Essays on the Impact of Presidential Elections on the U.S. Stock Market

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Abstract

This dissertation consists of two essays that are organized as chapters. In the first chapter, I examine the effect of presidential elections on the timing of turning points of stock market cycles in the United States. The empirical results from duration analysis show that compared to at other times, a market trough, the end of a bear market, is more likely in the period before an election when the incumbent is a Republican; meanwhile a market peak, the end of a bull market, occurs sooner following a Republican election victory. There is also evidence suggesting that bear markets are less likely to end after an election of a Republican president than in other periods. Results from further examination reveal that political control, the political alignment between the president and Congress, has a vital role in the timing of the turning points relative to the elections. In particular, political control found to reduce the probability of a market trough in the pre-election period and this reduction in the hazards for a bear market prior to an election is more significant for a Democratic president. Alternatively, political control boots the prospect of the completion of a bull market in the post-election period, especially when a Democrat was elected. Finally, political control in Congress can substantially shorten the duration of a bear market in the post-election period when the Republicans control both the White House and Capitol Hill.

In the second chapter, I develop a dynamic factor model to examine the relations among presidential elections, investor sentiment, and stock market returns simultaneously. Results in the study uncover that there is a sizeable improvement of investor sentiment prior to an election, and this pre-election upsurge in sentiment can explain a substantial portion of the presidential election cycle effect in the stock returns. However, data in the study fail to provide significant evidence that Democratic presidents can install more optimism in the stock market. My result does confirm that there was a market-wide panic during the height of the recent financial crisis in

2007-2008. Furthermore, results from the asset pricing tests show that in addition to the conventional risk factors, the market return factor and the factor of change in investment opportunity set, the factor of investor sentiment is a critical component in asset pricing and prediction. By including the sentiment factor, the proposed Augmented Intertemporal Capital Asset Pricing Model (AICAPM) in the paper improves upon the explanatory and predictive power of other competing models such as the Intertemporal Capital Asset Pricing Model of Merton (1973) (ICAPM) and the Fama-French (1993) 3-factor model (FF3).

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Abstract

This study examines the effect of presidential elections on the timing of turning points of stock market cycles in the United States. The empirical results from duration analysis show that compared to at other times, a market trough, the end of a bear market, is more likely in the period before an election when the incumbent is a Republican; meanwhile a market peak, the end of a bull market, occurs sooner following a Republican election victory. There is also evidence suggesting that bear markets are less likely to end after an election of a Republican president than in other periods. Results from further examination reveal that political control, the political alignment between the president and Congress, has a vital role in the timing of the turning points relative to the elections. In particular, political control found to reduce the probability of a market trough in the pre-election period and this reduction in the hazard for a bear market prior to an election is more significant for a Democratic president. Alternatively, political control can boost the prospect of the completion of a bull market in the post-election periods, especially when a Democrat was elected. Finally, political control in Congress can substantially shorten the duration of a bear market in the post-election period when the Republicans control both the White House and Capitol Hill.

JEL classification: G14, D72, D73

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1.1. Introduction

"By the Law of Periodical Repetition, everything which has happened once must happen again, and again, and again -- and not capriciously, but at regular periods, and each thing in its own period, not another's and each obeying its own law... The same nature which delights in periodical repetition in the sky is the Nature which orders the affairs of the earth. Let us not underrate the value of that hint." -- Mark Twain

Every four years, money and power collide at the intersection of Wall Street and Pennsylvania Avenue. Some of the most interesting historical patterns in the Stock Trader's Almanac relate to the occurrence and the outcome of presidential elections in the United States. Over the years, academics and market pundits have conducted numerous studies on the subject of the election cycles in an attempt to make a better prediction of future market trends. It has been widely discovered that in general, the U.S. stock market tends to ascend with an upcoming election and to descend once the election is over. Besides, the historical returns in the U.S. stock market have been higher under Democratic presidencies than under Republican administrations. Some have suggested that these two periodic patterns in the equity market related to elections are the reflections of the political business cycles in the financial market as stock prices reflect investors' forecasts of the future state of economy and firms.

Theories of political business cycles present different implications concerning the temporal relationships between elections and business cycle turning points. For instance, opportunistic political business cycle theories suggest that a business cycle trough, the beginning of an expansion phases of the business cycle, is likely in the period before an election as an incumbent attempts to maximize his chance of reelection. Meanwhile, a business cycle peak, the beginning of the contraction phase of a business cycle, follows soon after an election as the pre-election stimulus is quickly reversed. Rational partisan theory, on the other hand, suggests that a business cycle peak is more likely to occur in the wake of a Republican presidential victory than at other times, and is less likely after a Democratic presidential victory than at other times. Conversely, a business cycle trough is less likely after a Republican has won a presidential election than at other times, and is more likely after a Democrat has won than at other times.

To predict the future market movements is a critical task for all investors. It is impossible for one to predict future market movements correctly all the time, but that does not mean the stock market does not have patterns that could meaningfully add to investors' profits. It being said, history could be a good guide and a useful tool in considering entry and exit points in the stock market. There is a vast literature on the relationship between the stock market and macroeconomic fundamentals.[1] Since a major factor that affects the real economy is the economic policies of an incumbent government, its strategic decision for reelection or partisan preferences should have an impact on stock market movements. This potent critical link, however, has not been studied yet.

This study expands the existing literature on political economics and finance by investigating the temporal links between elections and stock market turning points in the United States. Specifically, I am interested in the following questions: 1) Compared to at other times, whether a bear market is more likely to end in the period leading up to a general election and

[1] See for example, Bodie (1976), Fama (1981), Geske and Roll (1983), Cutler, et al. (1989), Boyd, Hu, and Jagannthan. (2005), Flannery and Protopapadakis (2002), Hong, Torous, and Valkanov.2007), Diebold and Yilmaz (2008), Errunza and Hogan (1998), Erdem, Kaan, and Erdem (2005), Choi, et al. (1999), Engle, Ghysels and Sohn (2008).

whether the end of a bull market is more likely in the period shortly after the election; 2) Whether there are any differences in the likelihood of turning points across political parties.

Previous studies on the subject of election cycles in the U.S. stock market address the timing issue indirectly by focusing on the amplitude of returns and volatilities before and after the elections or across the tenure of different parties. This study provides a more direct test of the relationships between political and financial events. I use duration analysis to test whether the likelihood of the occurrence of a stock market cycle turning point in the United States (that is, either the end of a bear market or the end of a bull market) can be significantly affected by the occurrence and the outcome of an election.

Duration analysis is well suited for analyzing the temporal links between elections and stock market turning points. It allows for directly testing the determinants of the likelihood of the end of a market cycle phase in any period conditional upon the phase lasting up until that period. The determinants of the timing of turning points that I focus on in this study are the occurrence and the outcome of elections. Duration analysis enables an estimate of the effect of elections on the likelihood of the end of a stock market cycle phase holding constant other factors. In particular, duration analysis controls for *duration dependence* that arises when there is a changing probability of the end of a stock market cycle as the cycle itself progresses.[2]

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[2] Various studies have provided evidence of duration dependence in stock market. For example, Zhou and Ridgon (2011) find evidence of negative duration dependence in all samples of bull markets and evidence of positive duration dependence in complete, peacetime and post-World War I sample of bear markets. Using a duration-

The empirical results reported in the paper provide no statistical evidence that an ongoing bear market is more likely to end in the period before an election than in other periods regardless of the political party of the president. I do find, however, a significant increase in the likelihood of the end of a bear market ceterus paribas in the 24-month and the 16-month periods before an election when a Republican is incumbent. Data in the study fails to generate significant evidence that bull markets are more likely to end in the post-election period.

The result of post-election effects is further examined by disaggregating post-election period according to which party won the election. Results show that there is a significant rise in the likelihood of a market peak, the end of a bull market, occurring immediately after a Republican election victory and a significant decrease in the likelihood of a market trough, the end of a bear market, in the two years following an election of a Republican president. There is, however, no evidence of potential changes in the behavior of the stock market after Democratic election victories.

Results also show that political alignment between the White House and Congress, political control, has a critical role in the timing of the turning points relative to the elections. Compared to the presidents who have no political control, market troughs, the ends of bear markets, are less likely to occur in the pre-election period when the new administrations are politically aligned with Congress regardless of the partisanship. This reduction in the hazard for

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dependent Markov-switching model, Maheu and McCurdy (2000) find declining hazard functions (negative duration dependence) in both the bull and bear market states using monthly data from 1834-1995.

a bear market in the pre-election period is especially significant for Democratic incumbents. On the other hand, there is a significant upsurge in the likelihood of a market peak, the end of a bull market, following an election when the party of the elected president has full control over Congress. This increase in the hazard for a bull market in the post-election period is more advent for Democratic presidents. Finally, political control seems to let the Republican presidents substitute a higher likelihood of a market trough in the post-election period when the Republicans control both chambers of Congress for a lower one when they do not have such political advantage.

Because of the limited number of stock market cycles I have, I conduct two robustness tests in the study. First, to ensure the results are indeed related the presidential elections, not driven by some outliers in the data, I exclude the observations from the 1929 stock market crash period and the 2008 market crash period from my sample and find consistent results. I then replicate the study using the nominal stock prices as an alternative measure of the general market condition, and the new results reaffirm my initial findings.

In the next section of the paper, I provide a brief review of related literature and talk about hypotheses development. The empirical approach used to test my hypotheses is discussed in Section 3, which is followed by the empirical results presented in Section 4. Section 5 presents the results when the effect of political control is considered in regressions. Finally, before concluding the study in Section 7, two robustness tests are conducted in Section 6.

1.2. Literature Review and Hypothesis Development

1.2.1. Literature Review

Based on their assumptions across different dimensions, theories of political cycles can be classified into a two by two matrix. One of the dimensions concerns the nature of the economy itself. For example, the early models, such as that by Nordhaus (1975), Lindbeck (1976) and Hibbs (1977), assume that the economy is characterized by a stable inflation-output tradeoff, policymakers have direct control over inflation, and that inflation expectations are adaptive. More recent work expands early models by reflecting the rational expectation critique of these assumptions. The underlying assumptions of Persson and Tabellini (1990), Rogoff and Sibert (1988), Rogoff (1990) and Alesina (1987), for example, are that economic agents are forward-looking and make decisions based upon all information available to them at the time. The link between attempted political manipulation and the phases of the business cycle is more tenuous under these rational expectations assumptions than under the traditional assumption of a stable Phillips curve. In other words, there is a little scope for pre-election stimulation of the aggregate economy since the dates of quadrennial elections are known in advance, and the post-election effects are more short-lived when people are rational and forward-looking than when there is a stable Phillips curve in the traditional models.

The motivation of policymakers represents another critical aspect along which models of political business cycles can be categorized. Opportunistic political business models, such as Nordhaus (1975), assume that the goal of all policymakers is to maximize the chance to be reelected, and policy is used towards this end. In the rational opportunistic political business model of Persson and Tabellini (1990), the forwarding-looking behavior of economic agents mitigates the extent to which the economy can be manipulated by policy and makes the voters' goal to elect the most "competent" candidate regardless of ideology.

The goal for policymakers in partisan political business cycle models is not reelection but instead realizing ends commensurate with their ideology. In the work of Hibbs (1977, 1987), in which politicians can exploit a stable output-inflation tradeoff, this leads to differences across the tenure of left-wing (Democratic) and right-wing (Republican) governments. The rational partisan theory of Alesian (1987) preserves the assumption of policymakers pursuing ideological motives but tempers their ability to realize their goals by modeling an economy characterized by rational wage-setters who are temporarily bound by nominal contracts. In this model, wages are set equal to expected inflation. In the period before an election, the expected inflation rate is a weighted average of the likelihood of the election of the party more sensitive to costs of inflation (the Republicans) and the party less sensitive to inflation's costs (the Democrats). The election outcome determines the actual inflation rate and therefore whether the real wages are unexpectedly high (due to a Republican victory) and there is a contraction or whether the real wage is unexpectedly low (due to a Democratic victory) and there is an expansion. The length of the deviation of output from its natural rate in the model is the length of the wage contract, not the entire tenure of the administration as the Hibbs' model suggests.

The theories present different implications regarding the temporal relationship between elections and business cycle turning points. Opportunistic political business cycle theory predicts a higher likelihood of a business cycle trough (the end of a contraction) with the coming of an election. This theory also predicts that the onset of contraction (a business cycle peak) to offset the pre-election simulative policy is more likely following an election than at other times. These predictions stand regardless of presidents' partisanship. Alternatively, the party in power is central to the timing of business cycle turning points drawn from the insights of the partisan theory. Rational partisan theory predicts that the likelihood of a business cycle peak marking the end of an expansion is higher after the election of a Republican president than at other times and is lower after the election of a Democratic president than at other time. This theory also predicts that the likelihood of a business cycle trough marking the end of an expansion is lower after the election of a Republican president than at other times and higher after the election of a Democratic president than at other times.

Klein (1996) is the first one and probably the only one, who directly tests the timing implications of theories of political business cycles by using the dates of turning points of the business cycles identified by the National Bureau of Economic Research. The empirical results in his paper show that there is some evidence supporting the prediction from the opportunistic political business theory of an increased likelihood of the end of a contraction in the two-year period before an election, but only when there is a Democratic president. Other results presented in his paper are consistent with the post-election downturn predicted by the theory. Further examination of the post-election results shows consistency with rational partisan theory. There is a significantly higher likelihood of the end of an expansion occurring in any given month in periods following Republican presidential victories, and contractions are less likely to end following a Republican presidential victory than at other times but are more likely to end in the wake of a Democratic presidential victory than at other times.

Along with the research on theories of political business cycles, there is an increasing number of studies focusing on the relationships between the elections and the stock market. On the one hand, more and more studies recognize that stock market performance is a better predictor of presidential elections than the conventional economic indicators. It was widely believed that the state of the election-year economy is the most effective single predictor of the election outcomes (e.g., Jones, 2002; Fair, 2002). However, recent studies such as Chan and Jordan (2004) find that the equity market's performance for ten months prior to an election is a better predictor than GDP growth of the incumbents' election results in recent years. Similarly, Prechter, Goel, Parker, and Lampert (2012) find that compared to GDP, inflation, and unemployment rate, stock market performance is a more powerful predictor of the incumbent's reelection bids. As a result, incumbents might try to massage the economy and introduce market-friendly policies in the run-up to an election to foster a sense of prosperity to boost the chance of reelection. Such stimulation may result in a rising stock market before a coming election and sharp correction shortly after when the stimulus is withdrawn.

On the other hand, whether there are predictable patterns in the U.S. stock market relate to the occurrence and the outcome of the elections has been the subject for various research. Allvine and O'Neill (1980) find that stock prices rise relative to trend over the two years prior to a presidential election. Since then, Herbst and Slinkman (1984), Huang (1985), Gärtner and Wellershoff (1995, 1999) all find evidence in support of a four-year presidential election cycle in the United States, which suggests that the U.S. stock market generally provides higher returns in the last two years of a presidency than in the initial two years. Lobo (1999) also finds that stock volatility is higher in election years relative to nonelection years. Booth and Booth (2003) reaffirm the early findings and conclude that this presidential election cycle cannot be explained by the traditional business conditions proxies, the term spread, dividend yield, and default spread. There also are differences in returns and volatility along partisan lines. Riley and Luksetich (1980) and Hobbs and Riley (1984) find that stock returns are higher under Republican administrations in the United States. Huang and Schlarbaum(1982) and Huang (1985), however, find higher stock market returns during Democratic presidencies. For Hensel and Zimeba (1995) and Johnson, Chittenden, and Jensen (1999), the higher stock market returns during Democratic administrations are a manifestation of the small-firm effect, since they find that only small firms have significantly higher returns under Democratic presidencies, while the returns for large firms are not statistically different across the administrations of both major parties. In addition to finding higher returns on small-cap stocks, Lobo finds that the jump risk obtained from the volatility of the stock market is higher during Democratic administrations as well. Results from Santa-Clara and Valkanov (2003) suggest the higher excess return in the stock market under Democratic presidencies is attributable to a difference in unexpected returns.

1.2.2. Hypotheses Development

The aforementioned studies have paved the way to the question of whether the quadrennial election cycle can significantly affect the timing of turning points of stock market cycles in the United States. Based on the existing literature, I hypothesize the followings:

Hypothesis One: Compared to at other times, a bear market is more likely to end in the period leading up to an election; and a bull market is more likely to complete in the period immediately after an election regardless of the political party of the president.

Hypothesis Two: The likelihood of the end of a bull market is higher in the wake of a Republican election victory than at other times and is lower after a Democratic election victory. The likelihood of the end of a bear market is lower after an election of a Republican president than at other times and is higher after a Democratic election victory than in other periods.

