapid jump in selling activity implies higher trading volume, which is strongly correlated with high stock price volatility (Gallant et al. 1992; Foster and Vishwanathan 1995).

[6]See, for example, Kothari and Shanken (1992) and Timmerman (1996).

Second, our model proves that market volatility increases when traders expect the Republican candidate to win. This result crucially relies on two key findings from the literature on rational partisan theory[7] and increasing partisan polarization of post-election policies by Democratic and especially Republican administrations.[8] These are: (1) Republican presidents aggressively attempt to reduce inflation after winning elections (Alesina and Rosenthal 1995, p. 184), and (2) successive Republican administrations since the 1970s have tended to deviate more toward the right by following more conservative social and economic policies after winning elections.[9]

Based on these two findings, we argue that traders rationally anticipate that the Republican presidential candidate will pursue more conservative economic policies that promote lower taxes and inflation after winning elections. These policies are consequently expected to generate higher stock returns and a bull market. Ex ante expectations of a bull market increase the demand for stocks and lead to more volatile trading behavior that is characterized by rapid, short-term switching between buying and selling stocks. Our model proves that such volatile trading patterns increase the volatility in the price of traded assets and thus engender higher stock price volatility.

Comparative statics from our model show that higher ex ante uncertainty about which candidate will win the election engenders increased stock price volatility.[10] They also show a monotonic relationship between the arrival of political information about the potential electoral outcome and stock price volatility. Our model thus provides the following hypotheses that we test by estimating GARCH and Markov-switching models:

Hypothesis 1: Information arrival about electoral outcomes affects stock price volatility.

Hypothesis 2: Increased uncertainty about the electoral result increases volatility.

Hypothesis 3: If traders expect the Democratic candidate to win, then volatility decreases.

Hypothesis 4: If traders expect the Republican candidate to win, then volatility increases.

3 Why GARCH and Markov-Switching Models?

We chose to estimate and compare the forecasting performance of various GARCH and Markov-switching models for numerous substantive and econometric reasons. From a substantive viewpoint, two factors have influenced our choice of the two estimation techniques. First, as noted in the introduction, detailed statistical examination of variance/volatility dynamics in time-series data has emerged as an important area of inquiry in political science. Moreover, scholars such as DeBoef (2000) and Box-Steffensmeier and Smith (1996) have emphasized that time-series data in political science—for example, in the study of macropartisanship and presidential approval—are characterized by long memory in volatility, i.e., fractional integration, which may not be adequately captured by conventional estimation methods such as the error-correction model, for example.

Although political scientists increasingly focus on the volatility of their respective dependent variable and recognize the presence of long memory in volatility, they largely do not employ GARCH or Markov-switching models in their empirical analyses.[11] This is

[7]For details, see Hibbs (1987), Alesina and Rosenthal (1995) and Alesina et al. (1997).
[8]For this, see McCarty et al. (2002) and Jacobs and Shapiro (2000).
[9]For details, see McCarty et al. (2002) and Jacobs and Shapiro (2000).
[10]This concurs with the results of McGillivray (2003) and Freeman et al. (2000).
[11]The exception is Freeman et al. (2000), who estimate a Markov-switching model to estimate currency market volatility. Freeman et al. do not estimate GARCH models.

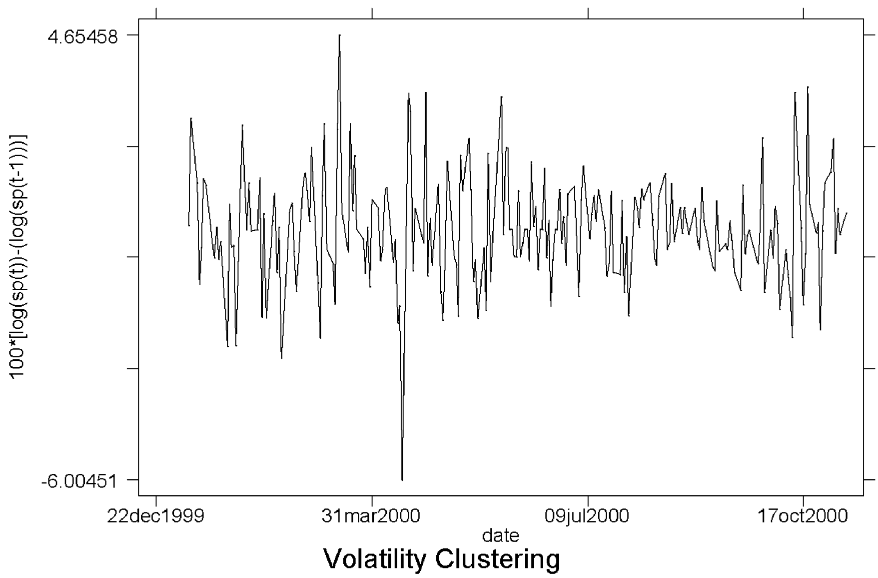

Fig. 1 Volatility clustering (log change of daily closing prices of S & P 500 Index, Jan. 2000–Nov. 2000).

surprising, because various GARCH and Markov-switching models provide a powerful, flexible, and parsimonious approximation to capture conditional variance/volatility dynamics. In addition, fractionally integrated GARCH models directly capture long memory in volatility that allows for more accurate estimation. Finally, both GARCH and Markov-switching models jointly capture the conditional mean and variance dynamics as well as nonlinearities in time-series data. This makes them well suited to analyze, for example, the macropartisanship series. Hence a broader objective of this article is to systematically describe the formal setup of linear and nonlinear (i.e., exponential) GARCH models as well as fractionally integrated (exponential) GARCH and Markov-switching models. This can be useful for political scientists who examine volatility dynamics in time-series data.

Second, and more specifically, scholars who have examined the impact of political uncertainty and government partisanship on the volatility of financial markets have not estimated GARCH models in their statistical analyses. Instead, techniques such as nonlinear least squares (Herron 2000) and the Markov-switching model (Freeman et al. 2000) have been used to study the effect of democratic politics on financial markets. This is problematic, because the failure to estimate GARCH models could lead to the fallacious substantive empirical result that financial market volatility (which includes stock prices) increases when agents expect the left-wing party (Democrats or Labor) to win elections. Indeed, as we will show, GARCH and fractionally integrated exponential GARCH models more accurately capture the degree and persistence of volatility in high-frequency time-series data compared to other estimation techniques used in the empirical literature. This has important substantive implications, because we find from estimating our GARCH models that market volatility decreases when agents expect the left-wing party to win elections, which confirms our theoretical rationale.

Our choice of GARCH and Markov-switching models has also been influenced by three features of the data that are common to time-series processes. First, our data are characterized by volatility clustering, which is common to most high-frequency financial time-series data. This is illustrated in Fig. 1, where we graph the returns (log changes in daily closing prices

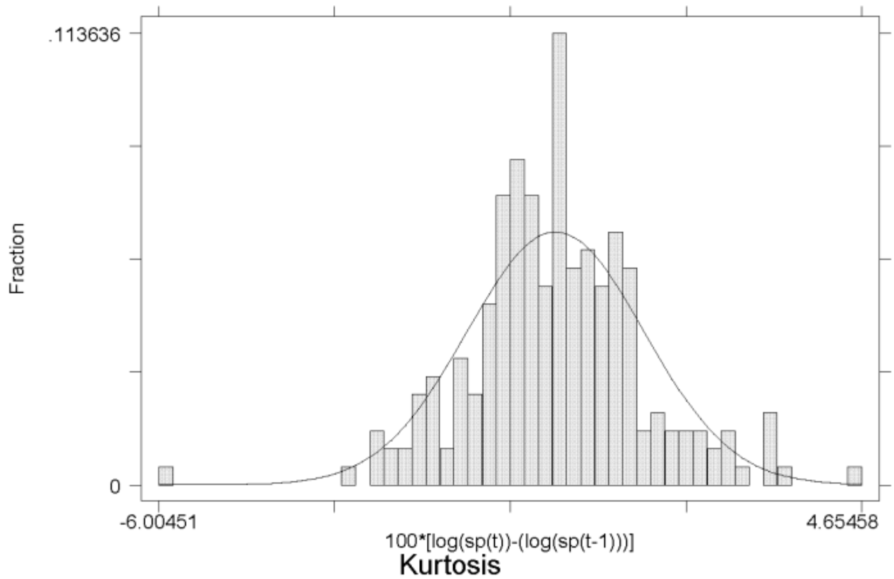

Fig. 2 Kurtosis in daily sample.

multiplied by 100) on the Standard and Poor's (S&P) 500 index—our dependent variable—from our sample of daily observations dated from January 6 to November 7, 2000. Volatility clustering is immediately apparent in Fig. 1, where one can observe that large (small) changes in the S & P 500 index are followed by large (small) changes.

A second feature of our financial time-series data is that it exhibits excess kurtosis or "fat tails" (the relatively frequent occurrence of extreme values in the conditional second moments). This is illustrated in Fig. 2, where the empirical distribution of the predicted residuals that are obtained by regressing changes in the S & P 500 index (from June 1 to June 11, 2000) on a constant and an error term. The excess mass in the tails of the distribution in Fig. 2 is clearly visible. As shown in Bollerslev (1986, 1990), we need to estimate GARCH models in order to account not only for volatility clustering but also for such kurtosis in the data. Indeed, the unconditional distribution of a GARCH process is symmetric and leptokurtic, which is precisely the feature that allows GARCH models to account for volatility clustering and kurtosis. In particular, the unconditional leptokurtosis of GARCH processes follows from the persistence in the conditional variance, which produces the clusters of low and high volatility in the center and in the tails of the unconditional distribution. Similarly, Meese (1990, pp. 129–130) and Hamilton (1989, 1994) have proved that Markov-switching models can also account for the fat-tailed distributions of stock returns, which is prevalent in our data.

Third, to check for the presence of ARCH in the residuals, we employed Engle's (1982) Lagrange-multiplier (LM) test,[12] which is as follows: (1) regress Y on X and obtain residuals, ε_t; (2) regress ε_t^2 on p lags of ε_t^2; that is, $\varepsilon_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \cdots \beta_{p\varepsilon_{t-1}^2}$; (3) assess the joint significance of $\beta_1 - \beta_p$. If the coefficient is statistically different from 0, then the null of homoskedasticity can be rejected. In the case of our data, Engle's LM test clearly indicates the presence of ARCH in the residuals. This necessitates the use of GARCH models to obtain accurate estimates (Engle 1982; Bollerslev 1986, 1990).

[12] $T * R^2$ is Engle's LM test statistic. Under the null of homoskedasticity, it is asymptotically distributed as $\chi^2(q)$.

4 Empirical tests

4.1 *Sample, Data, and Variables*

We test the hypotheses listed above on two distinct samples related to the 2000 presidential election. The first sample comprises daily observations during the 2000 presidential campaign—end-of-day returns for the S&P 500 and aggregated daily national polling results. The second sample examines how actors trading S&P futures during the night of November 7, 2000—the night of the election—responded to information regarding the likelihood of a candidate winning the Electoral College. These samples are discussed in turn.

4.1.1 The 2000 Presidential Campaign

We examine the response of stock market returns to the arrival of political information using a sample of daily observations from January 6 to November 6, 2000. We use returns (log changes in daily closing prices multiplied by 100) on the S&P 500 index as our dependent variable.[13] To measure political information that captures expectations of a Gore (i.e., Democrat) victory, we utilize polling data that indicates, for each day, Gore's share of the two major-party votes. These data, collected and used by Wlezien (2001) and Wlezien and Erikson (2001), are based on an aggregation of 295 separate national polls conducted during the 2000 presidential campaign. Missing values were filled in using linear interpolation.[14]

We also include additional variables to control for other unmeasured influences on stock market volatility. These include two dummy variables capturing *closing day's effects*; that is, effects on market activity that result from weekends or holidays. Closing day effects variables measure the number of days before day t that the market was closed and the number of days after day t that the market will be closed. It is expected that these variables will have a positive effect on stock market volatility. Finally, we include a variable measuring (the log of) trading volume, because studies find that including trading volume substantially accounts for observed volatility in stock market returns (Gallant et al. 1992). Since volume data are not available for the S & P 500 indexes, we use total daily volume traded on the New York Stock Exchange (hereafter, NYSE) as a proxy.

4.1.2. Election Night: November 7, 2000

A second laboratory within which to examine the effect of political information on stock market volatility was created on the evening of November 7, 2000. As the evening progressed, network and cable news outlets "called" the electoral outcome of each state. These calls constitute the arrival into the market of political information that affects the strategic decisions of traders.

The NYSE is open for trading between 9:30 am and 4:30 pm EST; it closes, therefore, prior to the reporting of election results. After-hours traders can trade options and futures contracts through the GLOBEX electronic trading system. Using the GLOBEX system, individuals can trade a variety of futures, options, and interest rates.

[13]The S&P 500 index includes 80% industrials, 3% utilities, 1% transportation, and 15% financial companies. For more details on the index, see www.standardpoors.com.

[14]See Wlezien (2001) for a detailed discussion of this variable.

The GLOBEX system reports information on the price and volume for every individual transaction during the trading session. We use this "tick" data to track the movements of futures prices for the S&P 500 index.[15] These tick data were aggregated to provide the average price and total volume of trades *for each minute* during the trading session. To avoid overlap with the NYSE, and because a five-minute lag is used, the sample period for the overnight data set is from 4:35 pm on November 7 through 8:59 am on November 8.

We measure the arrival of political information by constructing a variable that estimates the probability that Gore will win a majority of electors in the Electoral College and will thus become the 43rd president. This measure is based on state-level polls for each of the 50 states and exploits the fact that these polls contain a degree of sampling uncertainty. As each state is called over the evening of November 7 and into the morning of November 8, traders update their priors regarding the likelihood of a Gore victory.

The prior for each state is calculated using the final state-level poll available. Table 1 reports information regarding the sample size of the poll (sample size), the percentage of respondents responding with a preference for Gore (Gore %) and for Bush (Bush %), and the share of the two-party vote for Gore (Gore/[Bush+Gore]).[16] This information is used to test the null hypothesis that, in the population, Gore's share of the two-party vote is greater than or equal to 0.50001 against the alternative that Gore's share is less than 0.50001. The p values for rejection of the null are also listed in Table 1. Higher p values indicate the probability of making an error by rejecting the null that Gore will win the state. For example, Gore's share of the two-party vote in Massachusetts was 63.4%. The p value for rejection of the null that Gore would get at least 50% and win the state is 1.00, indicating that it is certain that an error will be made if that state's electoral votes are given to Bush. Likewise, the p value for rejection of the null for Texas is 0.000, meaning that there is zero chance out of a thousand that Gore will win that state.

Since these polls contain sampling uncertainty, there is a probability that an error will be made by rejecting the null hypothesis. The second step in variable construction is to exploit this sampling uncertainty. This is done by randomly drawing from a uniform [0,1] distribution and creating a variable Q with observations for each state. Denoting the p value for rejection of the null hypothesis P, if Q is less than P, then Gore wins state i and gets all of state i's electoral votes. This is done for each state. If Gore wins sufficient states to give him more than 270 electoral votes, then he wins the election. Third, the process in Step 2 is repeated 1000 times and the proportion of Gore victories is recorded. This measure constitutes the probability that Gore wins the Electoral College. Finally, this probability is updated over the course of the election as each state is called by CNN. As a state is called, the probability of winning the state in question goes to either zero or one, depending on whether the state is called for Bush or for Gore, and Steps 2 and 3 are repeated. Continuing this procedure until 6:21 am on November 8—when Wisconsin was called—results in a variable that measures the probability, for each minute, that Gore will win the Electoral College.

Similar to the daily data set, we control for the total volume traded during each minute. We also control for the anticipated time interval between the current and previous trade. Engle (1996) empirically implements this idea and argues that the expected duration between trades should have a statistically significant effect on the mean and price changes.

[15] A future is a legally binding agreement to buy or sell the cash value of the asset at a specific future date. In the case of the futures used here, the maturity date was November 15, 2000.

[16] We are grateful to Charles Franklin (2001) and Chris Wlezien (2001) for sharing these data.