1.3. Empirical Approach

The timing of the stock market cycle turning points relative to the quadrennial presidential election cycle implied by my hypotheses lends itself to an empirical investigation using duration analysis. The data used in duration analysis consist of *spells*. In this study, a spell represents the number of months in either a bear market or a bull market. The focus of duration analysis is the *hazard function*. The hazard function at time $t, h(t, x(t))$, is an estimate of the probability of the completion of a spell during the time interval $(t, t + dt)$, given that the spell has lasted up until time t. I estimate the hazard function for the probability of a peak (trough) in the U.S. stock market cycle during the next month given that the market has been in a bull (bear) market up until the beginning of that month[3]. The hazard function allows for *duration dependence* if its value at any moment is a function of the time already spent in a spell. The hazard function may shift due to exogenous factors, represented by the vector $\boldsymbol{x(t)}$, which are called *covariates*. In a continuous-time framework, the hazard function is defined as

$$h\big(t, x(t)\big) = \lim_{dt \to 0} \frac{\Pr(t \leq T < t + dt | T \geq t, x(t))}{dt} \tag{1}$$

[3] The regular quadrennial nature of U.S. election cycles insures that there is not a simultaneity problem whereby the spells determine the covariates. This problem may arise when studying a country with parliamentary system in which elections can be called at the discretion of the ruling party.

The hazard function can be understood as the probability of a turning point in the short interval dt after t, conditional on the current phase of the market cycle has lasted until time t.

There are several potential candidates for the functional form used to implement this analysis. The focus of attention in this study is the effect of the election covariates on the hazard rather than the estimation of the duration dependence of bull markets or bear markets. Therefore, I estimate the *Cox proportional hazard model*. This model factors the hazard into an arbitrary and unspecified baseline hazard, $h_0(t)$, and a function that depends upon a vector of explanatory variables, $\boldsymbol{x(t)}$, and the associated vector of coefficients, $\boldsymbol{\beta}$, as follows;

$$h(t, x(t), \beta, h_0) = h_0(t)\exp(x(t)\beta) \tag{2}$$

This specification satisfies the requirement of non-negativity of the hazard without imposing any restrictions on the coefficients $\boldsymbol{\beta}$. The exponent of the coefficient on pre-election or post-election covariates can be interpreted as the shift of the hazard during the relevant period as compared to the other times. [4]

The focus of this study is a set of covariates representing specified periods before or after elections. These pre-election and post-election periods are identified by dummy variables that enter as *time-varying covariates*, that is, covariates that can change over the course of a spell.[5]

[4] The arbitrary baseline hazard of the Cox proportional hazard model can have any shape and it is not estimated. The proportional hazard specification is well suited for investigating the effect of covariates on the relative risk of ending a spell, but it does not lead itself to an investigation of duration dependence.
[5] It is important to use time-varying covariates rather than simply identify those business cycles in which there was an election with a dummy variable that serves as a constant covariate because the longer the business cycle the more

Each of these covariates represents one of three different time frames and correspondingly is set equal to one in the 8-month, 16-month, or 24-month period either before or after an election. [6] The use of different time frames for the covariates allows for the investigation of the length of the period of the political effect on the hazard. The coefficients across different specifications of time frames are directly comparable since the hazard is the estimate of the likelihood of the completion of a market cycle phase in the next month conditional on its lasting up until that month.

To shed light on how the hazards may depend on the underlying state of the economy, I consider the effect of time-varying interest rates in some specifications as well.[7] Interest rate levels may be affected by a low-frequency component and therefore might not contain the same information over a sample as long as mine, whereas interest rate changes are more likely to track business cycle variation across the full sample. Thus, I include both levels and changes in interest rates. [8] The coefficients on the pre-election and post-election covariates represent the shift in a hazard during the specified period before or after an election, respectively, holding

likely that there would be an election during it. Therefore, the use of elections as a constant covariate would give rise to spurious results.

[6] In an alternative specification of the post-election covariates begin in the month following the new president's inauguration if he represented a different political party from his predecessor and began in the month after the election otherwise. This alternative is specification is more consistent with the notion that once in power, the government was able to affect the economy, while the specification based only on election dates is more consistent with the notion the effect of the election on the stock market was due to the "news" revealed by the outcome of the election. In any case, the results using either specification were very similar.

[7] Interest rates have been widely document to closely track the state of the business cycle and appear to be a key determinant of stock returns at the monthly horizon (see, e.g., Kandel and Stambaugh 1990; Fama and French 1988)

[8] My analysis of nominal stock prices uses nominal interest rates, whereas our analysis of real stock prices is based on real interest rates. Both interest rates are collected from Sheller's database.

constant the effect of duration dependence and controlling for the underlying economy (if interest rates are included).

The pre-election and post-election covariates used in tests of Hypothesis One do not distinguish between political parties. Hypothesis One predicts positive coefficients on the pre-election covariates in hazard estimates for bear markets. This infers that bear markets that have lasted until the period before an election are more likely to end at that time than at other times. The predicted post-election market downturn from the hypothesis is consistent with positive coefficients on post-election covariates in hazard estimates for bull markets.

The set of post-election covariates used to test Hypothesis Two includes separate covariates for the period after the election of a Republican president and for the period after the election of a Democratic president. Hypothesis Two says that the post-election effect depends upon the party won the election. Consistent with this hypothesis, estimates of hazard function for bull markets would include positive coefficients on the covariates representing the period following the election of a Republican president and negative coefficients on coefficients on the covariates representing the period following the election of a Democratic president. The hypothesis also predicts the estimates of hazard functions for bear markets include negative coefficients on the covariates representing the period following the election of a Republican president and positive coefficients on the covariates the represent the period following the election of a Democratic president.

It is reasonable to expect that the effects of presidential elections on the stock market cycle turning points may differ across sub-periods of the almost century and a half over which I have data. Accordingly, I estimate hazard functions for the full set of 44 bears and 43 bulls in the United States since 1872 as well as for subsamples of the 28 bears and 28 bulls in the period after World War I and the 22 bears and 21 bulls in the period after World War II.

1.4. Empirical Results

The key data in this analysis of the links between political and financial events are the dates of turning points of stock market cycle in the U.S. In this study, a turning point is when the stock market trend turns, i.e., goes from being generalized upward-moving to generalized downward-moving or vice versa. The upward-moving period is commonly called a bull market, and the downward-moving period is known as a bear market. Although bull and bear markets are familiar words to investors, there is no general academic definition for them.[9] To identify these market trends, I adopt the algorithm developed by Pagan and Sossounov (2003).[10] The turning points are peaks and troughs of the identified stock market cycles.[11] Since inflation has varied considerably over my sample period, and it can be argued that drift in the nominal prices does not have the same interpretation during periods of low and high inflation. To deal with effects

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[9] Recent usage in the financial press seems to have refined this to insist on the rise (fall) of the market being greater (less) than either 20% or 25% in order to qualify for these names. In many ways the more general definition given in the study would seem to be closer to that used to describe contractions and expansions in the business cycle literature while the new definition, by emphasizing extreme movements, would like analogous to 'booms' and 'bust' in the real economy.

[10] Procedure for programmed determination of turning points can be seen in the Appendix.

[11] I account a peak or a trough as the final month of the bull market or bear market, respectively.

arising from this, I choose the real prices as a proxy for the general market. The nominal prices are later used as an alternative proxy for robustness test. [12]

My sample begins with the peak in July 1872 and ends with the trough in February 2016. There are 43 bull markets (periods from troughs to peaks) and 44 bear markets (periods from peaks to troughs) covered in the entire sample. The duration of each of these bears and bulls is presented in Table l. The final two columns in the table report whether an election was held during that phase of the market cycle. It can be seen from Table 1 that 24 of the 36 elections held over the entire sample occurred during bull markets. This is broadly consistent with the implication of Hypothesis One that incumbents attempt to generate rising markets in the period leading up to elections to increase their chance of being returned to office.

Table 2 provides a first view of the timing of peaks and troughs relative to presidential elections. I calculate the number of months since the last election for each of the turning points by subsamples as well as by the party of the president. Except for the Democratic administrations in the post-World War II period, the average number of months between the last election and a market peak is consistently lesser than the average number of months between the last election and a market trough across samples and across political parties. This is in line with Hypothesis One that bull markets tend to end soon after a presidential election and bear markets tend to end before a presidential election. Hypothesis Two predicts differences across Republican and

[12] Both prices series are collected from Sheller's database. http://www.econ.yale.edu/~shiller/data.htm

Democratic administrations. Comparing the second and third panels of Table 1 shows that on average, peaks occur sooner after the election of a Republican than after the election of a Democrat. Also, on average, troughs occur later following Republican election victories than following Democratic victories. The standard deviations for all these statistics, however, are quite large relative to the averages.

Further information about the distribution of the number of months between market cycle turning points and elections is provided in the histograms in Figures 1 and 2. Figure 1 shows marked differences in the distribution of the number of months since the previous election across peaks and troughs. For the full sample, the mass points in the histogram of troughs occur later than the mass points in the histogram of peaks. Although this pattern reverses for the subsamples cover the later periods, it can be seen that there are much more peaks than troughs occur in the period shortly after an election. Histograms that differentiate across presidential parties are presented in Figure 2. The histograms of troughs indicate that more than half of the troughs occur in the first two years after a Democratic won the election while this portion is consistently below 45 percent for the two years after the elections of Republican presidents in the post-World War I and the post-World War II periods. The histograms of peaks, on the other hand, show that there are much more peaks occur within 8 months of the election of a Republican president than the election of a Democratic president.

While the above summary statistics are suggestive, more robust tests of the hypotheses are provided by duration analysis. Unlike the unconditional estimates in Table 2, duration analysis allows me to test the effects of elections on stock market cycles holding constant the effects of other factors such as the underlying economy and the time on the market cycle itself. The estimates of the Cox proportional hazard models for bear markets with the various pre-election periods serving as time-varying covariates are presented in Table 3. Although all the estimated coefficients on the pre-election dummy variables are of the expected positive sign, the only coefficients that significantly differ from zero are the 16-month covariate in the post-World War II period. Thus, the prediction of Hypothesis One that there is a higher likelihood of a bear market ending in the period before an election than in other periods (conditional upon its having lasted until that period) is not strongly supported by the data. A similar finding is also reported by Kelvin (1996) that there is no reliable evidence that a contraction in the U.S. business cycle is more likely to end in the period before an election than in other periods.

Hypothesis One does not suggest that there should be a difference across political parties in attempts to engineer a market expansion in the period before an election. It may be, however, that the likelihood of a bear market ending in the period before an election depends upon the party in power at the time. This possibility is investigated in Table 4. In that table, the covariates representing the period before an election distinguish between those times when a Republican holds the presidency and those times when a Democrat sits in the White House. As above, positive and significant values of the estimated coefficients would demonstrate a greater likelihood of the end of a bear market in the period leading up to an election than at other times.

As can be seen in Table 4, there is no evidence that a bear market is more likely to end in the period before an election than at other times when the incumbent is a Democrat. Interestingly, however, the coefficients on the dummy variables representing the pre-election period when there is a Republican president not only are all of the expected positive sign, but also those on the 24-month and the 16-month covariates are highly significant across samples. The coefficients on the 8-month covariate are also statistically significant in the Post-World War I period when a Republican is incumbent. Moreover, the point estimates on each of the covariates representing the period when there is a Republican president increase as the sample is restricted from the full sample to the subsamples. For instance, the estimates suggest that for the full sample, an ongoing bear market is 2.12 $[exp(0.75)]$ times more likely to end in any given month during the 16 months before an election when a Republican is a president than at other times. This likelihood of the end of a bear market in next month by virtue of an upcoming election and a Republican presidency rises to 3.00 $[ex\,p(1.100)]$ when the sample is constrained to the post-World War I era and 3.11 $[ex\,p(1.134)]$ when the sample is further constrained to the post-World War II era. Wong and McAleer (2009), too, find that, compared to Democrat presidents, Republican presidents tend to have greater cause to engage in active manipulation in the equity market to win reelections.

Table 5 presents the estimates for bull markets with post-election periods serving as time-varying covariates. Hypothesis One suggests that there is a higher likelihood of a bull market ending in the period shortly after an election than in other periods conditional on its having lasted until that period. This would be reflected in positive coefficients on the post-election covariates. Although none of the estimated coefficients on the post-election covariates is statistically different from zero, results in Table 5 exhibit some support for the hypothesis. For instance, the estimated coefficients on the post-election covariates are all of the expected positive sign. Within any one sample period, the coefficient on the 8-month covariate is larger than the coefficient on either the 16-month or the 24-month covariates, which is also consistent with the hypothesis.[13]

Tests of Hypothesis Two requires a more disaggregated specification that distinguishes between the parties in power. As discussed above, I use a specification that has separate time-varying covariates for the months since the election of a Republican and the months since the election of a Democrat. Hypothesis Two suggests that the likelihood of the end of a bull market is higher after the election of a Republican and lower after the election of Democrat than at other times. In hazard estimates of bull markets, this implies that the coefficients on the covariates representing the period after a Republican presidential election victory are positive while those on the period following a Democratic victory are negative. Hypothesis Two also suggests the likelihood of the end of a contraction is lower after the election of a Republican president and higher after the election of a Democrat than at other times. In hazard estimates of bear markets, this implies that the coefficients on the covariates representing the period in the wake of Republican presidential victory are negative and the coefficients on the covariates representing the period after a Democratic presidential victory are positive.

Results presented in Tables 6 and 7 provide support for Hypothesis Two as regards the effects of Republican presidential election victories in the post-World War I and post-World War

[13] The consistent positive coefficients on the covariate for interest rate levels seem to suggest that increasing in interest rate increases the hazard for a bull market. Additionally, the covariate is significant at the 10 percent level for both the 8-month and the 16-month time frames in the post-World War II sample.

II periods. In the estimates of the hazards for bull markets presented in Table 6, the estimated coefficients on the covariates representing the period after an election of a Republican are all of the expected positive sign. Specifically, those for the 8-month covariate are significant at the 10 percent level when interest rates are not included in the specification for the post-World War I sample and the 5 percent level for the post-World War II sample, respectively. The coefficient on the 16-month covariate is also significant at the 5 percent level when interest rates are excluded from the specification for the post-World War II sample. The second aspect of the hypothesis that a bull market is less likely to end in the period following the victory of a Democratic president, however, finds less support in the data. Although some of the coefficients on the Democratic covariates are of the expected negative sign, none of them reaches the conventional levels of significance. [14]

The coefficients on the Republican covariates are consistently larger than the corresponding coefficients on the post-election covariates that do not differentiate between the party of the president in the post-World War I and post-World War II estimates. As with the results in Table 5, the coefficients on the periods following the election of a Republican president are most significant for the 8-month covariate. For instance, the estimates suggest that a bull market is 2.86 $[exp\ (1.051)]$ times more likely to end within 8 months of a Republican victory than at other times in the post-World War I period and 4.3 $[exp(1.456)]$ times more likely to

[14] There are only two instances of a peak within 8 months of a Democratic presidential victory in the post-World War II period implying that the result for the post-World War II period in Table 5 is largely due to periods following a Republican presidential victory.

end within 8 months of an election of a Republican in the post-World War II period. This suggests that the post-election effect in hazards of bull markets has become more pronounced over time for the Republicans.

Results presented in Table 7 for the estimates for hazard functions for bear markets exhibit some effects consistent with Hypothesis Two.[15] As expected, the coefficients on the covariates representing the period following an election of a Republican president are all negative, and those for the 24-month covariate are significant at the 10 percent level in the post-World War I and the post-World War II periods when the regressions control for the underlying economic condition. These point estimates suggest that compared to at other times, there is a 57 percent reduction in the likelihood of a bear market ending in the two years following a Republican presidential election victory in the post-World War I period and this reduction in the hazard for a bear market rises to 63 percent in the post-World War II period.[16] While coefficients on the Democratic covariates are all of the expected positive sign in the post-World War II period, none of them is significant at the conventional levels. Thus, the data fails to support Hypothesis Two that a bear market is more likely to end in the period following the victory of a Democratic candidate than in other periods.

[15] There is only one instance of a stock market trough in the 8 months following the election of a Democratic president in the post-World War II period, making the estimate of the coefficient on the Democratic covariate for tis sub period is impossible.
[16] [1- $exp(-0.842)$]=57% and [1- $exp(-0.976)$]=63%

1.5. Political Control and Duration of Stock Market Cycles

Since presidents of the United States share authority with Congress, and they frequently have a little or no control over congressional actions, it is difficult to see presidents manipulating policies without support from Congress. Yantek (1986) argues that the degree of manipulation by an incumbent president is mostly dependent on whether the president and Congress share the same party affiliation. Congressional influence on the presidential cycle effects is, however, largely overlooked in the existing research. In this section, I fill this void by examining whether political alignment between the White House and Congress, political control, would attenuate or exacerbate the temporal links between elections and timing of turning points in the stock market. To investigate this effect of political control, I construct a dummy variable, *Congress*, which equals to one when the same political party controls the White House and Congress, and I interact it with the covariates representing the pre- and post-election periods.[17] I then re-estimate the above regressions controlling for political alignment between the White House and Congress. New estimates are presented in Tables 8-12.

As seen in Table 8, after controlling for the political alignment between the White House and Congress, clear evidence emerges that an ongoing bear market is more to end in the pre-election period when the party of the incumbent is not the majority in Congress. The new coefficient estimates on the pre-election period dummies not only are all of the expected positive

[17] Congress is controlled by the Democratic Party or the Republican Party when the party has control (holds the majority of seats) of both the House of Representatives and the House of Senate simultaneously (i.e. complete control of the legislative branch in the nation).

sign but also those corresponding to the covariates representing the 24-month and the 16-month periods before an election are highly statistically significant. Furthermore, the point estimates for coefficients on the 24-month and the 16-month covariates and their statistical significance increase over time. In particular, these estimates suggest that controlling for interest rates and duration dependence, an ongoing bear market is 2.60 [$exp(.956)$] times more likely to end in any given month during the 16 months before an election than in other periods when the incumbent has no political control in Congress. This likelihood of the end of a bear market in the next month by virtue of a proximate election and absence of political control in Congress rises to 5.28 [$exp(1.664)$] and 6.51 [$exp(1.873)$] when the sample is constrained to the post-World War I period and the post-World War II period, respectively. Similarly, the likelihood of a bear market ending in any given month during the two-year period before an election when there is no political control for the incumbent rises from 2.78 [$exp(1.022)$] for the full sample to 3.65 [$exp(1.296)$] for the post-World War I subsample and to 12.34 [$exp(2.513)$] for the post-World War I subsample.

Estimated coefficients on the political control dummy variable, *Congress*, are all of a positive sign and those for the 24-month and 16-month covariates are significant at the 5 percent level and 1 percent level in the post-World War I subsample and the post-World War II subsample, respectively. The positive coefficients suggest that, in general, political control can shorten the duration of a bear market. Despite this positive level effect of political control, coefficients on the interaction term, *Election*Congress*, are all of a negative sign and those for the 24-month and 16 month periods are significant at the 5 percent level and the 1 percent level in the post-World War I period and the post-World War II period, individually. These negative estimates imply that political support from Congress attenuates the pre-election surge in the hazards for bear markets.[18] Specifically, the point estimates show that there is a sizeable difference in the hazards in the pre-election period between an incumbent with political control and a one without such political privilege. For instance, a market trough is about 1 [$exp(-4.488)$] percent as likely to occur in the two years prior to an election when Congress is in the control of the president's party as when the presidential party does not have such control in the post-World War II era.

Table 9 displays stronger evidence that bear markets are more likely to end in the run-up to an election when there is a Republican president conditioning on whether the president has control in Congress or not. The inclusion of political control in the regressions improves the coefficient estimates on the covariates representing the time when there is a Republican president both economically and statistically. Besides, coefficients on the covariates representing the 24-month and 16-month periods before an election when there is a Democratic incumbent are all of the expected positive sign and the coefficient estimates are significant in some cases.

[18] One possible interpretation for the negative congressional effect in the hazards in the pre-election period is that the range of policy tools available to the government to win support from voters may increase when the party of an incumbent has the complete control over Congress. The incumbent could choose policies that benefit voters more directly, such as increasing transfer payments, and lowering taxes prior to an election rather than trying to manipulate the stock market.

Parallel to the results in Table 8, coefficient estimates on *Congress* remain positive and are most significant for the subsamples. The negative coefficient estimates on the interaction terms, *Republican*Congress* and *Democratic*Congress*, indicate that political control diminishes the prospect of a market trough occurring in the pre-election period.[19] The higher point estimates on *Democratic*Congress* suggests that this reduction in the hazard of a bear market in the pre-election period is more evident for Democratic incumbents. In fact, the estimates infer that political control can completely offset the pre-election increase in the likelihood of a market trough when the president is a Democrat.

Contrary to Hypothesis One, the negative coefficients on the covariates for the post-election time dummies in Table 10 suggest bull markets are less likely to end following an election when the Oval Office and Congress do not share the same partisanship.[20] Coefficients on the 24-month covariates are significant at the 5 percent level for the full sample and the 10 percent level for the subsamples when interest rates are included as covariates. Moreover, the point estimates imply that there is a remarkable difference in the hazard for a bull market between in the two-year period after an election of a president who has no political control in Congress and at other times. Precisely, the likelihood of the end of a bull market, given its

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[19] There is no instance of a market trough in the pre-election periods when the Republican party controls both the White House and Congress simultaneously in the post-World War II period, making the estimate for the coefficient on the *Republican*Congress* for this sub-period impossible. Also, there are insufficient observations for estimating the coefficient on the *Democratic*Congress* for the 8-month time period.

[20] One potential explanation for the negative sign is that it is less likely for the elected presidents to take policies to reverses the stimulus policies employed before elections immediately after the elections are over when the new governments are not politically well aligned with Congress.

survival up until that time, is 34 [$exp(-1.801)$] percent as likely to occur within two years after an election when there is no political control for the president as at other times in the full sample period. The larger point estimates for the post-World War I and post-World War II subsamples are even more striking; the likelihood of a bull market ending within 24 months of an election when the party of the elected president does not control both houses of Congress is 23 [$exp(-1.477)$] percent as likely as at other times in the post-World War I period and is less than 20 [$exp(-1.607)$] percent as likely as at other times in the post-World War II period.

The negative coefficients on *Congress* suggest that political alignment with Congress usually prolong the duration of a bull market. Within any one sample period, the point estimates for the covariate representing political control and their level of significance are found to increase as the time frame is restricted from the 8-month period to the 16-month period to the 24-month period. Alternatively, coefficients on the interaction term, *Election*Congress*, are all of a positive sign and many of them are statistically different zero. These positive estimates suggest that there is a higher likelihood of a market peak following an election when Congress is dominated by the party of an elected president. To illustrate the economic significance of this joint effect in the hazards for bull markets, the coefficient in the post-World War II sample is taken as an example. The coefficient suggests that, for the post-World War II sample, an ongoing bull market is 55 [$exp(4.017)$] times more likely to end in any given month during the two-year period after an election when Congress is controlled by the party of the new president than when the new government and Congress do not share the same party affiliation. Furthermore, the magnitude of estimates on the covariate for political control and interaction term increases as the sample is restricted from the full sample to the post-World War I subsample to the post-World

War II subsample. This suggests that the congressional influence in the timing of turning points relative to elections has become more noticeable over time.

After taking into account the effect of political control, Table 11 shows that there is no longer evidence that a bull market is more likely to end in the period following an election of a Republican. The new estimates on the covariates representing the periods following a Republican election victory are all statistically insignificant. Some are even with a negative sign. The negative estimates for the coefficients on the Democratic covariates in the full sample, on the other hand, exhibit some effects consistent Hypothesis Two that a bull market is less likely to end in the period following an election of a Democrat than at other times. Moreover, the coefficients on the covariate presenting the two years following an election a Democrat is found to be significant at the 5 percent level for the full sample.

As the results in Table 10, the point estimates for the coefficient on *Congress* continue to be negative, and they are significantly different from zero for the subsamples when interest rates are not included. Besides, the coefficients on the covariate representing the political alignment in Congress are found to be significant at the 5 percent level for the 24-month period in the full sample as well. The positive coefficients on the interaction terms, *Republican*Congress* and *Democratic*Congress,* imply that in the post-election period, a bull market is more likely to end when the executive branch and the legislative branch are simultaneously controlled by the same political party. Furthermore, the coefficients in the full sample period show that this joint effect is more significant for Democratic presidents than for Republican presidents. [21] Specifically, the point estimates suggest that the likelihood of a market peak in the two years after an election of a Democratic president who is supported by a Congress controlled by Democrats is 20 $[exp(2.989)]$ time as likely as when the president does not have such support. While this likelihood of a market peak in the two years after a Republican election victory when the Republicans control Congress is 6.34 $[exp(1.847)]$ times as likely as when the Republicans are not the majority in Congress. Additionally, the coefficients on *Republican*Congress* reveals that effect of political control in hazards of bull markets following Republican election victories are most noticeable in the post-World War II subsample, the most recent sample period.

Finally, results in Table 12 offer enhanced evidence of a market trough is less likely to occur following an election of a Republican president when Congress is not in the control of the Republicans than at other times. The new estimates on the covariates representing the period following an election of a Republican not only are all of the expected negative sign but also those for the 16-month and 24-month periods are significant at the conventional levels in many cases.[22] The insignificant coefficients on *Congress* suggest that political control itself does not have a meaningful effect on the hazards for bear markets. However, the estimates on the interaction term, *Republican*Congress*, are all of a positive sign and are highly significant in

[21] There are insufficient observations for estimating the coefficients on *Democratic*Congress* for the post-World War I and the post-World War II samples. There are insufficient observations for estimating the coefficients on *Democratic*Congress* for the 8-month and 16-month periods for the full sample as well.
[22] There are insufficient observations for estimating the coefficients on *Democratic*Congress* and the coefficients on *Republican*Congress* for the 8-month period.

most cases. These point estimates suggest that political alignment between the president and Congress causes a sizeable difference in the hazards for bear markets in the post-election period between when the elected Republican president enjoys full support from Congress and when the new administration is not entirely backed up by Congress. For instance, the point estimate in the post-World War II subsample period suggest that the likelihood of a market trough to occur in the two years following an election when the Republicans have both the White House and Congress is nearly 125 $[exp(4.829)]$ times as likely as when the elected Republican president who is not politically aligned with Congress after controlling for economic condition and for duration dependence..[23]

1.6. Robustness Tests

As a robustness test, and to ensure that the above results are not driven by some outlier in my sample, I exclude the observations from the 1929 stock market crash period and the 2008 market crash period from the sample. The results produced by the new sample data are mostly the same as the original results. [24] As an additional robustness test, I consider the nominal stock prices as an alternative measure of the general market condition. Table 13 reports the dates of turning points of the new cycles identified by using nominal prices and the duration of each of the new bear and bull markets and whether an election was held during that phases of the cycle.

[23] Coefficients on the *Interest Rate Changes* in the post-World War II are all significant at the 1 percent level. These negative coefficients indicate that rising in interest rate changes reduces the hazards for bear markets.
[24] To save space, I did not report the estimates for the robustness tests in the paper. These new estimates are available upon request.

Again, the elections held during the bull markets are twice as many as the elections held during the bear markets. The statistics on the timing of new turning pints relative to previous elections presented in Table 14 are almost identical to the statistics in Table 2. On average, bull markets tend to end soon after an election and bear markets tend to end before an election. Compared to the Republican election victories, market troughs occur sooner and peaks occur later after the Democratic presidential elections. Histograms in Figures 3 and 4 present similar patterns in the distribution of months between market cycle turning points and last elections as the patterns in Figures 1 and 2. For the full sample, the mass points in the histogram of peaks occur sooner than the mass points in the histogram of troughs. There are more peaks than troughs occur in the periods immediately after the elections. Histograms in Figure 4 show that there are more troughs in the pre-election period when the incumbents are Republicans than when the incumbents are Democrats. Nearly 60 percent of the market troughs during the Republican presidents occur in the two years before the elections while this proportion is below 40 percent for Democratic presidents. Furthermore, there are more peaks occur in the 8 months following an election of a Republican than a Democratic victory. Finally, the estimates from the Cox regressions reaffirm my earlier findings.

1.7. Conclusions

This study provides a more direct test of the timing of stock market cycle turning points relative to the elections in the United States than previous research, which only considers the amplitude of returns and volatility before and after presidential elections. Empirical results from duration analysis provide evidence suggesting that the likelihood of a market trough, the end of a bear market, is higher in the period before an election than in other periods, but only when a

Republican is a president. Further examination of the post-election effect reveals a difference by the party of the victorious presidential candidate. Consistent with Hypothesis Two, bull markets are found to be more likely to end following Republican presidential victories than at other times. Also, consistent with the hypothesis is the finding that bear markets are less likely to end following a Republican election victory.

Results from additional tests uncover that political control, the political alignment between the White House and Congress, holds a vital role in the timing of turning points of the stock market cycles relative to the elections. In particular, compared to the pre-election period when there is no political alignment between the Oval Office and Capitol Hill, there is a reduced chance for a bear market ending in the run-up to an election when the incumbent has full support from Congress regardless of the political party of the president. This reduction in the likelihood of a market trough, marking the end of a bear market, in the pre-election period is particularly evident for the Democratic incumbents. Alternatively, there is a substantial upsurge in the likelihood of the end of a bull market following an election when the elected president and Congress share the same partisanship. This rise in the likelihood of a market peak in the post-election period is more noticeable following a Democratic election victory. Finally, political control seems to let the Republican presidents substitute a higher likelihood of a market trough in the post-election period when the Republicans control both houses of Congress for a lower possibility when they do not have such political advantage.

This paper does not intend to provide a complete test of the election effects in the U.S. stock market as there are other implications that cannot be addressed by using duration analysis.

The findings presented in this paper, however, undoubtedly complement the existing literature and expand our knowledge of how presidential elections in the U.S. can affect its financial markets. A better understanding of the relationships between the timing of turning points of stock market cycles and political events is not only central to our understanding of the empirical relevance of political business cycle theories in financial markets but also it could help investors to make better investment decisions when combined with other information.