Table 1 State probabilities, polls, and *p* values (overnight sample)

State	*Sample size*	*Gore %*	*Bush %*	*Gore/ (Bush+Gore)*	*p value*	*Electoral votes*	*Time called by CNN (EST)*
Alabama	625	38	55	0.409	0.000	9	8:00pm (B)
Alaska	400	26	47	0.356	0.000	3	12:00am (B)
Arkansas	286	44	47	0.484	0.287	6	12:12am (B)
Arizona	423	39	49	0.443	0.010	8	11:51pm (B)
California	600	45	44	0.506	0.607	54	11:00pm (G)
Colorado	400	38	47	0.447	0.017	8	11:41pm (B)
Connecticut	447	48	32	0.600	1.000	8	8:00pm (G)
Delaware	625	42	46	0.477	0.127	3	8:00pm (G)
Florida	600	48	46	0.511	0.697	25	2:58 am (G)
Georgia	512	37	53	0.411	0.000	13	7:59pm (B)
Hawaii	261	50	31	0.617	1.000	4	11:00pm (G)
Idaho	633	30	56	0.349	0.000	4	10:00pm (B)
Illinois	600	50	42	0.543	0.983	22	8:00pm (G)
Indiana	600	30	53	0.361	0.000	12	6:00pm (B)
Iowa	603	44	43	0.506	0.609	7	5:00am (G)
Kansas	600	32	55	0.368	0.000	6	8:00pm (B)
Kentucky	625	41	51	0.446	0.003	8	6:00pm (B)
Louisiana	660	38	46	0.452	0.007	9	9:21pm (B)
Maine	400	47	36	0.566	0.996	4	10:10pm (G)
Maryland	627	52	38	0.578	1.000	10	8:00pm (G)
Massachusetts	401	52	30	0.634	1.000	12	8:00pm (G)
Michigan	600	51	44	0.537	0.964	18	9:24pm (G)
Minnesota	1015	47	37	0.560	1.000	10	10:25pm (G)
Mississippi	625	41	52	0.441	0.002	7	8:00pm (B)
Missouri	600	46	46	0.500	0.498	11	10:47pm (B)
Montana	628	37	49	0.430	0.000	3	10:00pm (B)
North Carolina	625	41	48	0.461	0.024	14	8:14pm (B)
North Dakota	586	35	47	0.427	0.000	3	9:00pm (B)
Nebraska	1007	31	56	0.356	0.000	5	9:00pm (B)
Nevada	625	43	47	0.478	0.132	4	1:31am (B)
New Hampshire	801	39	45	0.464	0.021	4	12:07am (B)
New Jersey	843	41	36	0.532	0.970	15	8:00pm (G)
New Mexico	425	45	45	0.500	0.498	5	not called[a]
New York	700	54	37	0.593	1.000	33	9:00pm (G)
Ohio	600	43	50	0.462	0.032	21	9:19pm (B)
Oklahoma	625	39	54	0.419	0.000	8	8:00pm (B)
Oregon	600	45	44	0.506	0.607	7	not called[a]
Pennsylvania	600	50	42	0.543	0.983	23	9:24pm (G)
Rhode Island	370	47	29	0.618	1.000	4	9:00pm (G)
South Carolina	625	38	53	0.418	0.000	8	7:00pm (B)
South Dakota	300	33	51	0.393	0.000	3	9:00pm (B)
Tennessee	500	46	51	0.474	0.124	11	11:03pm (B)
Texas	625	30	64	0.319	0.000	32	8:00pm (B)
Utah	914	27	59	0.314	0.000	5	10:00pm (B)
Vermont	400	52	36	0.591	1.000	3	7:00pm (G)
Virginia	625	41	49	0.456	0.013	13	7:33pm (B)
Washington	500	50	42	0.543	0.974	11	12:08am (G)
West Virginia	536	39	41	0.488	0.280	5	10:46pm (B)
Wisconsin	400	39	44	0.470	0.113	11	6:21am (G)
Wyoming	412	32	57	0.360	0.000	3	9:00pm (B)

[a]New Mexico and Oregon were not called before markets closed on November 8, 2000.

4.2 *The GARCH, EGARCH, FIEGARCH, and Markov-Switching Models*

Because we are interested in the effect of political information, expectations, and uncertainty on stock market volatility, we utilize the GARCH model introduced by Engle (1982) and extended by Bollerslev (1986). A GARCH model is composed of two equations: one for the conditional mean and the other for the conditional variance. In the GARCH (1,1) specification, the conditional mean can be written as:

$$\ln(\Delta P_t) = \lambda + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2), \tag{1}$$

where $\ln(\Delta P_t)$ is the log change in closing price of the stock market index observed at time *t*, λ is a constant, and ε_t is an error term that is normally distributed with mean zero and variance σ_t^2.[17] Note that the mean is specified as following a random walk with a drift; no exogenous variables are thought to influence the mean change in price.

The unique feature of GARCH models is that we can specify how the conditional variance evolves (σ_t^2) over time in response to both past values and exogenous shocks. The conditional variance for the standard GARCH (p, q) model is

$$\sigma_t^2 = \omega + \sum_{t=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2. \tag{2}$$

Using the lag or backshift operator, $\alpha(L) = \alpha_1 L + \cdots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \cdots + \beta_p L^p$, Eq. (2) can be rewritten as

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2. \tag{3}$$

In most cases there is one ARCH and one GARCH term. With exogenous variables affecting the conditional variance, the GARCH (1,1) can thus be written as

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \delta_i I_{i,t}, \tag{4}$$

The variance σ_t^2, called the conditional variance, is the one-period-ahead forecast variance based on all information available at time $t-1$. The conditional variance is a function of four terms: the constant (ω), the ARCH term (ε_{t-1}^2), the GARCH term (σ_{t-1}^2), and a set of exogenous variables ($I_{i,t}$). GARCH models are often used to analyze financial time series because it is assumed that economic agents form expectations about this period's variance based on the long-term mean of the variance (ω), the forecasted variance from the prior period (σ_{t-1}^2), and new information about volatility gleaned in the prior period (ε_{t-1}^2).

While the standard GARCH model is useful, it has two limitations. First, it assumes that positive and negative innovations or errors (ε_t^2) have the same—i.e., symmetric—effect on the conditional variance. This is problematic, since a positive (negative) shock or innovation may have a larger effect on the conditional variance than a negative (positive) one. The phenomenon of asymmetric effects of shocks on the volatility of stock returns occurs quite frequently when traders engage in herding behavior: in such cases—which are common—a negative shock (bad news) leads to greater volatility than a positive shock

[17] We can also use the generalized exponential, student-t, or double exponential distribution. We did not do so because the residuals from our estimated models are conditionally normal.

(good news). To take into account the possibility of asymmetric effects of shocks on volatility, Nelson (1991) developed an exponential GARCH (EGARCH) model, which relaxes the assumption of symmetric effects. More formally, from Eq. (3), the EGARCH model can be written as

$$\ln(\sigma_t^2) = \omega + \alpha z_{t-1} + \gamma_1(|z_{t-1}| - E(|z_{t-1}|)) + \beta_1 \ln(\sigma_{t-1}^2), \tag{5}$$

where z_t represents standardized innovations (ε_t/σ_t) and E is the expectations operator. In Eq. (5), the conditional variance is a function of four terms: the constant, the GARCH term (ε_{t-1}^2), and two ARCH terms—an asymmetric component (z_{t-1}) and a symmetric component ($|z_{t-1}| - E(|z_{t-1}|)$).

Consider first the symmetric component of the ARCH term, ($|z_{t-1}| - E(|z_{t-1}|)$). This component measures deviations between realized and expected innovations and can therefore capture how unexpected innovations affect conditional volatility. γ is typically greater than zero. Hence standardized innovations that are larger in absolute magnitude than the expected value ($|z_t| > E|z_t|$) will increase future volatility higher than its average level. However, if $|z_t| < E|z_t|$, then future volatility will be lower than average. The αz_{t-1} term provides for the asymmetric effect of the standardized innovations. If $\gamma > 0$, then a positive (negative) value for α implies that positive (negative) shocks will have a larger effect on future volatility than negative (positive) shocks. That is, an unexpected large innovation will increase future volatility more than an unexpectedly small innovation will decrease future volatility.