Figure 1.1 Timing of Peaks and Troughs Relative to Election

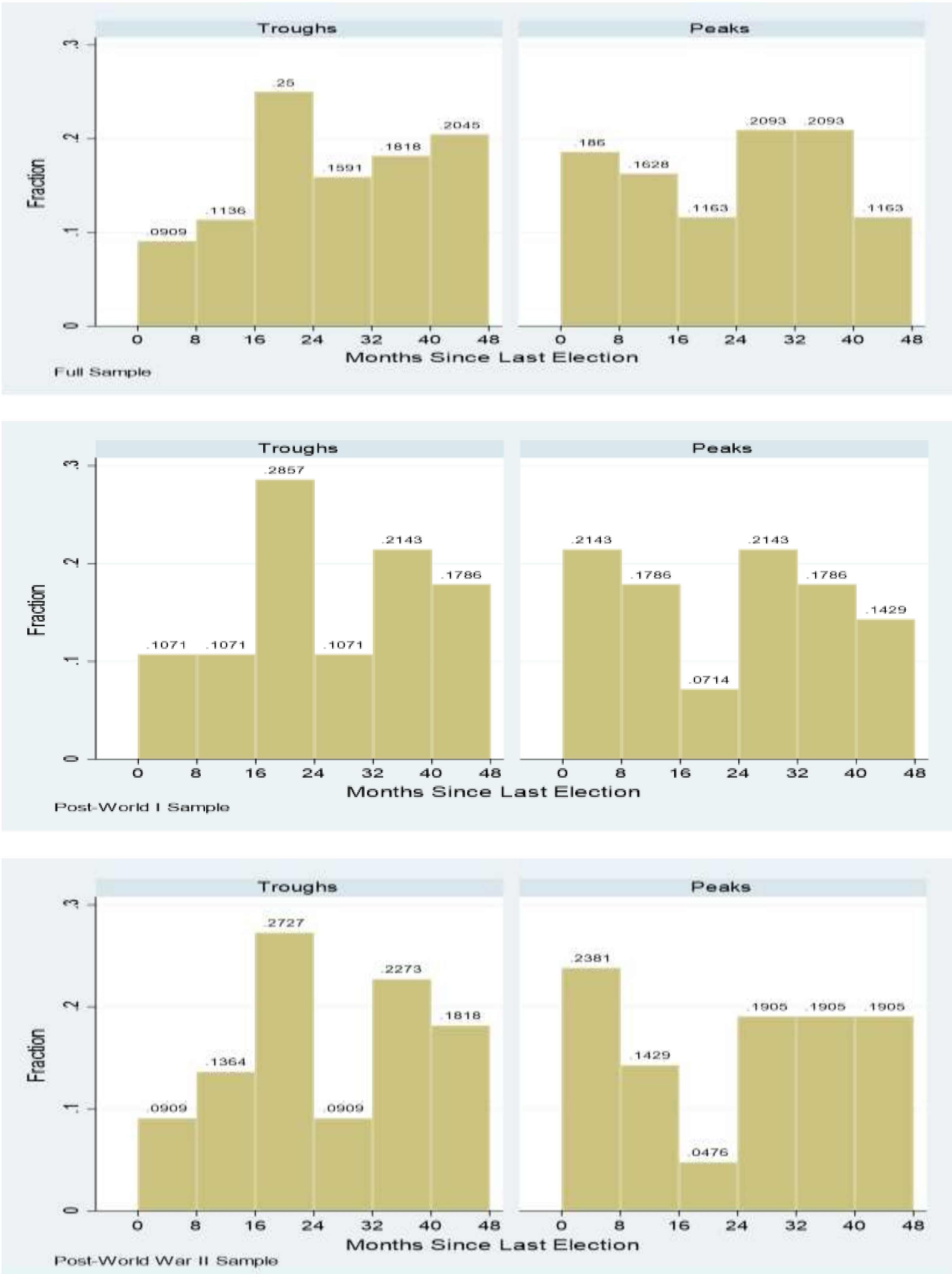

Figure 1.2 Timing of Peaks and Troughs Relative to Election By Political Party

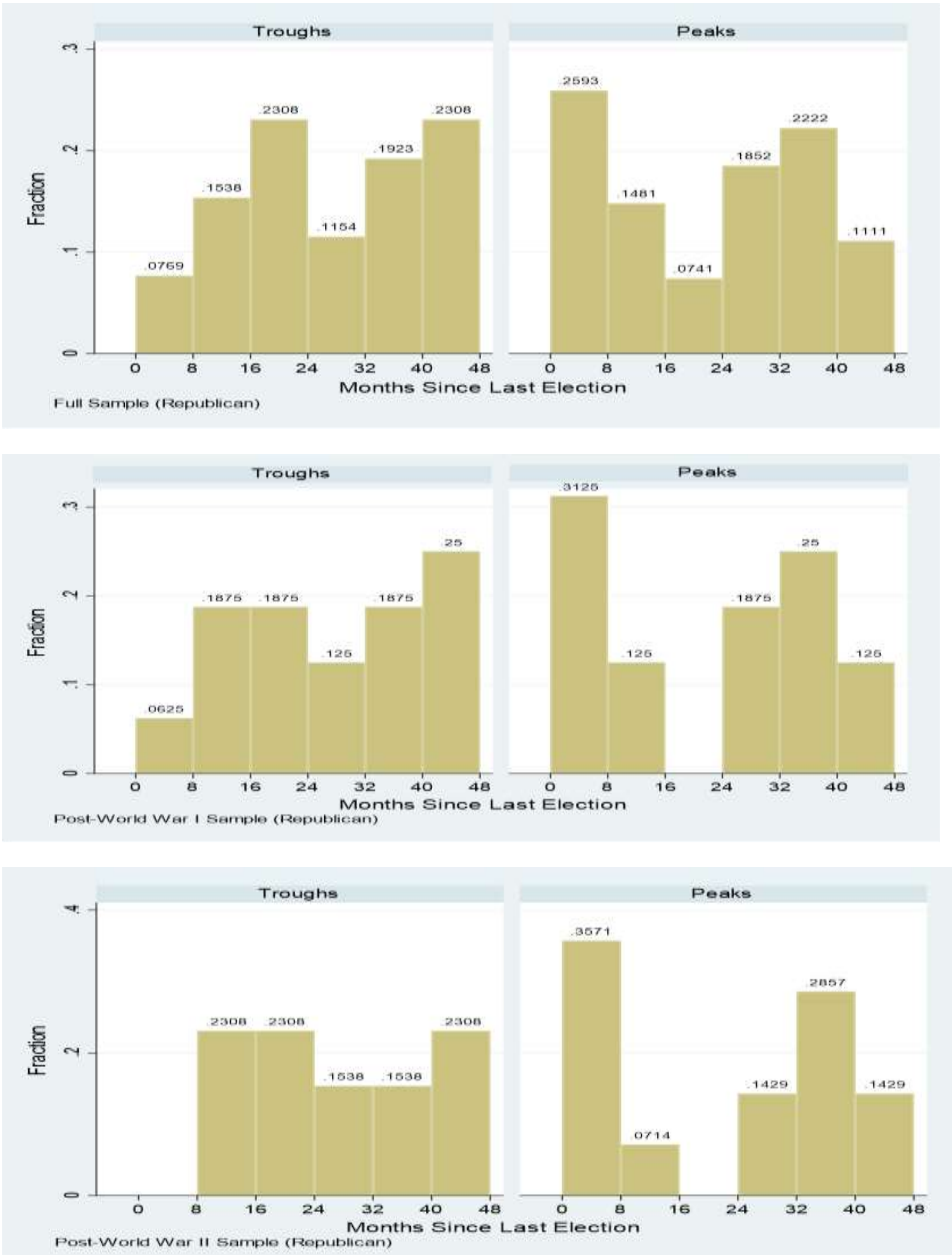

Figure 1.2 (Continued)

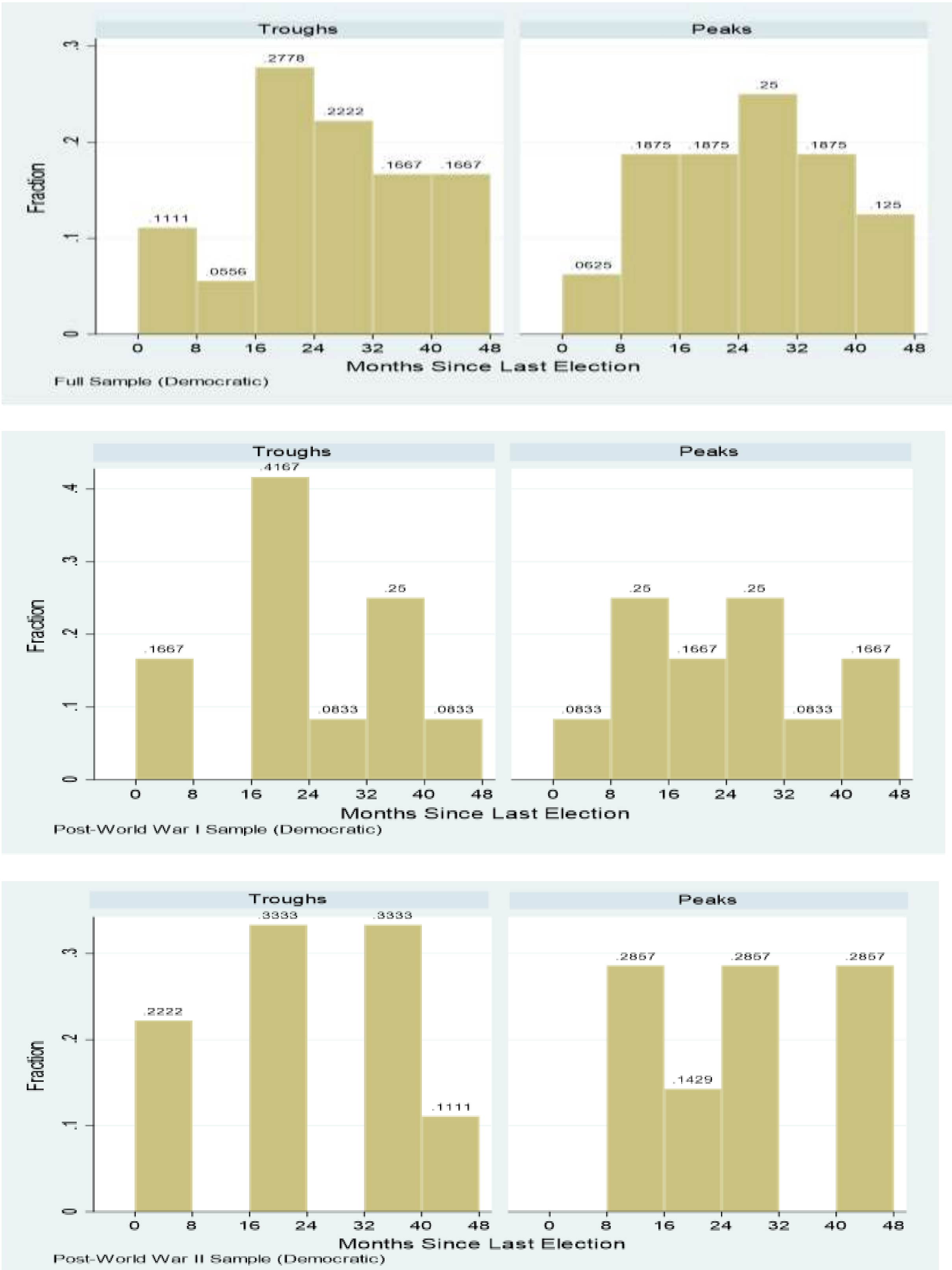

Figure 1.3 Timing of Peaks and Troughs Relative to Elections (Nominal Prices)

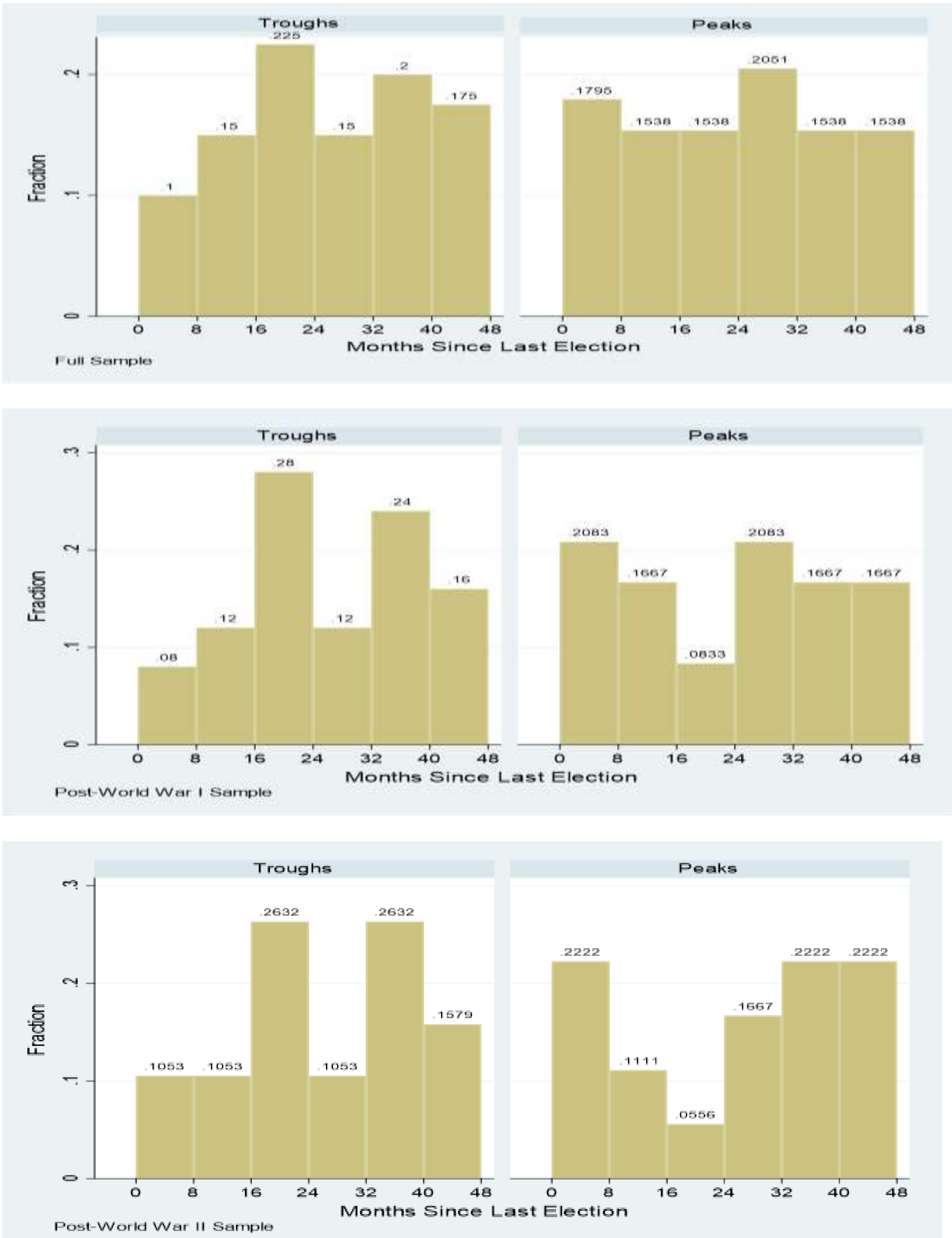

Figure 1.4 Timing of Peaks and Troughs Relative to Elections By Party (Nominal Prices)

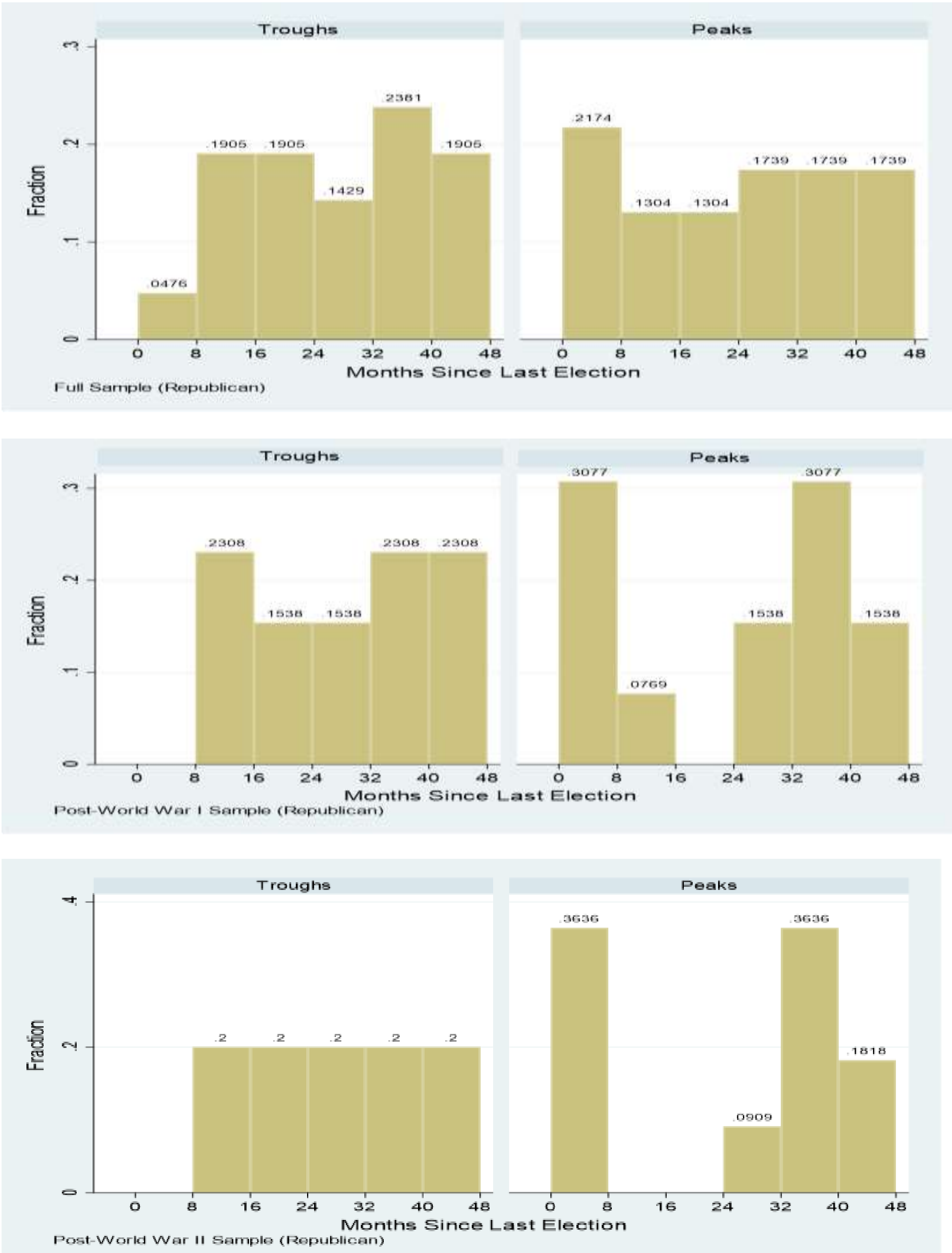

Figure 1.4 (Continued)