A second limitation of the standard GARCH model is that it cannot account for the *persistence* of volatility in high-frequency time-series data. This is a serious drawback, considering that persistent volatility is common to high-frequency time-series data. To deal with this problem, Bollerslev and Mikkelsen (1996) developed the integrated GARCH (IGARCH) model. The development of the IGARCH model follows from Eq. (3). To see how, first rewrite the expression for the conditional variance in Eq. (3) by dropping the exogenous variables, adding ε_t^2 to both sides, and moving σ_t^2 to the right-hand side:

$$\varepsilon_t^2 = \omega + (\alpha_1 + \beta_1)\varepsilon_{t-1}^2 + \nu_t - \beta_1 \nu_{t-1}, \tag{6}$$

where $\nu_t = \varepsilon_t^2 - \sigma_t^2$. Note that the GARCH (1,1) representation in Eq. (6) can be thought of as an Autoregressive Moving Average (ARMA) model for ε_t^2. It follows that the GARCH (1,1) model is covariance stationary if and only if $\alpha_1 + \beta_1 < 1$. As noted above, persistence of volatility in high-frequency time-series data is common. In other words, it is often the case that $\alpha_1 + \beta_1 = 1$, which is an IGARCH model since $\alpha_1 + \beta_1 = 1$ implies a unit root for ε_t^2 in Eq. (6). As in an ARMA model, the existence of a unit root means that shocks to the conditional variance die out very slowly (Baillie et al. 1996, p. 15). This is in contrast to the expectation that volatility is mean reverting. When the autoregressive polynomial contains a unit root, the IGARCH model can be rewritten as

$$\phi(L)(1 - L)\varepsilon_t^2 = \omega + \nu_i - \beta_1 \nu_{t-1}. \tag{7}$$

We mentioned earlier that in GARCH (1,1) models, the sum of the estimates of α_1 and β_1 is typically close to 1, with α_1 small and β_1 large. This implies that the impact of shocks on the conditional variance diminishes very slowly. However, the decay is still at an exponential rate, which might be too fast to mimic the observed autocorrelation patterns of the empirical time series. Unfortunately, the IGARCH model in Eq. (7) is unable to capture the rate of decay of the shocks and as a result can provide inaccurate estimates. To solve the aforementioned problem, Baillie et al. (1996) suggested that the autocorrelations of squared and even absolute stock returns decline only at a hyperbolic rate. This type of behavior of the autocorrelations can be modeled by means of long memory in volatility or, in other words, as a fractionally integrated process.

More formally, Baillie et al. (1996) introduced the fractionally integrated GARCH, or FIGARCH, (p,d,q) model. Denoting the fractional integration parameter by d and adding d to the first difference operator, the FIGARCH model is defined as

$$\phi(L)(1-L)^{d}\varepsilon_t^2 = \omega + \nu_i - \beta_1\nu_{t-1}, \tag{8}$$

where $0 < \mathrm{d} < 1$. As in standard Autoregressive Integrated Moving Average (ARIMA) type models, the fractional differencing parameter, d, indicates the speed at which shocks to ε_t^2 die out—that is, the rate of decay—over time. This solves the problem in the IGARCH model mentioned above.

While the FIGARCH model captures the rate of decay as long memory in volatility (i.e., fractional integration), it does not account for the asymmetric effect of shocks. Hence Bollerslev and Mikkelsen (1996) introduced the fractionally integrated exponential (FIEGARCH) model, which accounts for both long memory in volatility and the asymmetric effect of shocks on volatility. The FIEGARCH model is simply a combination of the FIGARCH and the EGARCH models and is developed as follows. First, rewriting Eq. (5) using the backshift operator yields

$$\ln(\sigma_t^2) = \omega + [1-\beta(L)]^{-1}[1+\alpha(L)]g(z_{t-1}), \tag{9}$$

where $g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$. Factorizing the autoregressive polynomial as $[1-\beta(L)] = \phi(L)(1-L)^d$, Bollerslev and Mikkelsen (1996) derive the FIEGARCH model:

$$\ln(\sigma_t^2) = \omega + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g(z_{t-1}). \tag{10}$$

Adding the set of exogenous variables, $(\delta_I x_{i,t})$, to Eq. (10) yields

$$\ln(\sigma_t^2) = \omega + \delta_i I_{i,t} + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g(z_{t-1}). \tag{11}$$

In Eq. (11), $[1-\beta(L)]^{-1} = \phi(L)(1-L)^d$ and $g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$. Ignoring the $g(z_{t-1})$ term for a moment, equation Eq. (11) says that (the log of) volatility is a function of the constant (ω), a set of exogenous variables $(\delta_I x_{i,t})$ measured at time t, the ARCH term (α), the GARCH term (β), and the fractional integration parameter (d). As in standard ARIMA models, d measures the speed at which shocks to the dependent variable (in this case, the variance) die out over time. If d equals zero then shocks have no memory and Eq. (11) collapses to the standard EGARCH model. However, if d equals 1 then Eq. (11) becomes the integrated EGARCH model.

Turning our attention to the $g(z_{t-1})$ term in Eq. (11), this part of the equation captures the idea that volatility responds differently to good news than to bad news. Nelson (1991) noted that "to accommodate the asymmetric relation between stock returns and volatility changes . . . the value of $g(z_t)$ must be a function of both the magnitude and the sign of z_t." This is accomplished with the θ and γ terms in $g(z_{t-1})$, where θ captures the sign and

γ captures the magnitude of past errors. Substantively this term means that the negative errors in the prior period will have a larger effect on the conditional variance than positive shocks. If θ and γ in $g(z_{t-1})$ equal zero then Eq. (11) becomes the FIGARCH (p,d,q) model.

We also test our hypotheses by estimating a Markov regime-switching model with time-varying transition probabilities (Diebold et al. 1994).[18] A critical advantage of the Markov-switching model—in addition to correcting for volatility clustering, kurtosis, and serial correlation—is that it can capture "switches" in stock price mean and volatility. That is, it can capture switches from a state of low mean and volatility to a state of high mean and volatility (or vice versa) in stock prices. This is important because application of the Hansen (1992) and Garcia (1998) tests on our daily and overnight sample rejects the null hypothesis of no switching in the mean and variance at the 1% level in both data sets.[19]

Since the Hansen (1992) and Garcia (1998) tests reveal the existence of switching between two states of the mean and volatility of stock prices in our data, we assume that the stock price series in our Markov-switching model is governed by a two-state, first-order Markov-switching process. Each state is characterized by a high (or low) variance and mean that correspond to a separate regime. The series that we observe is thus a "mixture" of these two regimes[20] where this mixture is determined by a probabilistic transition between the two states. More formally, we estimate an autoregressive specification in which the mean and variance are subject to switches between two states that evolve according to a first-order Markov process:

$$\ln(\Delta P_t) = \mu_{S_t} + \phi(\Delta p_{t-1} - \mu_{S_{t-1}}) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2_{S_t}), \quad S_t \in \{0,1\}$$
$$\begin{cases} \mu_{S_t} & = S_t\mu_1 + (1 - S_t)\mu_2 \\ \sigma^2_{S_t} & = S_t\sigma^2_1 + (1 - S_t)\sigma^2_2 \\ \Delta P_t \sim N(\mu_1, \sigma^2_1); \Delta P_t \sim N(\mu_2, \sigma^2_2). \end{cases} \tag{12}$$

In Eq. (12), μ_1 denotes high mean and σ^2_1 high variance, while μ_2 represents low mean and σ^2_2 low variance. ϕ denotes the AR coefficient. The states, S_t, are generated by a realization of the first-order Markov process with transition probabilities,

$$\begin{aligned} &\Pr(S_t = 1 \mid S_{t-1} = 1) = p_{11}, \qquad \Pr(S_t = 2 \mid S_{t-1} = 1) = 1 - p_{11} \\ &\Pr(S_t = 2 \mid S_{t-1} = 2) = p_{22}, \qquad \Pr(S_t = 1 \mid S_{t-1} = 2) = 1 - p_{22}. \end{aligned} \tag{13}$$

p_{11} denotes the probability of the state of high volatility, $S_t = 1$, and p_{22} indicates the probability of the low volatility state $S_t = 2$. From Eq. (13), the transition probability matrix can be defined as

[18] A Markov-switching model can also account for nonstationarity, clustering, serial correlation, and fat-tailed distributions of stock price volatility (Hamilton 1989, 1994).

[19] Garcia (1998) and Hansen (1992) provide likelihood-ratio tests of the null of a single regime in the mean and variance. Garcia derives the asymptotic null distribution of the LR statistic to obtain critical values; in his test, the 1% critical value for rejecting the null is 17.67. Hansen (1992) uses empirical process theory to derive the upper bound of his standardized LR statistic. Moreover, for the daily sample, Wald tests reject the null hypothesis of equality of means (7.97) and variances (12.85). For the overnight sample, Wald tests reject the null hypothesis of equality of means (6.83) and variances (12.46).

[20] Similar to Hamilton's (1994, pp. 685–696) Markov-switching model, stock prices and volatility in our Markov model are drawn from a mixture of two normal densities. Following the theoretical finance literature, we assume that high volatility corresponds to a high mean and low volatility to a low mean (Turner et al. 1989).

$$\Pr(S_t = j \mid S_t = i, x_{t-1}) = p_{ij,t} \quad i,j = 1,2, \tag{14}$$

where x_{t-1} is a $(k \times 1)$ vector of exogenous economic or political variables plus a constant that affect the state's transition probabilities. To examine the effect of these exogenous variables on volatility, we allow the transition probabilities in Eq. (14) to depend on electoral uncertainty, information arrival, partisanship, and trading volume via

$$\Pr(S_t = i \mid S_{t-1} = i, x_{t-1}; \beta_i) = \frac{\exp(x'_{t-1}\beta_i)}{1 + \exp(x'_{t-1}\beta_i)} \quad i = 1,2, \tag{15}$$

where β_i is a $(k \times 1)$ vector of parameters to be estimated. Notice in Eq. (15) that if $\beta_i > 0$ ($\beta_1 < 0$), then $\frac{\partial p_{11}}{\partial x'_{t-1}} > 0$ ($\frac{\partial p_{11}}{\partial x'_{t-1}} < 0$) $\forall x'_{t-1} \in \Re_+$. This implies that if the coefficient of β_1 is positive (negative), then the probability of remaining in a state of high volatility and mean increases (decreases). Likewise, if the coefficient of β_1 is positive (negative), then the probability of remaining in state of high volatility and mean increases (decreases). The log-likelihood of the Markov-switching model in Eq. (12) is given as

$$L_T(\boldsymbol{\theta}) = \sum_{t=1}^{T} \log f(\underline{y}_t \mid \underline{y}_{t-1}, \underline{x}_{t-1}; \boldsymbol{\theta}). \tag{16}$$

The steps used to derive the log-likelihood can be seen at the *Political Analysis* Web site. We use the EM algorithm (Diebold et al. 1994, pp. 690–695) to estimate our Markov-switching model, which is as follows:

1. Assign an initial guess to $\boldsymbol{\theta}^{(0)}$.
2. Generate the following smoothed state probabilities conditional on $\boldsymbol{\theta}^{(0)}$ $\forall t$:

$$\Pr(S_t = 1 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$
$$\Pr(S_t = 2 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$
$$\Pr(S_t = 1, S_{t-1} = 1 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$
$$\Pr(S_t = 2, S_{t-1} = 1 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$
$$\Pr(S_t = 1, S_{t-1} = 2 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$
$$\Pr(S_t = 2, S_{t-1} = 2 \mid \underline{y}_t, \underline{x}_t; \boldsymbol{\theta}^{(0)})$$

3. Generate complete data log likelihood conditional on $\boldsymbol{\theta}^{(0)}$: $E \log f(\underline{y}_T, \underline{s}_T | , \underline{x}_T; \boldsymbol{\theta}^{(0)})$
4. Produce updated parameter estimate $\boldsymbol{\theta}^{(1)}$ from arg max $E[f(\underline{y}_T, \underline{s}_T | , \underline{x}_T; \boldsymbol{\theta}^{(0)})]$ conditional on the smoothed state probabilities obtained in Step 2.
5. Iterate Steps (2)–(4) to convergence, i.e., until $\|\boldsymbol{\theta}^{(m)} - \boldsymbol{\theta}^{(m+1)}\| < \varepsilon$.

4.3 *Results from the GARCH, EGARCH, FIEGARCH, and Markov-Switching models*

We estimate GARCH models on the daily and overnight samples. The results of these models are contained in Tables 2 and 3. Cell entries in both tables are maximum likelihood parameter estimates with Bollerslev-Wooldridge semirobust standard errors in parentheses.

Table 2 Daily GARCH models ($n = 218$ in all models)

	(1)	(2)	(3)
Mean			
Intercept	−0.009	0.005	−0.001
	(0.074)	(0.075)	(0.072)
Variance			
Intercept	−60.267*	−82.08*	−53.82*
	(0.378)	(0.285)	(1.81)
ARCH	0.138	0.134	0.136
	(0.084)	(0.127)	(0.139)
GARCH	0.628*	0.726*	0.704*
	(0.144)	(0.207)	(0.254)
Before	−0.656	−1.09	−0.313
	(0.739)	(1.78)	(0.818)
After	0.572*	0.545	0.822
	(0.228)	(0.308)	(0.551)
log(Volume)	3.14*	4.195*	2.49*
	(0.003)	(0.015)	(0.009)
Gore	−0.134*		
	(0.007)		
Entropy		−0.07*	
		(0.003)	
D(Gore)			−0.175
			(0.154)
Diagnostics	p value	p value	p value
LB(10)	0.1742	0.1742	0.1742
$LB^2(10)$	0.1050	0.0978	0.0965
Jarque-Bera	0.6201	0.6209	0.6207

Note. Cell entries are maximum likelihood estimates with semirobust standard errors in parentheses.
*10% level, **5% level, ***1% level.

Beginning with the daily sample in Table 2, we note that the Ljung-Box Q statistic, indicating no residual serial correlation, suggests that the differenced S&P price series follows a random walk. The squared Ljung-Box statistic is also statistically insignificant; this suggests that there is no remaining ARCH in the residuals. The Jarque-Bera statistic also prevents us from rejecting the null hypothesis of normally distributed residuals.

Turning our attention to the specification in column 1 in Table 2, the ARCH term (α) is not statistically significant while the GARCH term (β) is significant at the .05 level. This means that while random errors from the prior period (ε_{t-1}^2) do not significantly affect the conditional variance at time t, the conditional variance from time $t-1$ does. We also note that the sum of the ARCH and GARCH terms ($\hat{\alpha} + \hat{\beta}$) is significantly less than zero, indicating a nonintegrated GARCH process.

In column 1 we test the third hypothesis, which predicts that expectation of Gore's victory decreases stock market volatility. Column 1 uses the percentage of people polled expressing a preference for Gore to test Hypothesis 3.[21] The coefficient on the GORE

[21]We report the results of contemporaneous information arrival—that is, at time t. There is no substantive or statistical difference if we use lagged measures of information arrival.

Table 3 Overnight GARCH models ($n = 985$ in all models)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Mean					
Intercept	−0.001*	−0.0004	−0.0004	−0.0004	−0.0004
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
AR(1)	0.025	0.413*	0.279*	0.274*	0.268*
	(0.26)	(0.159)	(0.150)	(0.130)	(0.133)
MA(1)	0.066	−0.239	−0.151	−0.131	−0.132
	(0.248)	(0.175)	(0.167)	(0.167)	(0.150)
Duration	−0.0027*	−0.0005	−0.0005	−0.0006	−0.0005
	(0.0010)	(0.001)	(0.001)	(0.002)	(0.003)
Variance					
Intercept	0.0015*	−1.64*	−3.09*	−3.67*	−4.603*
	(0.00003)	(0.117)	(0.344)	(0.373)	(0.487)
ARCH	0.158*	0.30*	0.459*	0.468*	0.443*
	(0.026)	(0.03)	(0.045)	(0.046)	(0.045)
GARCH	0.686*	0.801*	0.049	0.063	0.120
	(0.008)	(0.014)	(0.048)	(0.048)	(0.048)
EGARCH		0.025	0.060	0.089*	0.081*
		(0.068)	(0.037)	(0.040)	(0.038)
Fraction (d)			0.121*	0.124*	0.071*
			(0.018)	(0.018)	(0.018)
Duration	0.0001	0.120*	0.332*	0.350*	0.399*
	(0.001)	(0.015)	(0.034)	(0.034)	(0.036)
Volume	0.001*	0.018*	0.080*	0.080*	0.085*
	(0.0001)	(0.002)	(0.006)	(0.007)	(0.007)
P[$\text{Gore}_{t\text{-}5}$]	−0.0024*	−0.406*	−1.11*		
	(0.0004)	(0.075)	(0.218)		
$\text{Entropy}_{t\text{-}5}$				0.232*	
				(0.100)	
Info $\text{Arrival}_{t\text{-}5}$					1.544*
					(0.700)
Diagnostics					
LB(12)	0.5176	0.5043	0.5269	0.4764	0.4682
$\text{LB}^2(12)$	0.0725	0.1151	0.1345	0.1254	0.1201
Jarque-Bera	0.0000	0.0000	0.0000	0.0000	0.0000

Note. Cell entries are maximum likelihood estimates with semirobust standard errors in parentheses. *10% level, **5% level, ***1% level.

variable is negative and statistically significant. This indicates that a higher likelihood that Gore will win the popular vote for president in 2000 decreased the volatility of the S&P 500 index, as predicted in Hypothesis 3.