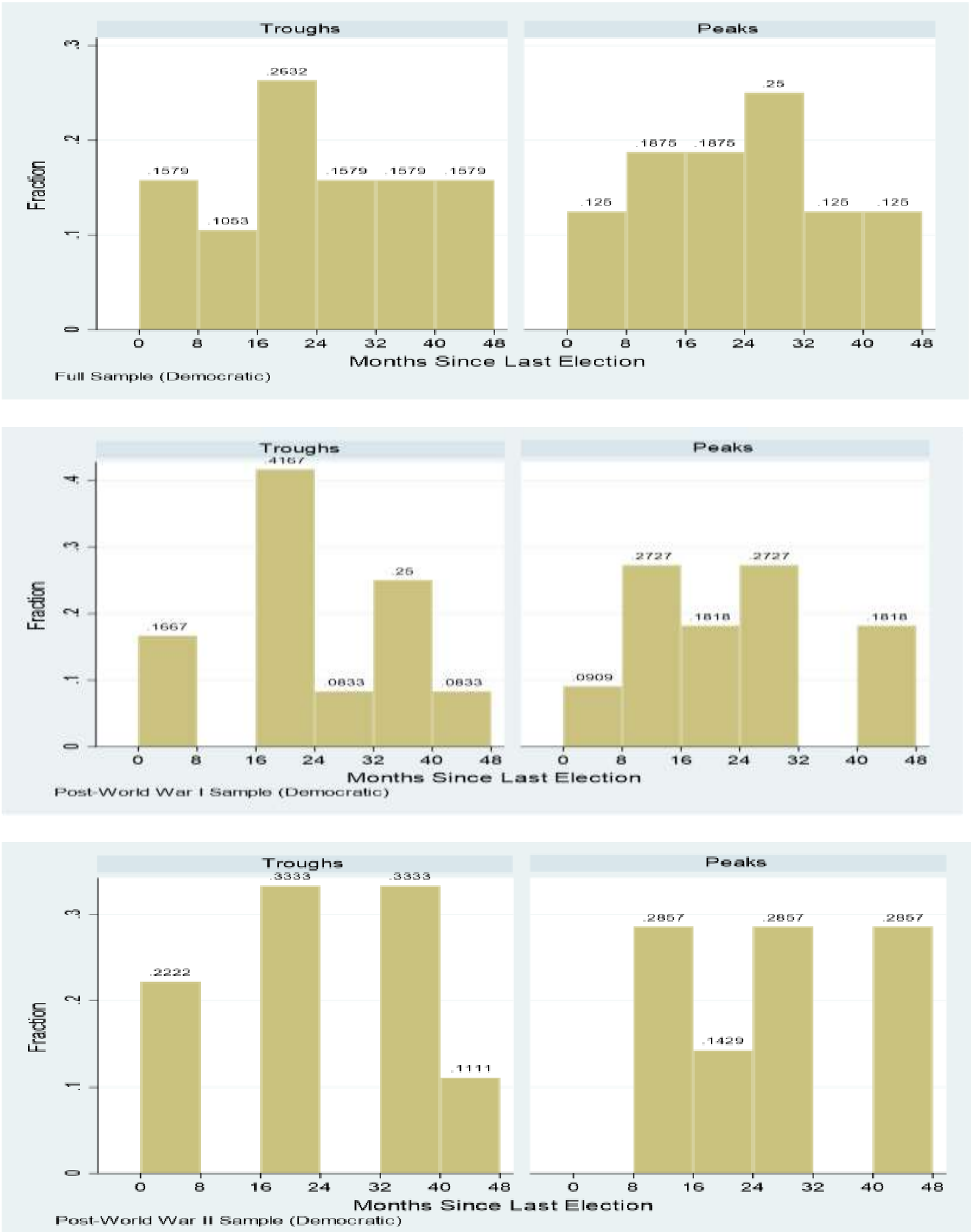

Table 1.1 Dates of Turning Points in U.S. Stock Market

Date of		Duration (in months)		Was an Election Held during the	
Trough	Peak	Bear	Bull	Bear	Bull
	7/1872				
11/1873	2/1876	16	27	YES	NO
6/1877	6/1881	16	48	YES	YES
6/1882	7/1883	12	13	NO	NO
6/1884	11/1886	11	29	NO	YES
3/1888	5/1890	16	26	NO	YES
12/1890	5/1892	7	17	NO	NO
7/1893	4/1894	14	9	YES	NO
4/1895	9/1895	12	5	NO	NO
8/1896	9/1897	11	13	NO	YES
5/1898	3/1899	8	10	NO	NO
9/1900	6/1901	18	9	NO	YES
10/1903	9/1906	28	35	NO	YES
11/1907	8/1909	14	21	NO	YES
7/1910	6/1911	11	11	NO	NO
12/1914	12/1915	42	12	YES	NO
1/1919	7/1919	37	6	YES	NO
12/1920	3/1923	17	27	YES	NO
10/1923	9/1929	7	71	NO	YES(2 ELECTIONS)
6/1932	7/1933	33	13	NO	YES
3/1935	2/1937	20	23	NO	YES
4/1938	11/1938	14	7	NO	NO
5/1942	4/1946	42	47	YES	YES
2/1948	6/1948	22	4	NO	NO
6/1949	1/1953	12	43	YES	YES
9/1953	4/1956	8	31	NO	NO
12/1957	7/1959	20	19	YES	NO
10/1960	12/1961	15	14	NO	YES
6/1962	1/1966	6	43	NO	YES
10/1966	12/1968	9	26	NO	YES
7/1970	4/1971	19	9	NO	NO
11/1971	1/1973	7	14	NO	YES
12/1974	9/1976	23	21	NO	NO
3/1978	8/1978	18	5	YES	NO
4/1980	11/1980	20	7	NO	YES
7/1982	6/1983	20	11	NO	NO
7/1984	8/1987	13	37	NO	YES
12/1987	8/1989	4	20	NO	YES
10/1990	1/1992	14	15	NO	NO
10/1992	8/2000	9	94	NO	YES(2 ELECTIONS)
2/2003	12/2004	30	22	YES	YES
10/2005	10/2007	10	24	NO	NO
3/2009	2/2011	17	23	YES	NO
9/2011	5/2015	7	44	NO	YES
2/2016		9		NO	

Notes: Along a row, Bear market refers to period from peak in pervious row to trough in the next row. Bull market refers to period from trough in that raw to peak in that row.

Table 1.2 Statistics on Timing of Peaks and Troughs Relative to Elections

Full Sample	Months Since Last Election							
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	22.60(13.96)	0	46	43	26.52(13.09)	1	47	44
Post WWI	21.96(15.05)	0	46	28	26.21(13.49)	1	47	28
Post WWII	23.48(16.14)	0	46	21	26.91(13.37)	4	47	22

Republican Administrations	Months Since Last Election							
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	21.59(15.07)	0	46	27	27.31(13.66)	1	47	26
Post WWI	21.13(16.76)	0	46	16	28.06(14.30)	1	47	16
Post WWII	21.43(17.64)	0	46	14	28.46(13.11)	10	47	13

Democratic Administrations	Months Since Last Election							
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	24.31(12.12)	3	45	16	25.39(12.52)	4	45	18
Post WWI	23.08(13.06)	3	45	12	23.75(12.50)	4	41	12
Post WWII	27.57(12.83)	13	45	7	24.67(14.20)	4	41	9

Table 1.3 Estimates of Hazard Functions for Bear Markets

1. Full Sample		Dummy Variables: Months Before an Election		
Equation	Variable	24 months	16 months	8 months
A.	*Election*	0.385	0.393	0.221
		(0.28)	(0.28)	(0.36)
B.	*Election*	0.424	0.411	0.235
		(0.31)	(0.28)	(0.34)
	Interest rates	0.053	0.047	0.048
		(0.05)	(0.05)	(0.05)
	Interest Rate Changes	-0.011	-0.023	-0.058
		(0.05)	(0.12)	(0.08)

2. Post-World War I		Dummy Variables: Months Before an Election		
Equation	Variable	24 months	16 months	8 months
A.	*Election*	0.211	0.337	0.153
		(0.37)	(0.30)	(0.45)
B.	*Election*	0.567	0.512	0.161
		(0.41)	(0.34)	(0.42)
	Interest rates	-0.068	0.021	0.054
		(0.07)	(0.07)	(0.06)
	Interest Rate Changes	1.075 **	0.354	0.104
		(0.49)	(0.29)	(0.19)

3. Post-World War II		Dummy Variables: Months Before an Election		
Equation	Variable	24 months	16 months	8 months
A.	*Election*	0.448	0.642 *	0.547
		(0.42)	(0.36)	(0.44)
B.	*Election*	0.549	1.020 **	0.851
		(0.47)	(0.45)	(0.55)
	Interest rates	-0.074	-0.070	-0.043
		(0.11)	(0.08)	(0.08)
	Interest Rate Changes	0.785	1.128	0.679
		(1.00)	(0.71)	(0.78)

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.4 Estimates of Hazard Functions for Bear Markets by Party

1. Full Sample		Dummy Variables: Months Before an Election, By Party					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	0.653	**	0.741	**	0.484	
		(0.31)		(0.32)		(0.38)	
	Democratic	0.056		0.118		-0.297	
		(0.36)		(0.45)		(0.71)	
B.	*Republican*	0.723	**	0.750	**	0.499	
		(0.36)		(0.32)		(0.38)	
	Democratic	0.105		-0.095		-0.285	
		(0.37)		(0.44)		(0.67)	
	Interest Rates	0.048		0.042		0.048	
		(0.05)		(0.05)		(0.05)	
	Interest Rate Changes	-0.044		-0.037		-0.061	
		(0.06)		(0.11)		(0.09)	
2. Post-World War I		Dummy Variables: Months Before an Election, By Party					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	0.747	*	1.005	***	0.778	*
		(0.45)		(0.37)		(0.46)	
	Democratic	-0.479		-0.455		-0.871	
		(0.52)		(0.60)		(1.04)	
B.	*Republican*	0.897	**	1.100	***	0.829	**
		(0.45)		(0.34)		(0.39)	
	Democratic	-0.021		-0.293		-0.918	
		(0.54)		(0.68)		(1.00)	
	Interest Rates	-0.070		-0.008		0.036	
		(0.07)		(0.06)		(0.06)	
	Interest Rate Changes	0.953	**	0.366		0.225	
		(0.46)		(0.26)		(0.20)	
3.Post-World War II		Dummy Variables: Months Before an Election, By Party					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	0.977	**	0.925	**	0.479	
		(0.48)		(0.47)		(0.51)	
	Democratic	-0.139		0.255		0.779	
		(0.54)		(0.60)		(0.52)	
B.	*Republican*	1.147	**	1.134	**	0.763	
		(0.51)		(0.49)		(0.55)	
	Democratic	-0.086		0.728		1.222	
		(0.57)		(0.81)		(0.82)	
	Interest Rates	-0.110		-0.067		-0.050	
		(0.11)		(0.08)		(0.08)	
	Interest Rate Changes	0.983		0.989		0.702	
		(0.98)		(0.81)		(0.81)	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively . Numbers in paranthesis are robust standard errors.

Table 1.5 Estimates of Hazard Function for Bull Markets

1. Full Sample		Dummy Variables: Months Since an Election				
Equation	Variable	8 months		16 months		24 months
A.	*Election*	0.172		0.039		0.031
		(0.41)		(0.32)		(0.31)
B.	*Election*	0.186		0.074		0.041
		(0.41)		(0.33)		(0.32)
	Interest rates	0.035		0.057		0.026
		(0.06)		(0.07)		(0.07)
	Interest Rate Changes	-0.018		-0.261	**	-0.269
		(0.12)		(0.13)		(0.13)

2. Post-World War I		Dummy Variables: Months Since an Election				
Equation	Variable	8 months		16 months		24 months
A.	*Election*	0.667		0.395		0.063
		(0.48)		(0.38)		(0.44)
B.	*Election*	0.629		0.419		0.093
		(0.48)		(0.41)		(0.44)
	Interest rates	0.107		0.103		0.042
		(0.07)		(0.08)		(0.07)
	Interest Rate Changes	0.060		-0.163		-0.413
		(0.39)		(0.49)		(0.60)

3. Post-World War II		Dummy Variables: Months Since an Election				
Equation	Variable	8 months		16 months		24 months
A.	*Election*	0.543		0.529		-0.029
		(0.57)		(0.44)		(0.51)
B.	*Election*	0.540		0.371		-0.069
		(0.57)		(0.48)		(0.51)
	Interest rates	0.129	*	0.123	*	0.072
		(0.08)		(0.07)		(0.08)
	Interest Rate Changes	0.119		0.463		0.143
		(0.61)		(0.82)		(0.79)

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively .
Numbers in paranthesis are robust standard errors.

Table 1.6 Estimates of Hazard Functions for Bull Markets by Party

1. Full Sample		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	0.348	0.236	0.027
		(0.47)	(0.37)	(0.37)
	Democratic	-0.212	-0.323	0.037
		(0.67)	(0.49)	(0.37)
B.	*Republican*	0.350	0.211	-0.015
		(0.47)	(0.39)	(0.37)
	Democratic	-0.184	-0.202	0.123
		(0.68)	(0.50)	(0.40)
	Interest Rates	0.032	0.050	0.029
		(0.06)	(0.07)	(0.07)
	Interest Rate Changes	-0.011	-0.242 *	-0.280 **
		(0.12)	(0.13)	(0.14)
2. Post-World War I		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	1.051 *	0.710	0.069
		(0.57)	(0.53)	(0.62)
	Democratic	0.149	0.067	0.057
		(0.70)	(0.50)	(0.45)
B.	*Republican*	0.855	0.618	0.083
		(0.58)	(0.59)	(0.70)
	Democratic	0.292	0.208	0.100
		(0.74)	(0.53)	(0.46)
	Interest Rates	0.094	0.088	0.043
		(0.08)	(0.08)	(0.09)
	Interest Rate Changes	0.043	-0.174	-0.411
		(0.38)	(0.48)	(0.62)
3.Post-World War II		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	1.465 **	1.239 **	0.408
		(0.58)	(0.58)	(0.67)
	Democratic		-0.221	-0.479
			(0.59)	(0.59)
B.	*Republican*	1.243 **	0.894	0.303
		(0.61)	(0.64)	(0.71)
	Democratic		-0.278	-0.445
			(0.64)	(0.63)
	Interest Rates	0.099	0.078	0.045
		(0.08)	(0.08)	(0.09)
	Interest Rate Changes	0.130	0.513	0.140
		(0.62)	(0.78)	(0.78)

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.7 Estimates of Hazard Functions for Bear Markets by Party

1. Full Sample		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	-0.397	-0.480	-0.296
		(0.71)	(0.43)	(0.34)
	Democratic	-0.326	-0.799 *	-0.509
		(0.44)	(0.43)	(0.39)
B.	*Republican*	-0.410	-0.526	-0.369
		(0.73)	(0.45)	(0.38)
	Democratic	-0.307	-0.783 *	-0.478
		(0.45)	(0.42)	(0.39)
	Interest Rates	0.024	0.034	0.047
		(0.05)	(0.04)	(0.05)
	Interest Rate Changes	-0.036	-0.052	-0.002
		(0.09)	(0.91)	(0.05)
2. Post-World War I		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	-0.675	-0.473	-0.455
		(1.14)	(0.55)	(0.46)
	Democratic	0.221	-0.251	0.199
		(0.59)	(0.50)	(0.40)
B.	*Republican*	-0.775	-0.679	-0.842 *
		(1.11)	(0.55)	(0.48)
	Democratic	0.163	-0.310	-0.047
		(0.61)	(0.49)	(0.43)
	Interest Rates	0.026	0.043	-0.027
		(0.06)	(0.05)	(0.07)
	Interest Rate Changes	0.139	0.407	0.925 **
		(0.19)	(0.31)	(0.42)
3.Post-World War II		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	–	-0.910	-0.873
			(0.58)	(0.50)
	Democratic	0.473	0.260	0.486
		(0.58)	(0.46)	(0.46)
B.	*Republican*	–	-0.831	-0.976 *
			(0.61)	(0.54)
	Democratic	0.749	0.316	0.384
		(0.67)	(0.49)	(0.50)
	Interest Rates	-0.039	-0.022	-0.030
		(0.05)	(0.05)	(0.11)
	Interest Rate Changes	-1.556 **	-0.370	0.576
		(0.74)	(0.72)	(0.92)

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.8 Estimates of Hazard Functions for Bear Markets with Political Control

1. Full Sample		Dummy Variables: Months Before an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Election*	0.827	*	0.749	**	0.347	
		(0.43)		(0.36)		(0.47)	
	Congress	0.456		0.350		0.104	
		(0.48)		(0.41)		(0.34)	
	*Election*Congress*	-0.831		-0.779		-0.354	
		(0.63)		(0.70)		(0.86)	
B.	*Election*	1.021	**	0.956	***	0.440	
		(0.45)		(0.36)		(0.47)	
	Congress	0.707		0.538		0.203	
		(0.49)		(0.43)		(0.35)	
	*Election*Congress*	-1.187	*	-1.090		-0.585	
		(0.64)		(0.71)		(0.89)	
	Interest rates	0.081	*	0.048		0.035	
		(0.05)		(0.05)		(0.04)	
	Interest Rate Changes	0.040		0.149		0.105	
		(0.06)		(0.13)		(0.10)	

2. Post-World War I		Dummy Variables: Months Before an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Election*	0.995	*	1.133	***	0.823	
		(0.53)		(0.41)		(0.57)	
	Congress	1.126	**	0.977	**	0.535	
		(0.54)		(0.43)		(0.45)	
	*Election*Congress*	-1.852	**	-2.038	**	-1.879	
		(0.85)		(1.02)		(1.40)	
B.	*Election*	1.296	**	1.664	***	1.027	*
		(0.52)		(0.20)		(0.61)	
	Congress	1.520	**	1.557	***	0.859	
		(0.60)		(0.52)		(0.56)	
	*Election*Congress*	-2.283	**	-3.019	**	-2.578	
		(0.90)		(1.20)		(1.58)	
	Interest rates	0.106	*	0.093		0.064	
		(0.06)		(0.06)		(0.05)	
	Interest Rate Changes	0.231		0.378	*	0.320	
		(0.24)		(0.24)		-0.17	