Hypothesis 2 suggests that electoral uncertainty increases stock market volatility. In column 2 we operationalize the idea of uncertainty by calculating a measure of entropy $E = 1 - 4(p - .5)^2$ where p is Gore's share of the two-party vote. The entropy measure is greatest when p is closest to .5, the intuition being that there is little uncertainty about an outcome when the probability of an electoral victory is .10 or .90 and great uncertainty about an outcome when the probability is equal to .5 (see Freeman et al. 2000). The entropy measure is substituted for the GORE variable in column 2. Interestingly, when incorporated in the GARCH model the entropy variable has a negative, as opposed to its hypothesized positive, effect on stock market volatility. This is not only contrary to expectations but to prior (e.g., Freeman et al. 2000) research as well as to the results we report later using the overnight sample. Testing Hypothesis 1 is difficult to operationalize using polling data. We conceive of information arrival in terms of changes in the percentage of the population reporting a preference for Gore. We use the change in GORE to measure this concept. As indicated in column 3, this variable is negative but not statistically significant.

A second laboratory within which to examine the effect of political information, expectations, and uncertainty on stock market volatility was created the evening of November 7, 2000. As the evening progressed, network and cable news outlets (as well as the major wire services) "called" the electoral outcome of each state. These calls constitute the arrival into the market of political information, information that affects the strategic behavior of traders.

Table 3 includes a variety of econometric specifications to capture the price dynamics of S&P futures the night of November 7, 2000. In the initial specification of the GARCH model, residual diagnostics revealed remaining serial correlation so AR(1) and MA(1) terms were included. This is consistent with Bollerslev and Mikkelsen (1996) and the findings summarized in Dacorogna et al. (2001) that volatility in high-frequency financial data is persistent. In addition, because the Jarque-Bera test consistently rejects the null hypothesis of normality we utilize Bollerslev-Wooldridge semirobust standard errors.

Column 1 is the basic GARCH specification that includes the lagged (by five minutes) variable measuring the probability that Gore will win the electoral college.[22] While the coefficient on this variable is negative and statistically significant—providing support for hypothesis three—the Ljung-Box test reveals remaining ARCH in the residuals. We re-estimate the model in column 1 using an EGARCH specification under the assumption that accounting for the asymmetric nature of shocks to volatility will render the residuals as white noise. This intuition is borne out in column 2: again the variable measuring the probability that Gore will win the Electoral College is negative and statistically significant and the diagnostics reveal no remaining ARCH. Solving one problem, however, leads to another, as we now see that the sum of ARCH and GARCH terms ($\hat{\alpha} + \hat{\beta}$) is significantly greater than zero, indicating the existence of an integrated GARCH process.

The solution, as presented in columns 3–5, is to estimate a FIEGARCH model. The coefficients for these models lend support for our third hypotheses. The FIEGARCH model using the probability that Gore will win the Electoral College is well behaved and passes all diagnostic tests. The coefficient on GORE is negative and statistically significant, providing support for Hypothesis 3. Political uncertainty, operationalized as entropy, exerts a positive and statistically significant effect on stock market volatility. Finally, the arrival of political information, measured by the calling of "tossup" states, increases volatility.

We obtain the same results if we substitute the return on NASDAQ futures for S&P futures. (Unfortunately, futures for the Dow Jones Industrial Average did not exist in 2000.) The results are also unchanged if we include a set of dummy variables reflecting the times when Florida was called for and subsequently taken away from both Gore and Bush.

[22]A five-minute lag was chosen because that is the average amount of time it takes for a trade to be executed by the GLOBEX system.

Table 4 Markov-switching estimates for daily sample ($n = 218$)

Parameters	*(1) Entropy*	*(2) Gore*	*(3) Information*	*(4) Volume*
μ_1	1.113	0.392	0.413	−0.141
	(1.720)	(1.654)	(1.429)	(1.807)
μ_2	0.702	1.436	1.031	0.375
	(1.663)	(7.073)	(4.225)	(4.573)
β_1	2.254	−0.415	−0.397	0.698
	(3.371)	(1.047)	(1.221)	(6.345)
c_1	1.710	0.895	0.593	0.190
	(3.339)	(1.609)	(1.422)	(1.341)
β_2	−0.471	3.142	2.119	0.423
	(1.629)	(7.954)	(6.540)	(1.596)
c_2	1.587	1.280	0.977	0.147
	(1.622)	(1.675)	(1.314)	(1.080)
σ_1^2	2.360	0.183	0.237	0.598
	(7.492)	(0.813)	(1.590)	(3.960)
σ_2^2	0.325	3.134	1.874	0.147
	(0.505)	(6.121)	(4.472)	(1.441)
ϕ	0.334	0.359	0.293	0.264
	(0.927)	(7.479)	(5.745)	(3.940)
p_{11}	0.966	0.712	0.664	0.950
	(12.048)	(1.216)	(2.235)	(4.439)
p_{22}	0.684	0.974	0.955	0.708
	(1.293)	(5.381)	(4.462)	(3.093)
Wald tests				
$H_0 : \mu_1 = \mu_2$ 7.97**				
$H_0 : \sigma_1^2 = \sigma_2^2$ 12.85**				
$H_0 : p_{22} = 1 - p_{11}$ 59.61**				
LRT tests:				
Garcia 85.14**				
Hansen 5.98**				
Log-likelihood	−245.342	−230.246	−211.348	−316.022
Ljung-box Q-statistics				
LB-1	0.141 (0.718)	0.157 (0.697)	0.125 (0.724)	0.158 (0.530)
LB-3	0.925 (0.428)	0.976 (0.411)	0.912 (0.433)	0.934 (0.522)

Note. t statistics reported in parentheses.
*10% level, **5% level, ***1% level.

Results from estimating the Markov-switching model on the daily data set (see Table 4) provides strong support for our theoretical hypotheses. Specifically, the coefficient of β_1 for the entropy variable in model (1) of this table is positive and significant. The estimated transition probability $p_{11} = 0.966$ is significant and almost equal to 1. This implies that increased uncertainty over the presidential electoral outcome in 2000 significantly increased the probability that stock prices entered and remained in a state of high volatility.

In model (2) of this table, the coefficient of β_1 is negative and significant and the coefficient of low variance σ_2^2 is roughly 17 times higher than the coefficient of high

Table 5 Markov-switching estimates for overnight sample ($n = 985$)

Parameters	*(5) Entropy*	*(6) Gore*	*(7) Bush*	*(8) Information*	*(9) Volume*
μ_1	1.462	0.282	0.564	0.555	−0.156
	(1.715)	(1.709)	(1.837)	(1.728)	(1.925)
μ_2	0.341	1.012	0.196	0.482	0.450
	(0.636)	(3.222)	(0.680)	(1.393)	(4.891)
β_1	1.941	−0.335	2.424	0.276	0.677
	(5.237)	(1.120)	(7.895)	(1.491)	(5.549)
c_1	1.027	0.583	0.632	0.373	0.208
	(6.491)	(1.729)	(1.497)	(1.952)	(0.660)
β_2	−0.558	3.529	0.714	0.459	0.222
	(1.754)	(8.586)	(1.798)	(1.471)	(1.597)
c_2	0.664	1.119	0.878	0.248	0.135
	(1.672)	(1.624)	(1.681)	(1.265)	(0.784)
σ_1^2	1.862	0.185	4.056	0.458	0.662
	(8.541)	(0.811)	(8.227)	(1.563)	(4.797)
σ_2^2	0.265	2.977	0.386	0.677	0.148
	(0.646)	(6.891)	(1.762)	(1.531)	(1.701)
ϕ	0.455	0.413	0.298	0.340	0.236
	(16.851)	(6.891)	(8.764)	(0.615)	(3.868)
p_{11}	0.988	0.771	0.991	0.797	0.932
	(7.904)	(3.849)	(7.803)	(0.403)	(6.427)
p_{22}	0.701	0.989	0.698	0.824	0.783
	(1.174)	(6.773)	(4.950)	(1.977)	(4.099)
Wald tests					
$H_0: \mu_1 = \mu_2$ 6.83**					
$H_0: \sigma_1^2 = \sigma_2^2$ 12.46**					
$H_0: p_{22} = 1 - p_{11}$ 39.21**					
LRT tests:					
Garcia 85.27**					
Hansen 7.25**					
Log-likelihood	−127.686	−165.801	−138.452	−179.062	−314.311
Ljung-box Q-statistics					
LB-1	0.104 (0.836)	0.129 (0.784)	0.157 (0.695)	0.138 (0.755)	0.215 (0.731)
LB-3	0.819 (0.514)	0.929 (0.371)	1.233 (0.299)	1.011 (0.205)	1.226 (0.512)

Note. t statistics reported in parentheses.
*10% level, **5% level, ***1% level.

variance σ_1^2. The estimated transition probability $p_{22} = 0.794$ here is close to 1 and highly significant. These results demonstrate that as the probability of a Democrat's (i.e., Gore's) victory increases, stock price volatility declines and the persistence of the low-volatility state increases, as predicted in Hypothesis 3.[23]

[23]The coefficient of the parameter ϕ is also highly significant in all four columns in Table 5. Finally, the Ljung-Box (LB) Q-statistics for lags 1 and 3 for each model show that the Markov-switching model eliminates serial correlation.