3.Post-World War II		Dummy Variables: Months Before an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Election*	1.584	**	1.677	***	0.881	
		(0.62)		(0.52)		(0.59)	
	Congress	2.195	***	1.994	***	0.954	
		(0.60)		(0.57)		(0.60)	
	*Election*Congress*	-3.513	***	-3.146	***	-0.918	
		(0.84)		(0.91)		(1.17)	
B.	*Election*	2.513	***	1.873	***	0.743	
		(0.75)		(0.53)		(0.84)	
	Congress	2.927	***	2.158	***	0.930	
		(0.86)		(0.57)		(0.59)	
	*Election*Congress*	-4.488	***	-3.595	***	-0.525	
		(1.02)		(0.82)		(1.56)	
	Interest rates	0.079		0.062		-0.045	
		(0.08)		(0.07)		(0.08)	
	Interest Rate Changes	-1.526	***	0.057		-0.208	
		(0.47)		(0.88)		(0.48)	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.9 Estimates of Hazard Functions for Bear Markets by Party with Political Control

1. Full Sample		Dummy Vriables: Months Before an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	0.918	**	0.902	**	0.554	
		(0.45)		(0.40)		(0.47)	
	Democratic	0.716		0.616		-0.274	
		(0.57)		(0.52)		(1.00)	
	Congress	0.448		0.386		0.112	
		(0.49)		(0.41)		(0.34)	
	*Republican*Congress*	-0.418		-0.078		-0.155	
		(0.67)		(0.76)		(0.57)	
	*Democratic*Congress*	-1.212		-1.877	*	-0.048	
		(0.77)		(1.00)		(1.56)	
B.	*Republican*	1.072	**	1.065	***	0.625	
		(0.49)		(0.41)		(0.45)	
	Democratic	1.139	*	1.026	**	-0.142	
		(0.66)		(0.52)		(1.03)	
	Congress	0.787		0.657		0.210	
		(0.54)		(0.45)		(0.35)	
	*Republican*Congress*	-0.481		-0.228		-0.354	
		(0.71)		(0.74)		(0.57)	
	*Democratic*Congress*	-1.799	**	-2.473	***	-0.314	
		(0.88)		(0.91)		(1.58)	
	Interest Rates	0.112	*	-0.079		0.035	
		(0.06)		(0.05)		(0.04)	
	Interest Rate Changes	-0.045		0.126		0.095	
		(0.08)		(0.13)		(0.10)	

2. Post-World War I		Dummy Vriables: Months Before an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	1.285	**	1.668	***	1.111	**
		(0.61)		(0.41)		(0.50)	
	Democratic	0.436		0.573		-1.216	
		(0.76)		(0.74)		(1.09)	
	Congress	1.250	**	1.155	**	0.576	
		(0.63)		(0.45)		(0.43)	
	*Republican*Congress*	-0.711		0.450			
		(0.66)		(0.65)			
	*Democratic*Congress*	-1.982	*	-2.369	**		
		(1.04)		(1.11)			
B.	*Republican*	1.503	***	2.115	***	1.285	**
		(0.57)		(0.54)		(0.52)	
	Democratic	0.815		1.425	*	-1.634	
		(0.96)		(0.86)		(1.16)	
	Congress	1.626	**	1.837	**	0.979	*
		(0.67)		(0.57)		(0.53)	
	*Republican*Congress*	-0.956		0.408			
		(0.67)		(0.67)			
	*Democratic*Congress*	-2.501	**	-3.799	***		
		(1.21)		(1.06)			
	Interest Rates	0.094		0.091	*	0.056	
		(0.07)		(0.06)		(0.05)	
	Interest Rate Changes	0.315		0.503	*	0.329	**
		(0.25)		(0.21)		(0.16)	

Table 1.9 (CONTINUEED)

3. Post-World War II		Dummy Variables: Months Befoe an Election					
Equation	Variable	24 months		16 months		8 months	
A.	*Republican*	2.549	***	2.462	***	0.916	
		(0.80)		(0.83)		(0.58)	
	Democratic	0.739		0.897		-0.091	
		(0.97)		(1.03)		(0.80)	
	Congress	2.728	***	2.468	***	0.967	*
		(0.83)		(0.80)		(0.59)	
	*Democratic*Congress*	-3.198	***	-2.952	***		
		(0.95)		(0.95)			
	Republican	2.650	***	2.431	***	0.794	
		(0.81)		(0.83)		(0.80)	
B.	*Democratic*	2.067		0.829		0.120	
		(1.43)		(1.18)		(0.91)	
	Congress	2.969	***	2.467	***	0.953	*
		(0.87)		(0.78)		(0.57)	
	*Democratic*Congress*	-4.179	***	-2.922	***		
		(1.31)		(1.08)			
	Interest Rates	0.060		0.018		-0.044	
		(0.09)		(0.07)		(0.08)	
	Interest Rate Changes	-1.314	**	-0.305		-0.202	
		(0.64)		(0.62)		(0.46)	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.10 Estimates of Hazard Functions for Bull Markets with Political Control

1. Full Sample		Dummy Variables: Months Since an Election					
Equation	Variable	8 months		16 months		24 months	
A.	*Election*	*-0.716*		*-0.753*		*-1.113*	**
		(0.63)		*(0.56)*		*(0.48)*	
	Congress	*-0.516*		*-0.687*	*	*-1.452*	**
		(0.33)		*(0.40)*		*(0.58)*	
	*Election*Congress*	*1.465*	*	*1.368*	*	*2.367*	***
		(0.84)		*(0.75)*		*(0.78)*	
B.	*Election*	*-0.714*		*-0.666*		*-1.081*	**
		(0.61)		*(0.56)*		*(0.48)*	
	Congress	*-0.519*		*-0.663*		*-1.388*	**
		(0.39)		*(0.43)*		*(0.60)*	
	*Election*Congress*	*1.456*	*	*1.179*		*2.244*	***
		(0.83)		*(0.78)*		*(0.78)*	
	Interest rates	*-0.011*		*0.008*		*-0.007*	
		(0.08)		*(0.08)*		*(0.09)*	
	Interest Rate Changes	*-0.011*		*-0.222*		*-0.100*	
		(0.13)		*(0.14)*		*(0.15)*	

2. Post-World War I		Dummy Variables: Months Since an Election					
Equation	Variable	8 months		16 months		24 months	
A.	*Election*	*-0.528*		*-0.480*		*-1.357*	
		(1.01)		*(0.74)*		*(0.88)*	
	Congress	*-0.958*	**	*-1.233*	**	*-2.085*	***
		(0.38)		*(0.50)*		*(0.78)*	
	*Election*Congress*	*1.920*	*	*1.714*	*	*3.031*	**
		(1.19)		*(1.00)*		*(1.22)*	
B.	*Election*	*-0.470*		*-0.544*		*-1.477*	*
		(1.00)		*(0.76)*		*(0.91)*	
	Congress	*-0.821*	*	*-1.113*	**	*-2.047*	**
		(0.44)		*(0.56)*		*(0.84)*	
	*Election*Congress*	*1.842*		*1.756*	*	*3.212*	***
		(1.16)		*(1.03)*		*(1.23)*	
	Interest rates	*0.048*		*0.056*		*0.052*	
		(0.09)		*(0.08)*		*(0.10)*	
	Interest Rate Changes	*0.401*		*0.009*		*0.139*	
		(0.40)		*(0.46)*		*-0.42*	

3.Post-World War II		Dummy Variables: Months Since an Election					
Equation	Variable	8 months		16 months		24 months	
A.	*Election*	*-0.498*		*-0.448*		*-1.082*	
		(1.04)		*(0.75)*		*(0.90)*	
	Congress	*-1.076*	*	*-1.648*	*	*-2.195*	*
		(0.59)		*(0.90)*		*(1.18)*	
	*Election*Congress*	*2.115*		*2.448*	*	*3.001*	*
		(1.48)		*(1.42)*		*(1.04)*	
B.	*Election*	*-0.549*		*-1.057*		*-1.607*	*
		(1.04)		*(0.77)*		*(0.88)*	
	Congress	*-0.955*		*-1.534*		*-2.436*	*
		(0.82)		*(1.09)*		*(1.48)*	
	*Election*Congress*	*2.256*		*3.035*	**	*4.017*	**
		(1.54)		*(1.52)*		*(1.84)*	
	Interest rates	*0.077*		*0.114*		*0.157*	*
		(0.09)		*(0.07)*		*(0.09)*	
	Interest Rate Changes	*0.205*		*1.355*	**	*1.150*	*
		(0.79)		*(0.60)*		*(0.66)*	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively
Numbers in paranthesis are robust standard errors.

Table 1.11 Estimates of Hazard Functions for Bull Markets with Political Control by Party

1. Full Sample		Dummy Variables: Months Since an Election, By Party					
Equation	Variable	8 months		16 months		24 months	
A.	*Republican*	-0.307		-0.162		-0.825	
		(0.62)		(0.55)		(0.61)	
	Democratic	-0.162		-0.251		-1.723	**
		(0.67)		(0.52)		(0.75)	
	Congress	-0.401		-0.425		-1.458	**
		(0.32)		(0.35)		(0.58)	
	*Republican*Congress*	1.141		0.724		1.954	**
		(0.87)		(0.80)		(0.93)	
	*Democratic*Congress*					3.122	***
						(0.96)	
B.	*Republican*	-0.315		-0.139		-0.812	
		(0.64)		(0.58)		(0.63)	
	Democratic	-0.108		-0.177		-1.660	**
		(0.67)		(0.51)		(0.80)	
	Congress	-0.292		-0.415		-1.416	**
		(0.37)		(0.39)		(0.60)	
	*Republican*Congress*	1.080		0.549		1.847	*
		(0.90)		(0.86)		(0.95)	
	*Democratic*Congress*					2.99	***
						(0.95)	
	Interest Rates	0.005		0.013		-0.017	
		(0.08)		(0.08)		(0.09)	
	Interest Rate Changes	-0.172		-0.223		-0.091	
		(0.13)		(0.14)		(0.16)	

2. Post-World War I		Dummy Variables: Months Since an Election, By Party					
Equation	Variable	8 months		16 months		24 months	
A.	*Republican*	0.140		0.445		-0.351	
		(0.99)		(0.81)		(0.95)	
	Democratic	0.300		0.249		0.290	
		(0.68)		(0.55)		(0.51)	
	Congress	-0.764	**	-0.759	*	-0.822	*
		(0.37)		(0.43)		(0.49)	
	*Republican*Congress*	1.517		0.614		0.934	
		(1.18)		(1.06)		(1.18)	
B.	*Republican*	0.043		0.245		-0.596	
		(1.05)		(0.93)		(1.15)	
	Democratic	0.359		0.319		0.356	
		(0.70)		(0.56)		(0.53)	
	Congress	-0.663	*	-0.685		-0.757	
		(0.41)		(0.48)		(0.51)	
	*Republician*Congress*	1.721		0.788		1.160	
		(1.22)		(1.16)		(1.36)	
	Interest Rates	0.048		0.046		0.054	
		(0.09)		(0.10)		(0.12)	
	Interest Rate Changes	-0.477		-0.043		-0.044	
		(0.45)		(0.43)		(0.38)	

Table 1.11 (CONTINUED)

3. Post-World War II		Dummy Variables: Months Since an Election, By Party					
Equation	Variable	8 months		16 months		24 months	
A.	*Republican*	0.045		0.326		-0.398	
		(1.00)		(0.81)		(0.93)	
	Democratic			0.052		-0.159	
				(0.80)		(0.77)	
	Congress	-1.104	**	-1.029	*	-1.045	*
		(0.56)		(0.61)		(0.65)	
	*Republican*Congre*	3.395	**	2.148	*	2.001	
		(1.66)		(1.30)		(1.34)	
B.	*Republican*	-0.155		-0.243		-1.032	
		(1.02)		(0.78)		(1.10)	
	Democratic			0.027		0.114	
				(0.83)		(0.83)	
	Congress	-0.963		-0.777		-0.963	
		(0.70)		(0.68)		(0.68)	
	*Republican*Congre*	3.558	**	2.114	*	2.646	*
		(1.61)		(0.09)		(1.51)	
	Interest Rates	0.067		0.100		0.143	
		(0.09)		(0.09)		(0.11)	
	Interest Rate Chang	0.006		0.944		0.422	
		(0.78)		(0.74)		(0.79)	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels,
Numbers in paranthesis are robust standard errors.

Table 1.12 Estimates of Hazard Functions for Bear Markets with Political Control by Party

1. Full Sample		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	-0.402	-0.985 *	-0.618
		(0.70)	(0.60)	(0.45)
	Democratic	-0.321	-0.750 *	-0.433
		(0.43)	(0.42)	(0.40)
	Congress	-0.024	-0.160	-0.212
		(0.30)	(0.33)	(0.38)
	*Republican*Congress*		1.384 *	0.874
			(0.72)	(0.74)
B.	*Republican*	-0.390	-1.060 *	-0.809 *
		(0.71)	(0.57)	(0.49)
	Democratic	-0.324	-0.725 *	-0.323
		(0.43)	(0.41)	(0.40)
	Congress	-0.003	-0.188	-0.310
		(0.30)	(0.35)	(0.40)
	*Republican*Congress*		1.795 **	1.279
			(0.75)	(0.83)
	Interest Rates	0.009	0.035	0.074
		(0.04)	(0.04)	(0.05)
	Interest Rate Changes	0.028	0.132	0.044
		(0.09)	(0.11)	(0.06)

2. Post-World War I		Dummy Variables: Months Since an Election, By Party		
Equation	Variable	8 months	16 months	24 months
A.	*Republican*	-0.637	-1.087	-0.857 *
		(1.14)	(0.75)	(0.54)
	Democratic	0.187	-0.171	0.493
		(0.59)	(0.49)	(0.45)
	Congress	0.126	-0.136	-0.455
		(0.40)	(0.45)	(0.53)
	*Republican*Congress*		2.153 ***	1.582
			(0.82)	(1.10)
B.	*Republican*	-0.648	-1.140	-1.102 **
		(1.12)	(0.74)	(0.53)
	Democratic	0.179	-0.197	0.546
		(0.64)	(0.52)	(0.47)
	Congress	0.205	-0.062	-0.424
		(0.40)	(0.42)	(0.51)
	*Republican*Congress*		2.126 ***	1.857 *
			(0.82)	(1.10)
	Interest Rates	0.033	0.049	0.094
		(0.06)	(0.05)	(0.06)
	Interest Rate Changes	0.014	0.153	0.224
		(0.19)	(0.28)	(0.25)

Table 1.12 (CONTINUED)

3. Post-World War II		Dummy Variables: Months Since an Election, By Party					
Equation	Variable	8 months		16 months		24 months	
A.	*Republican*			-1.852	**	-1.406	**
				(0.93)		(0.60)	
	Democratic	0.158		0.155		0.848	*
		(0.60)		(0.55)		(0.51)	
	Congress	0.732	*	0.169		-0.459	
		(0.44)		(0.52)		(0.56)	
	*Republican*Congress*			2.643	***	2.841	***
				(0.99)		(0.85)	
B.	*Republican*			-1.901	*	-2.573	***
				(1.03)		(0.88)	
	Democratic	-0.252		-0.061		0.818	
		(0.54)		(0.55)		(0.53)	
	Congress	0.544		0.145		-0.831	
		(0.45)		(0.57)		(0.54)	
	*Republican*Congress*			3.027	***	4.829	***
				(1.16)		(1.35)	
	Interest Rates	-0.034		-0.068		0.072	
		(0.07)		(0.07)		(0.09)	
	Interest Rate Chang	-1.711	***	-1.379	***	-1.999	***
		(0.40)		(0.50)		(0.51)	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels,
Numbers in paranthesis are robust standard errors.

Table 1.13 Dates of Turning Points in U.S. Stock Market (Nominal Prices)

Date of		Duration (in months)		Was an Election Held during the	
Trough	Peak	Bear	Bull	Bear	Bull
	5/1872				
11/1873	4/1875	18	17	YES	NO
6/1877	6/1881	26	48	YES	YES
1/1885	5/1887	43	28	YES	NO
6/1888	5/1890	13	23	NO	YES
12/1890	8/1892	7	20	NO	NO
8/1893	4/1894	12	8	YES	NO
3/1895	9/1895	11	6	NO	NO
8/1896	9/1897	11	13	NO	YES
4/1898	4/1899	7	12	NO	NO
9/1900	9/1902	17	24	NO	YES
10/1903	9/1906	13	35	NO	YES
11/1907	12/1909	14	25	NO	YES
7/1910	9/1912	7	26	NO	NO
12/1914	11/1916	27	23	YES	YES
12/1917	7/1919	13	19	NO	NO
8/1921	3/1923	25	19	YES	NO
10/1923	9/1929	7	71	NO	YES(2 ELECTIONS)
6/1932	2/1934	33	20	NO	YES
3/1935	2/1937	13	23	NO	YES
4/1938	11/1938	14	7	NO	NO
4/1942	5/1946	41	49	YES	YES
2/1948	6/1948	21	4	NO	NO
6/1949	1/1953	12	43	YES	YES
9/1953	7/1956	8	34	NO	NO
12/1957	7/1959	17	19	YES	NO
10/1960	12/1961	15	14	NO	YES
6/1962	1/1966	6	43	NO	YES
10/1966	12/1968	9	26	NO	YES
6/1970	4/1971	18	10	NO	NO
11/1971	1/1973	7	14	NO	YES
12/1974	9/1976	23	21	NO	NO
3/1978	9/1978	18	6	YES	NO
4/1980	11/1980	19	7	NO	YES
7/1982	10/1983	20	15	NO	NO
7/1984	8/1987	9	37	NO	YES
12/1987	8/2000	4	152	NO	YES(3 ELECTIONS)
2/2003	10/2007	30	56	YES	YES
3/2009	5/2011	17	26	YES	NO
9/2011	5/2015	4	44	NO	YES
2/2016		9		NO	

Notes: Along a row, Bear market refers to period from peak in pervious row to trough in the next row.
Bull market refers to period from trough in that raw to peak in that row.