Table 6 Forecasts from GARCH models for out-of-sample observations

	Daily sample			*Overnight sample*			
	GARCH (RpctGore)	*GARCH (entropy)*	*GARCH (info. arrival)*	*GARCH (P[Gore])*	*EGARCH (P[Gore])*	*FIEGARCH (P[Gore])*	*FIEGARCH (info. arrival)*
Panel A. Error forecasts							
RMSE	0.134	0.134	0.134	0.001	0.001	0.001	0.001
MAE	0.011	0.011	0.011	0.0003	0.0003	0.0005	0.0005
Panel B. Volatility regression							
$\hat{\alpha}$	1.32**	1.33**	0.94	0.0001	0.0002**	0.0001	0.0001
	(0.58)	(0.57)	(0.51)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\hat{\beta}\hat{\sigma}^2_{t-1}$	−0.07	−0.068	0.13	0.26**	0.328**	−0.0001	−0.0001
	(0.28)	(0.26)	(0.23)	(0.087)	(0.101)	(0.0001)	(0.0001)
R^2	0.0009	0.0009	0.0037	0.0261	0.0252	0.023	0.022

Note. Standard errors in parentheses.
*10% level, **5% level, ***1% level.

Results from estimating the Markov-switching model on our overnight sample (see Table 5) also support our hypotheses. The positive and significant coefficients of β_1 and σ_1^2 for the entropy variable in model (5), Table 5, show that there was certainly a significant correlation between increased uncertainty over which candidate would win the election and higher volatility during the night of November 7. In contrast, the positively significant coefficients of $\beta_2 > 0$, $\sigma_2^2 > 0$ for the Gore variable in this data set (see model [6]) suggest that when expectations of a Gore (a Democrat's) victory increased on the night of November 7, stock market volatility decreased. Finally, the significant coefficients of $\beta_1 > 0$ and $\sigma_1^2 > 0$ for the Bush variable in model (6) show that when expectations of a Bush victory increased on that night, stock volatility increased.[24]

5 Comparing Volatility Forecasts

We examine below which estimator—GARCH, EGARCH, FIEGARCH, or the Markov-switching model—provides more accurate volatility forecasts by first comparing out-of-sample forecast errors from all the estimated models. Out-of-sample tests are effective since they control for the possibility of overfitting and hence provide a useful framework for evaluating the merits of competing models. We used 80 observations from August 17, 2000, to November 6, 2000, in the daily data set for the out-of-sample forecast evaluation.[25] Similarly, we used 350 observations from the last six hours in the overnight data set for the out-of-sample forecast evaluation.[26] Two well-known criteria were used to evaluate the forecast errors from the models across both data sets. These are the RMSE and the MAE.[27] Panel A of Table 6 reports the RMSE and MAE statistics for the GARCH, EGARCH, and

[24] The AR parameter ϕ is highly significant in all five models in Table 6. The LB Q-statistics demonstrate that each Markov-switching model eliminates serial correlation.

[25] We estimated the GARCH and Markov-switching models on this smaller subsample of 80 observations (results not reported here). We then evaluated the out-of-sample-error forecasts.

[26] We estimated the GARCH, EGARCH, FIEGARCH, and Markov-switching models on this smaller subsample of 359 observations (results not reported here) and then evaluated the out-of-sample error forecasts.

[27] The (root) mean squared error provides a quadratic loss function, which weighs large forecast errors more heavily relative to mean absolute error.

Table 7 Forecasts from Markov-switching models for out-of-sample observations

	Daily sample			*Overnight sample*			
	Markov (RpctGore)	*Markov (Entropy)*	*Markov (info. arrival)*	*Markov (P[Gore])*	*Markov (Bush)*	*Markov (Entropy)*	*Markov (info. arrival)*
Panel A. Error forecasts							
RMSE	1.227	1.273	1.351	1.184	1.878	1.367	1.421
MAE	0.385	0.379	0.371	0.329	0.401	0.388	0.390
Panel B. Volatility regression							
$\hat{\alpha}$	−0.406	−0.418	−0.402	−0.327	−0.319	−0.334	−0.309
	(0.284)	(0.288)	(0.291)	(0.290)	(0.279)	(0.293)	(0.282)
$\hat{\beta}\hat{\sigma}^2_{t-1}$	3.993**	4.112**	4.079**	5.643**	5.187**	5.889**	5.074**
	(1.048)	(0.997)	(1.023)	(1.482)	(1.311)	(1.263)	(1.107)
R^2	0.0003	0.0002	0.0005	0.0009	0.0011	0.0012	0.0010

Note. Standard errors in parentheses.
*10% level, **5% level, ***1% level.

FIEGARCH models, while Panel A of Table 7 reports the RMSE and MAE statistics for all the Markov-switching models from the out-of-sample observations in both data sets.

Note that for the daily data set, the RMSE statistic of all the GARCH models is 0.134 and the MAE statistic is 0.011. These values are substantially lower than the lowest RMSE (1.227) and MAE (0.319) statistics from the Markov-switching models for this data set. The RMSE value for the GARCH, EGARCH, and FIEGARCH models based on 350 observations from the overnight data set is 0.001, while the MAE statistic is either 0.0003 or 0.0005 for these models. Once again, these values are significantly lower than the lowest RMSE (1.184) and MAE (0.329) statistics obtained from the Markov-switching models for this data set. Put together, the RMSE and MAE statistics unambiguously demonstrate that all the GARCH, EGARCH, and FIEGARCH models provide more accurate forecasts and fit the data better than any of the Markov-switching models.

To check and compare the out-of-sample volatility forecasts, we also estimated the following ex post volatility regression[28] for each GARCH and Markov-switching model,

$$\sigma^2_t = \alpha + \beta\hat{\sigma}^2_{t-1} + u_t. \tag{17}$$

In Eq. (17), the measure of ex post (i.e., realized) volatility, σ^2_t, is the square of log change of daily closing prices (× 100) of the S&P 500 index for the daily data set and the square of log change of prices (× 100) of S&P 500 futures for the overnight data set. The term $\hat{\sigma}^2_{t-1}$ denotes the forecasted conditional variance derived from the estimated out-of-sample GARCH and Markov-switching models. The procedure that we adopted to estimate the above volatility/variance regression is as follows. We first estimated each of the GARCH (Table 2), GARCH, EGARCH, FIEGARCH (Table 3), and Markov-switching (Tables 4 and 5) models on the out-of-sample observations from the daily and overnight data sets. We then derived the forecasted conditional variance for each of these estimated models.

The method used to estimate the forecasted conditional variance from the Markov-switching models is as follows: Let $\mu_{s_t} = \alpha_1 S_t + \alpha_2$ and $\sigma^2_{s_t} = \omega_1 S_t + \omega_2$; recall $\varepsilon_t \sim N(0, \sigma^2_{s_t})$.

[28]This regression is also known as the Mincer-Zarnowitz (1969) regression.

Suppose that the stock price index was in regime 1 at $t-1$. From Pagan and Schwert (1990: 275), $\hat{\sigma}_t^2$ is derived from

$$[E\{\sigma(S_t) \mid S_{t-1}=1\}]^2 + \mathrm{var}\{\sigma(S_t) \mid S_{t-1}=1\} + E\{[\mu(S_t) - E(\mu(S_t))]^2 \mid S_{t-1}=1\}, \tag{18}$$

which yields

$$[\omega_2 + \omega_1 p_{11}]^2 + \omega_1^2 p_{11}(1-p_{11}) + \alpha_1^2 p_{11}(1-p_{11}). \tag{19}$$

Suppose that the stock price index was in regime 2 at $t-1$. Then $\hat{\sigma}_t^2$ is derived from

$$[E\{\sigma(S_t) \mid S_{t-1}=2\}]^2 + \mathrm{var}\{\sigma(S_t) \mid S_{t-1}=2\} + E\{[\mu(S_t) - E(\mu(S_t))]^2 \mid S_{t-1}=2\} \tag{20}$$

$$[\omega_2 + \omega_1(1-p_{22})]^2 + \omega_1^2 p_{22}(1-p_{22}) + \alpha_1^2 p_{22}(1-p_{22}). \tag{21}$$

Multiplying Eqs. (19) and (21) by the estimates of the conditional probabilities of being in each state given data through $t-1$ gives the estimate of $\hat{\sigma}_t^2$, which is then lagged to obtain $\hat{\sigma}_{t-1}^2$.

After estimating Eq. (17) for each model, we checked to see if $\hat{\alpha}=0$ and $\hat{\beta}=1$ (in each case) because the aforementioned hypothesized values indicate that the relevant model provides perfect forecasts. Note that if the estimated β for a model is $\hat{\beta} > (<)\ 1$, then that model underestimates (overestimates) the true realized volatility in the data (Pagan and Schwert 1990, p. 283). Results from estimating Eq. (17) for each GARCH and Markov-switching model for the daily data set are reported in Panel B, Table 6 and Panel B, Table 7, respectively. The estimated coefficient, $\hat{\alpha}$, from the GARCH models for the daily data set is well above 0. The estimated $\hat{\beta}$ coefficient of the same GARCH models (-0.07, -0.068, 0.13) is insignificant and below 1. The estimated $\hat{\alpha}$ of all the GARCH, EGARCH, and FIEGARCH models for the overnight data set is approximately equal to zero. It is also significant for the EGARCH [p(gore)] and FIEGARCH (entropy) models. The estimates of $\hat{\beta}$ for the FIEGARCH models are disappointing since they are insignificant and well below 1. However, the estimated $\hat{\beta}$ for the EGARCH model is slightly encouraging because it is significant and marginally different from 1.

The intercept $\hat{\alpha}$ estimate from all the Markov-switching models for the daily and overnight data sets is much below 0, while the insignificant slope coefficient estimate $\hat{\beta}$ of these models is much higher than 1. This demonstrates that there exists a substantial bias in the forecasts from the Markov-switching models and that these models are under-estimating the degree of volatility in the daily data set. It also suggests that the GARCH models provide relatively better forecasts than the Markov-switching models, even though the volatility forecasts from the GARCH models are not very accurate. Finally, note that the R^2 statistics from the volatility regressions estimated for the GARCH models are higher than the R^2 statistics from the Markov-switching models for both data sets. In short, our out-of-sample forecasting tests indicate that the GARCH models certainly fit both of the data sets much better than the Markov-switching models.[29]

[29]The RMSE, MAE, and realized volatility regression results from the full daily and overnight sample also indicate that the various GARCH models fit the data better than the Markov-switching models. For details, see the reported results at the *Political Analysis* Web site.

The results presented above raise a key question: Why do Markov-switching models provide poor volatility forecasts relative to the GARCH models? We posit three reasons in answer to this question. First, note that in each specification for the standard linear and fractionally integrated GARCH model, we introduced numerous explanatory and control variables. In contrast, we introduced only one explanatory variable in each specification of the various Markov-switching models. This was not deliberate; rather, we could introduce only one explanatory variable in each of the Markov-model specifications because it is impossible to achieve convergence of the EM algorithm and hence estimate the Markov-switching model when we introduce more than one variable. The aforementioned constraint that occurs while estimating a Markov-switching model is crucial, since the inability to control for more than one variable at a time weakens the power of the Markov model to accurately forecast volatility.

Second, unlike the Markov-switching model, the EGARCH and FIEGARCH models formally capture the *persistence* of volatility and the differential effects of positive and negative shocks on stock price volatility. This can be seen mathematically. For example, the EGARCH model captures the impact of persistent volatility via its ARCH (αz_{t-1}) and GARCH [$\beta_1 \ln(\sigma^2_{t-1})$] terms, while the FIEGARCH model does so through $\phi(L)(1 - L)^d = 1 - \beta(L)$ and $1 + \alpha(L)$. Likewise, the EGARCH model accounts for the impact of shocks on volatility through $\gamma_1(|z_{t-1}| - E|z_{t-1}|)$) and the FIEGARCH model does so via $g(z_t) = \theta(|z_t| - E|z_t|)$). The Markov-switching model, in contrast, merely contains an AR(1) term, $\phi(.)$, and does not account for the presence of ARCH and GARCH effects. Moreover, in terms of its mathematical construction, a Markov-switching model can capture volatility switches only from the previous period; that is, it cannot capture persistence of volatility over longer periods of time. The Markov-switching model in Eq. (12) also does not conceptualize the differential effects of shocks on stock price volatility. These are all serious shortcomings of the Markov-switching model, since the significant coefficients of the ARCH and GARCH terms in most of the GARCH models demonstrate that volatility persistence and differential effects of shocks clearly affect the degree of realized volatility in our data sets.

Third, Pagan and Schwert (1990, p. 283) have demonstrated that the Markov-switching model places an upper bound on the conditional variance that is too small. As a result, volatility estimates from the Markov-switching models are typically too low, which weakens their ability to predict realized volatility. This problem is evident in our case, where the estimates of $\hat{\beta}$ from the volatility regressions of the Markov-switching models show that these models are seriously underestimating the degree of volatility in the two data sets.

One could plausibly argue that we should estimate a Markov-switching ARCH (SWARCH) model (Hamilton and Susmel 1994) rather than a standard Markov-switching model. While SWARCH may provide better forecasts, the SWARCH model—like the Markov-switching model—captures neither the persistence of volatility nor the asymmetric effects of shocks on volatility in time-series data. This is problematic because the fact that the EGARCH and FIEGARCH models provided superior forecasts in our case suggests that persistent volatility and asymmetric effect of shocks are common in high-frequency time-series data. Hence, the failure to explicitly model the aforementioned factors—which is the case with the SWARCH model—can lead to poor forecasts.

6 Conclusion

This paper makes two main contributions. First, in contrast to the existing literature, we have argued and empirically demonstrated that anticipation of a Democratic victory *decreases* stock price volatility. Second, in sharp contrast to methodological claims in the literature, our forecasting tests show that the GARCH and EGARCH models provide more accurate forecasts of stock volatility than the Markov-switching models.

The empirical analysis in this paper gives rise to two questions. First, how generalizable is the substantive and original finding presented here that agents' expectations of electoral victory by the Democrats, a left-wing party, serve to decrease, not increase, stock market volatility? To answer this question, we estimated various GARCH models to analyze the impact of partisan expectations on stock market volatility in each presidential election year from 1944 to 2000 (Leblang and Mukherjee 2004). The results from the additional presidential election years show unambiguously that expectation of a Democratic victory decreased stock market volatility, thus indicating the generalizability of our substantive result (Leblang and Mukherjee 2004).

Second, why do our results on partisanship and stock market volatility differ from those in the current literature? The answer to this question lies in the fact that there are significant differences in the econometric models and specifications that we estimated compared with the models in the literature. For example, as noted earlier, existing studies on democratic politics and financial markets simply do not estimate nonlinear fractionally integrated GARCH models and thus wrongly ignore the potential consequences of "long memory," autoregressive conditional heteroskedasticity, nonlinearities, and volatility persistence on the conditional variance of financial market returns in the data. We believe that the failure to directly model autoregressive conditional heteroskedasticity, and volatility persistence in particular, could have led to erroneous results in existing empirical analyses. In addition, note that unlike the Markov-switching model of Freeman et al. (2000), the Markov-switching model estimated here not only directly introduced an AR(1) component, but also examined how this component is affected by switches in the mean and variance of stock market returns. This allowed us to capture temporal correlation in the data more comprehensively than the model used by Freeman et al. (2000) and could explain why our results differ from the literature. Finally, with respect especially to our GARCH specifications, we controlled for critical variables such as trading volume, duration of time between trades, and information arrival, which was not done by Freeman et al. (2000) or Herron (2000). Our use of a more comprehensive specification—with less room for key omitted variables—could have also contributed to different substantive results.

Our analysis will be more cogent if we sample our data sets at different intervals and if we compare the different estimation techniques on data from additional election years. We lack the space to do either or both of those tasks. However, in future research, it is likely that we will extend our analysis to strengthen the results presented here.

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