Table 1.14 Statistics on Timing of Peaks and Troughs Relative to Elections (Nominal Prices)

Full Sample	Months Since Last Election							
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	23.28(14.21)	0	46	39	25.30(13.28)	2	47	40
Post WWI	23.08(15.06)	0	46	24	25.96(12.84)	4	47	25
Post WWII	25.33(16.15)	0	46	18	26.32(13.18)	4	47	19

Republican Administrations	Months Since Last Election							
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	23.39(15.37)	0	46	23	26.81(13.04)	7	47	19
Post WWI	22.85(17.23)	0	46	13	28.08(13.23)	9	47	13
Post WWII	23.55(18.35)	0	46	11	27.80(12.76)	10	47	10

Democratic Administrations								
	Peaks				Troughs			
	Av'g (s.d.)	Min.	Max.	Obs.	Av'g (s.d.)	Min.	Max.	Obs.
Full Sample	23.13(12.83)	0	45	16	23.63(13.90)	2	45	19
Post WWI	23.36(12.86)	3	45	11	23.67(12.54)	4	41	12
Post WWII	28.14(12.77)	13	45	7	24.67(14.20)	4	41	9

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Appendix

Procedure for Determination of Turning Points:

1. Determination of initial turning points in raw data.
   a. Determination of initial turning points in raw data by choosing local peaks (troughs) as occurring when they are the highest (lowest) values in a window eight months on either side of the date.
   b. Enforcement of alternation of turns by selecting the highest of multiple peaks (or lowest of multiple troughs).

2. Censoring operations (ensure alternation after each).
   a. Elimination of turns within 6 months of beginning and end of series.
   b. Elimination of peaks (or troughs) at both ends of series which are lower or higher).
   c. Elimination of cycles whose duration is less than 16 months.
   d. Elimination of phases whose duration is less than 4 months (unless fall/rise exceeds 20%).

3. Statement of final turning points

Chpater 2. Presidential Elections, Investor Sentiment, and Stock Returns

Abstract

This study develops a dynamic factor model that allows for a simultaneous examination on the relationships among presidential elections, investor sentiment, and stock returns in the United States. Results reported in the paper uncover that there is a sizeable improvement of investor sentiment before an election. More importantly, this pre-election surge in investor sentiment can explain a substantial portion of the presidential election cycle effect in the U.S. stock returns. Furthermore, results from the asset pricing tests clearly show that investor sentiment is a critical component in asset pricing and prediction. By including the sentiment factor, the proposed Augmented Intertemporal Capital Asset Pricing Model (AICAPM) in the paper improves upon the explanatory and predictive power of other competing models such as the Intertemporal Capital Asset Pricing Model of Merton (1973) (ICAPM) and the Fama-French (1993) 3-factor model (FF3).

JEL classification: G4, D72

Key Words: Presidential Elections, Investor Sentiment, Stock Returns

2.1. Introduction

Over the years, researchers and market practitioners have examined whether the political process and stock market are interrelated. As part of those research efforts, one of the most commonly analyzed subjects is the relationship between presidential elections and the stock market in the United States. Extant research such as Herbst and Slinkman (1984) and Huang (1985) attempt to answer this question by examining the correlation between stock returns and the occurrence and the outcome of elections. Additionally, Nordhaus (1975) and Hibbs (1977, 1987) establish that primarily, the goal of being re-elected and the differences in partisan preference are reflected in the macro-economy and hence, equity returns.

However, a vastly ignored but essential factor in this discussion is the role of investor sentiment in the relationship between elections and the stock market. Naturally, presidential elections invoke a degree of sentiment in an investor, with the valence depending on the investor's perception of the macroeconomic growth potentials and possible changes in fiscal and monetary policies before and after the elections. Recent studies such as Baker and Wurgler (2006, 2007) suggest that investor sentiment has a significant role in determining asset prices. Thus, a secondary channel through which presidential elections affect stock returns might be through the effect on investor sentiment. This secondary channel, however, is not yet studied by existing research. This paper contributes to the existing literature by formally studying this new hypothesis via examining the relationships among presidential elections, investor sentiment, and stock returns in the U.S. stock market simultaneously.

Until recent, investor sentiment had no role in asset pricing. Classical asset pricing models assume that investors are rational, will diversify to reduce the risk their portfolios, and the cross-section of systematic risk will determine the cross-section of expected returns in assets. Moreover, if any irrational investors exist, the effects of their actions will be nullified by that of arbitrageurs in the market. Hence, investor sentiment had no role in determining prices. However, evidence in recent studies such as Baker and Wurgler (2006, 2007) suggests that investor sentiment has a significant role in determining asset prices.

There is yet a universally accepted academic definition of investor sentiment. In this study, investor sentiment is defined to be a latent psychological factor (i.e., market feeling or market mood), which can be affected by investors' perceptions of political events and policy preferences of different political parties. Thus, to simultaneously study the relations among presidential elections, investor sentiment, and stock returns, a dynamic factor model is constructed. I employ the Kalman filter to estimate the unobservable risk factors in the model (i.e., investor sentiment).

The maximum likelihood estimates show that there is a significant improvement of investor sentiment in the last two years of a presidency before an election. More importantly, this pre-election sentiment upsurge found to explain a significant portion of the higher returns in the election years, the election cycle effect in the U.S stock market. Moreover, the result confirms that there was a market-wide panic during the height of the recent financial crisis in 2007-2008. However, data in this study fails to provide evidence that investors are more optimistic when Democrats are sitting in the White House. Furthermore, with the extracted factors, I then compare the performance of the proposed model in the paper, Augmented Intertemporal Capital Asset Pricing Model (AICAPM), with that of existing assets pricing models using the 25 size- and BTM-sorted portfolios. Results from the asset pricing tests in both the in-sample and out-of-sample contexts show that the proposed risk factors in the model are a crucial component in asset pricing and prediction. Particularly, the high explanatory and predictive power of the loading on the sentiment factor leads the AICAPM to outperform other competing models such as the ICAPM of Merton (1973) and the Fama-French (1993) 3-factor model (FF3) in both tests.

The remainder of the paper is organized as follows. Section 2 provides a brief review of related literature. The empirical method is discussed in Section 3. Section 4 describes the sample data, which followed by the empirical results presented in Section 5. In Section 6, I conduct in-sample performance tests of the AICAPM and compare the results with those of alternative models. In Section 7, I perform out-of-sample tests and present pair-wise comparisons of the accuracy in 1-step ahead forecasts. Finally, Section 8 concludes the study.

2.2. Literature Review

The importance of the political process to the U.S. financial markets has been long recognized by market pundits and academia. Some of the most interesting patterns in the Stock Traders' Almanac relate to the occurrence and the outcome of presidential elections. For instance, it has been widely documented that the U.S stock market generally ascends with a coming election and descends once the election is over. This pattern of higher returns in the second half of a presidency, the election years, than in the first half of a presidency is commonly referred to as *the presidential election cycle*. Studies such as Allvine and O'Neill (1980), Huang (1985), Gartner and

Wellershoff (1995) and Booth and Booth (2003) all find that the differences in returns across the first half and the second half of a presidential term are both economically and statistically significant. Huang even suggests that based on this presidential election cycle, i.e., switching investors out of stocks and into Treasury bills during the first two years of the presidential term can produce returns superior to a traditional buy and hold strategy.

There are also differences in returns along the partisan lines. Huang (1985) reports that annual rates of return on stocks from 1929-1980 are stronger under Democratic presidents than under Republican presidents. Siegel (2002) find similar results over a more extended period from 1888 to 2001. Johnson, Chittenden, and Jens (1999) study the period of 1929-1996, they fail to discern a partisan difference in the returns of the Standard & Poor's 500 Index. However, they do find a pronounced party effect in favor of the Democrats when examining an index of small stocks. Santa-Clara and Valkanov (2003) discover that excess returns for the value-weighted and equal-weighted portfolio are 9% and 16 % higher, respectively, under Democratic and Republican administrations for the period 1927:01-1998:12. They describe this pattern of higher returns during Democratic presidencies than during their counterparts as *the presidential partisan cycle*.

How to explain these two presidential cycle effects has puzzled academics for years. Several market efficiency explanations have been put forward. First, the presidential cycle effects might merely proxy for variations in expected returns due to business cycle fluctuations. However, Santa-Clara and Valkanov (2003) and Booth and Booth (2003) find that the effects remain robust even after taking control of the business condition, individually. Second, the relationship between stock returns and the elections might be concentrated around and limited to election dates. Santa-

Clara and Valkanov find no significant evidence of stock price changes immediately before, during, or immediately after presidential elections. Third, the difference in returns relative to elections might be the compensation for the additional risk. Market volatility could be simply higher in the second half of a presidential term or during Democratic presidencies, thereby explaining the higher returns. Santa-Clara and Valkanov and Campbell and Li (2004), however, indicate that the difference in returns cannot be justified by differences in market volatility, respectively. Finally, the presidential cycle effects might be driven by the impact of outliers in the sample data. Studies by Santa-Clara and Valkanov as well as Gärtner and Wellershoff (1995) find that both presidential effects are not the result of individual outliers in the data.

The failure of market efficiency explanations give rise to an interesting question: Do these patterns imply that the market is inefficient since the timing of the U.S. presidential election can be known in advance? While efficient market hypothesis and its prefect rationality assumption have contributed considerably to our understanding of asset pricing, they have been challenged by both academic and market professionals over the years. Traditional theories built on efficient market hypothesis claim that stock prices mirror the discounted value of expected cash flows and irrationalities among market participants are removed by arbitrageurs. In contrast, behavioral finance argues that when arbitrage is limited, investor sentiment can persist in financial markets and affect asset prices.

Theoretically, Black (1986); De Long, Shleifer, Summer, and Waldmand (1990); Barberries, Shleifer, and Vishny (1998) have modeled the role of investor sentiment in the financial markets. In their models, the economy is characterized by two types of investors:

professional investors who rationally anticipate asset prices and noise traders whose expectations lead to periods of over, or undervaluation, of financial assets. Both types of investors are risk-averse and the equilibrium price reflects everyone's expectations. It follows that noise traders' sentiment influences asset prices. The theoretical studies point out that asset prices can significantly diverge from fundamental values. Moreover, because arbitrage has practical limits, rational investors fail to fully offset the effect of noise traders' sentiment. Thus, the "noise trader risk", also known as the "sentiment risk", becomes a priced factor by financial markets.

The risk introduced by noise traders in the financial markets may not be diversifiable because their views could be correlated and affect many assets. Therefore, assets subject to "noise trader risk" should provide higher returns than those assets not subject to that risk, and their price should be below their fundamental value. As noted by Lee, Shleifer, and Thaler (1991, p81), *"Like fundamental risk, noise trader risk arising from the stochastic investor sentiment will be priced in equilibrium. As a result, assets subject to noise trader risk will earn a higher expected return than assets not subject to such risk. Relative to their fundamental values, these assets will be underpriced".*

Empirical studies have mostly explored the predictive ability of investor sentiment on the cross-section of stock returns (e.g., Clarke and Statman, 1998; Neal and Wheatly, 1998; Brown and Cliff, 2004; Lemmon and Portnaiguina, 2006; Baker and Wurgler, 2006, 2007). Few studies have tested the existence of noise trader's systematic risk priced by financial markets. According to Zweig (1973), this type of tests is essential, as the question of whether investor sentiment drives returns is a necessary but insufficient condition for noise trader hypothesis. Additionally, the studies were undertaken often led to mixed conclusions. Some show that financial markets do not price psychological factors (Elton, Gruber, and Busse, 1998; Sias, Starks, and Tinic, 2001; Glushkov, 2006). Others find that sentiment is a critical factor in the return generating process of common stocks (Lee, Shleifer, and Thaler, 1991; Lee, Jiang, and Indro, 2002; Kumar and Lee, 2006). Therefore, the sentiment risk introduced by noise traders in the financial market remains an open empirical question.

There are even fewer studies have their focus on the relationship between presidential elections and investor sentiment. Daniel, Chong, and Bahram (2014) find that in addition to higher stock returns during Democratic presidencies, both investor sentiment and the covariance between investor sentiment and stock market are higher when Democrats control the White House. Adjei and Adjei (2017) also find that realized and excess returns are higher during Democratic presidencies than Republican presidencies. More interestingly, they find that investor sentiment levels are lower but improve during Democratic presidencies and are higher but decline during Republican presidencies. Furthermore, they infer that a Democratic president instills more optimism in the stock market that contributes to the higher returns during the term. Colon-De-Armas, Rodriguez, and Romero (2017), on the other hand, examine the shifts in investor sentiment around the last seven U.S. presidential elections (1988 through 2012) as measured by changes in closed-end fund discounts. They find that the discounts are significantly diminished from two weeks before an election to a week before the election, and persist until the week after the election, suggesting an increase in investors optimism during that period, particularly when a Democrat is elected.

The aforementioned studies have pointed out a link between presidential elections and stock returns, a link between investor sentiment and stock returns, and a link between presidential elections and investor sentiment. One of the contributions of this study to the existing literature is to connect those three separate links via empirically investigating the relationships among elections, investor sentiment, and stock returns at the same time. Specifically, I am interested in the following questions: 1) Whether investor sentiment changes with presidential elections? 2) If so, how much of the presidential cycle effects in stock returns can be related to the change in investor sentiment? To accomplish this, I propose a dynamic factor model with the factors being extracted via the Kalman filter. [25] Furthermore, with the extracted factors, this study makes another attempt to address the question of whether investor sentiment is a priced risk factor in the equity market.

2.3. The Empirical Approach

2.3.1. The Framework

Stock and Watson (1989, 1991) form a composite index of coincident economic indicators based on the notion that co-movements in observed macroeconomic time series have a common component that can be captured by a single time-varying latent variable. Along the lines of Stock and Watson, I develop a multifactor model of stock returns, with each of the factors being latent and identified within a pre-specified factor structure. According to the Intertemporal Capital

[25] My motivation for proposing a dynamic factor model is to incorporate features of price dynamics and the motivation for using the Kalman filter is to utilize an economic technique that helps to extract more efficient state variables.

Asset Pricing Model of Merton (1973) (ICAPM), an asset's expected return depends on its covariance with market return (D^{MKT}) and change in investment opportunity set ($D^{\Delta OPP}$). However, like other models based on the efficient market hypothesis, the ICAPM does not allow for a role of investor sentiment either. To capture this missing psychological risk factor, I augmented the ICAPM with an additional risk factor, market sentiment (D^{SENT}). As a result, my proposed model decomposes the asset returns into four components: market return, change in investor opportunity set, sentiment, and idiosyncratic. Since the model is essentially an extension of the ICAPM, I refer it as the Augmented Intertemporal Capital Asset Pricing Model (AICAPM).

2.3.2. The Indicators

In order to identify the proposed risk factors ($D^{MKT}, D^{\Delta OPP}, D^{SENT}$), a group of observable indicators are used. In existing studies, risk factors of the market return and the change in investment opportunity set are commonly approximated by return on a market portfolio or an index, and by innovations in a set of state variables that are believed to capture uncertainty about investment opportunities in the future, respectively. For this study, the indicator picked for the factor of market return is the return on the value-weighted CRSP index (r_m), and the selected state variables are the short-term T-bill rate (r_f), the term spread ($term$), the dividend yield ($dyield$), and the default spread (def). There is yet a universally accepted measure of investor sentiment to date. Current financial literature proposes two main categories of proxies for investor sentiment, direct and indirect indicators.[26] Direct indicators are based on polling market participants through surveys. Alternatively, indirect indicators are made up of a time series of macroeconomic and financial variables used to represent the unobserved sentiment factor. To better capture investor sentiment in the stock market, I utilize both measures in this study. My direct measure of investor sentiment is obtained from Investors' Intelligence (II) and the composite index constructed by Baker and Wurgler (2007) (BW) is my indirect measure.

2.3.3. Model Specification and Factor Identification

Given that market capitalization (size) and book-to-market equity (BTM) are found to relate to investor sentiment and change in investment opportunity set (see Baker and Wurgler, 2006; Petkova, 2006), I conjecture that the 6 size- and book-to-market equity (BTM) sorted portfolios could provide useful information about the proposed risk factors. Therefore, I start with the 6 portfolios as the initial test assets and they are notated as SL, SM, SH, BL, BM, and BH.[27] I also let R_t, Z_t and S_t denote the vectors contain the excess returns on the test assets, the chosen state variables, and the sentiment measures at month t, individually. Finally, D_t, the risk

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[26]For example, authors like Brown and Cliff (2004), Klein and Zwergel (2006) belong to the first branch and use explicitly sentiment data sets, such as investor sentiment surveys. On the other hand, Neal and Wheatley (1998) start the second branch and they use three popular market ratios as indicators of investor sentiment. Using a similar way to approach market sentiment, Baker and Wurgler (2007) construct a sentiment indicator based on typical sentiment proxies though the Principal Component Analysis (PCA).

[27] As usual, S and B denote "small" and "big" in firm size, respectively. Similarly, L, M, and H denote "low", "medium", and "high" in the BTM ratio, respectively.

factor vector, contains the three proposed risk factors, market return (D_t^{MKT}), change in future investment opportunity set ($D_t^{\Delta OPP}$), and sentiment (D_t^{SENT}), at month t.[28]

By my AICAPM, returns on the 6 portfolios should be well explained by the 3 risk factors specified above. In other words,

$$R_t = B^R D_t + W_t^R \tag{1}$$

where B^R is a 6x3 constant factor-load matrix, and W_t^R is a vector of idiosyncratic returns on the 6 portfolios.

For identification purpose, I assume that the chosen indicators only contain information about the corresponding risk factors. Thus, the relation between the market return indicator and the proposed risk factors can be simply given as:

$$r_{m.t} = \beta^{rm} D_t + W_t^{rm} \tag{2}$$

where β^{rm} is a 1x3 vector of factor-loading with the last two elements are fixed to be zeros and W_t^{rm} is the idiosyncratic return on the return on the CRSP index.

I compute innovations that believed to describe the change in the investment opportunity set ($D_t^{\Delta opp.set}$) by specifying an AR (1) process for each state variable. Then, the relation between the innovations and the risk factors can be shown as:

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[28] $R_t \equiv [r_{sl,t},\ r_{sm,t}\ ,\ r_{sh,t},\ r_{bl,t},\ r_{bm,t},\ r_{bh,t}\ ]'$; $Z_t \equiv [dyield_t,\ def_t,\ term,\ rf_t\ ]'$; $S_t \equiv [II_t,\ BW_t\ ]'$, and $D_t \equiv [D_t^{MKT}, D_t^{\Delta OPP}, D_t^{SENT}]'$; all the values used in the model are demeaned first.

$$Z_t = AZ_{t-1} + B^z D_t + W_t^Z \tag{3}$$

where A and B^z are 4x4 and 4x3 constant factor-loading matrices, respectively, and W_t^Z is a vector that contains idiosyncratic errors for the systemic variables. Since the innovations are obtained by an AR (1) process for each state variable, A is a diagonal matrix. Additionally, these innovations are assumed to model the change in the investment opportunity set ($D_t^{\Delta opp.set}$) exclusively, the factor-loadings on the first and third columns of B^z are restricted to be zeros.

Finally, the sentiment indicators, II and BW, are assumed to measure investor sentiment (D_t^{Senti}) only, and their relationship with the risk factors can be represented by:

$$S_t = B^S D_t + W_t^S \tag{4}$$

where B^S is a 2x3 constant factor-loading matrix with zero loadings on the first two columns, and W_t^S is a vector that contains idiosyncratic errors for the two indicators.

Combining equations 1 to 4, the measurement equation for the state space representation of my proposed model can be easily expressed in matrix form by the following system of equations:

$$Y_t = \begin{bmatrix} 0 \\ 0 \\ A \\ 0 \end{bmatrix} [Z_{t-1}] + \begin{bmatrix} B^R \\ \beta^{rm} \\ B^Z \\ B^s \end{bmatrix} [D_t] + W_t \tag{5}$$

where $Y_t \equiv [R_t', r_{m,t}, Z_t', S_t']'$ is the dependent vector contains the demeaned values of the excess returns on the initial test assets, excess return on the CRSP index, state variables, and sentiment measures; and $W_t \equiv [W_t^{R\prime}, W_t^{rm\prime}, W_t^{Z\prime}, W_t^{S\prime}]'$ is the error vector that contains all the idiosyncratic errors.

Furthermore, my transition equation is assumed to be in the following matrix form:

$$D_t = \Phi D_{t-1} + C_t + V_t \tag{6}$$

where Φ is a 3x3 diagonal matrix whose diagonal elements consist of AR(1) coefficients, $\phi^{MKT},\ \phi^{\Delta OPP}, and\ \phi^{SENT}$, that capture the time-series predictability of the three risk factors; C_t is a 3x1 vector with the first two elements are set to be zeroes and the third element, d_t, is specified as: $d_t = \theta_1 HLF2_t - \theta_2 HLF2_{t-1} + \theta_3 DP_t - \theta_4 DP_{t-1} + \theta_5 Crisis_t - \theta_6 Crisis_{t-1}$,[29] where $\theta_2 = \phi^{SENT}.\theta_1$, $\theta_4 = \phi^{SENT}.\theta_3$ and $\theta_6 = \phi^{SENT}.\theta_5$. As a result, d_t captures the initial change in investor sentiment caused by an upcoming presidential election and a Democratic election victory, along with the initial impact from the unprecedented financial crisis of 2007-2008.

I also make the following conventional assumptions for W_t and V_t that both W_t and V_t follow joint normal distributions, which can be given as:

$$\begin{bmatrix} W_t \\ V_t \end{bmatrix} \sim i.i.d\ N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \Omega^W & 0 \\ 0 & \Omega^V \end{bmatrix}\right] \tag{7}$$

where the covariance matrices, Ω^W and Ω^V, are assumed to be in a diagonal shape. Besides, I normalize the variances so that each of the risk factors has a unit variance (i.e., $\sigma^2_{Mkt} = \sigma^2_{\Delta Opp.set} = \sigma^2_{Senti} = 1$). Finally, by construction, the 3 proposed risk factors are mutually uncorrelated (i.e., diagonal Φ and Ω), with zero means and unit residual variances.[30]

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[29] $Yr34$, DP and $Crisis$ are dummy variables which are discussed in section III.

[30] Under the assumptions in equation 7, the Kalman filter is a statistically optimal procedure to extract the unobserved factors from a finite set if observed returns. The procedures for extracting the factors via the Kalman filter is briefly described in the Appendix

2.4. Data

Following Santa-Clare and Valkanov (2003), I divide my data set into four categories: return series, systematic variables, dummy variables, and sentiment measures. All the series are at monthly frequency and span from 1965:07 to 2010:12. During the period, there are 11 presidential elections, 4 Democratic and 5 Republican administrations.

2.4.1. Return Series

The test assets employed in this study are the portfolios formed by the intersection of market value of equity (size) with ratio of book value of equity to market value of equity (BTM). Return series on the portfolios are collected from Professor Kenneth R. French's website.[31] Monthly returns on 30-day T-bill rate from the Center for Research in Security Prices (CRSP) are used to calculate the excess returns.

2.4.2. State Variables

The four chosen state variables to capture the uncertainty in investment opportunity set are the dividend yield of the CRSP value-weighted portfolio (computed as the sum of dividends over the last 12 months, divided by the level of the index), the term spread (the difference between the yields of a 10-year and a 1-year government bond), the default spread (the difference between the yields on Moody's Baa-rated corporate bonds and Moody's Aaa-rated

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[31] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

corporate bonds), and the short term interest rate (1-month T-bill rate). Data on bond yields are from the FRED database of the Federal Reserve Bank of St. Louis.

2.4.3. Dummy Variables

To capture the effects of the presidential partisan cycle and presidential election cycle, I define the following political indicators:

- $DP_t = 1$ if a Democrat is in the White House at time t; $DP_t = 0$ otherwise.
- $HLF2_t = 1$ if time t is in the second half of a presidency before an election; $HLF2_t = 0$ otherwise.

Furthermore, to control for the impact of the unprecedented financial crisis in 2007-2008 in the U.S. stock market, I define the following crisis indicator:

$Crisis_t = 1$ if time t is in the period of 2007 to 2008; $Crisis_t = 0$ otherwise.

2.4.4. Investor Sentiment Measures

This study utilizes both direct and indirect measures to capture investor sentiment. The indirect measure is the composite index created by Baker and Wurgler (2007). Baker and Wurgler (2006) create their sentiment index as the first principal component of six common investor sentiment proxies: closed-end fund discounts; NYSE share turnover; the number of initial public offerings (IPO); average first-day IPO returns; the percentage of equity in new issues; and the dividend premium between dividend-paying and dividend-non-paying firms. To distinguish between a common sentiment component and a common business cycle component, a new index is constructed in 2007 by explicitly removing business cycle variation from each of the six proxies prior to the principal components analysis. This index is available at monthly frequency from July 1965 to December 2010 from Professor Jeffrey Wurgler's website.[32]

Investors' Intelligence (II), on the other hand, provides a direct sentiment measure. The editors of Investors' Intelligence assess the stance of authors on the stock market for over a hundred of independent market newsletters every week.[33] These letters are categorized into three groups: bullish, bearish, or correction. The bull-bear spread, which is calculated from II survey results as the percentage of bullish sentiment minus the percentage of bearish sentiment, is widely used by the financial press, for example, *Barron's* and *The Wall Street Journal*. Consequently, I use bull-bear spread as well for the study. To match the monthly frequency of composite index, I assume that the month-end sentiment prevails throughout the month.

2.5. Empirical Results

2.5.1. Descriptive Statistics and Estimated Parameters

The descriptive statistics in Panel A of Table 1 provide an initial view of the presidential election cycle effect and presidential partisan cycle effect on the excess returns for the 6 portfolios. As can be seen that the average excess returns are higher during Democratic presidencies and elections years (second half of a presidency), respectively. Compared to the big-stock group (portfolios formed by stocks with large market capitalization), the differentials

[32] http://people.stern.nyu.edu/jwurgler/
[33] http://us.investorintelligence.com/us-advisor-sentiment-report/

in mean returns are more evident for the small-stock group (portfolios formed by stocks have small market capitalization). Furthermore, it can be seen that the return differentials are most significant for the portfolio formed by growth stocks, stocks with a low level of BTM ratio, in the small-stock group; while the differentials are smallest for the portfolio formed by stocks with a medium level of BTM ratio in the big-stock group. Overall, the cycle effects exhibit most influences over returns on growth stocks with small capitalization but exhibit less impact on returns on big stocks with a medium BTM ratio.

Panel B of Table 1 presents the maximum likelihood estimates for parameters in the state-space model specified above.[34] Nearly all the parameter estimates are statistically significant at the 1% level with the unreported t-value (absolute) are several times larger than 1.96. These results suggest that the excess returns on the 6 portfolios used as test assets largely conform to the 3-dimensional factor structure proposed for the study.

Specifically, when holding the BTM ratio, the loadings on the market factor (D^{MKT}) are significantly larger in the small-small group than in the big-stock group. This suggests that the market factor captures well the notion that small stocks are relatively riskier than big stocks. Furthermore, the factor loadings display a decreasing trend with the BTM ratio for both groups providing evidence of the growth and value effects. As for the loadings on the factor of change in investment opportunity set $(D^{\Delta OPP})$, the positive loadings in the small-stock group indicate that

[34] For brevity, the parameters for generating the innovations in the systematic variables are exclude from the table.

returns on small stocks are positively exposed to the factor of change in investment opportunity set; while the native loadings in the big-stock group suggest that returns on big stock are generally inversely related to this risk factor. The magnitude of the factor loadings decreases with the BTM ratio in the small-stock group but increases with the BTM ratio in the big-stock group. This is in line with the market folklore that stocks with large capitalization and undervalued by the market may provide the desired hedging effect against the potential changes in the investment opportunity set. Previous studies find that investor sentiment affects more on stocks whose valuations are highly subjective and are difficult to arbitrage. Some of the characterizations of those stocks including small in market value or have an extreme BTM ratio. In this study, the loadings on the sentiment factor are highly statistically significant for all the test assets except for the one (BL) formed by stocks with large market capitalization and a low BTM ratio.[35] As expected, the loadings on the sentiment factor in the small-stock group are several times larger than in the big-stock group. Moreover, the factor loadings found to be largest for the portfolios formed by value stocks, stocks with a high BTM ratio, for both size groups.

Except for the default spread, the estimates on the state variables are all statistically significant. Return on the CRPS index is found to be closely related to the market factor. The positive factor loading is both statistically and economically significant. Besides, the estimates show that the unexpected dividend yield and short-term interest rate (T-bill Rate) are positively

[35] One possible explanation for the insignificant factor loading is that stocks consisted in the BL portfolio are commonly the blue chip stocks, stocks issued by well-established firms. Compared to other stocks, blue stocks have the least arbitrage limitations, thus the sentiment impact on these stocks could be weakest.

related to the factor of change in investment opportunity set; while the unexpected term spread is negatively correlated with the factor. Finally, the factor loadings on the two sentiment measures show that the composite index of Baker and Wurlger (2007), the indirect measure, found to be inversely related to the sentiment factor. There is, however, a positive correlation between the direct measure (II) and the sentiment factor. Furthermore, compared to the composite index, the factor loading on the direct measure is statistically more significant. Chau, Deesomsak, and Koutmos (2016) also find that sentiment-driven investors are more apt to trade on survey-based indicators rather than market-based indicators.

As for the predictability of the dynamic factors, results in Panel B of Table 1 show that the AR (1) coefficients on the three factors specified in equation (6) are all statistically significant at the conventional levels. A change in the factor realizations by one standard deviation in the current month will affect the unobserved factor realizations by 8.1% to 14.6% in the next month. More importantly, the estimates on the dummy variables representing the election years (HLF2) and the 2007-2008 financial crisis are statistically significant at the 5% and 1% levels, respectively. Nevertheless, the estimate on the dummy variable representing the time when the White House is controlled by a Democrat (DEMO) is not significantly different from zero.

The positive estimate on HLF2 implies that the market generally tends to feel more optimistic during the second half of a presidential term before an election. Furthermore, this pre-election surge in investor sentiment is found to be responsible for a significant portion of the presidential election cycle effect in the U.S. stock market. To put this key finding of the study in perspective, Figure 1 demonstrates how much of the presidential election cycle effect on excess returns of the 6 test assets can be attributed to the change in returns caused by the improved sentiment before elections. From the figure, we can see that the additional return stemmed from the pre-election upsurge in investor sentiment is responsible for a significant share of the presidential election effect. In particular, in the small-stock group, the sentiment induced returns found to contribute more than 40% of the return difference for SH (42.7%), close to 40% for SM (37.4%) and nearly 30% for SL (28.9%), respectively. Although stocks with large market capitalization are less subject to investor sentiment, the additional returns generated by the improved sentiment before an election are found to be responsible for more than 15% of the difference for BH (15.9%) and almost 10% for BM (8.9%). Figure 2 shows that the extracted sentiment roughly lines up with the anecdotal accounts of fluctuations in the U.S. stock market during the sample period. For instance, the sentiment factor captures the major bear markets in1968 to 1970, 1973 to 1974, 1980 to 1982, October 1987, 2000 to 2002, and 2007 to 2009. It also coincides with the bull markets in the 1960s (The go-go years), the 1970s (The Nifty Fifty), the Roaring 90s, and the housing boom (2002-2007). This correspondence with the anecdotal accounts seems to confirm that my sentiment factor captures the intended variation. Finally, the negative estimate on the dummy variable for the financial crisis in 2007 and 2008 are both economically and statistically significant, which confirms that there was a market-wide panic during the height of the crisis.

2.6. Testing the Augmented ICAPM (AICAPM)

From this section, I focus on testing the AICAPM and compare it with other alternative models. For expositional convenience, I first conduct in-sample tests in this section and then perform out-of-sample tests in the following section.

2.6.1. Competing with the ICAPM of Merton (1973)

Following Cochrane (2005) and Brennan et al. (2004), I conduct the asset pricing tests to the AICAPM using the 25 size- and BTM -sorted portfolios as test assets through the 2-pass regressions.

A. Time-Series Regressions

The first pass of the 2-pass regression procedure is to estimate the factor loadings with respect to the three proposed risk factors by running a multiple time-series regression. Specifically, I run the following time-series regression for each asset:

$$R_{i,t} = a_i + \beta_i^1 D_t^{MKT} + \beta_i^2 D_t^{\Delta OPP} + \beta_i^3 D_t^{SENTI} + u_{i,t} \tag{8}$$

where $R_{i,t}$ is the excess return on portfolio i $(i = P11, \ldots, P55)$.[36]

Panel A of Table 2 contains the estimated risk exposures to the proposed risk factors in the model from the time-series regression for the 25 portfolios. For comparison purposes, the corresponding results for the ICAPM are reported in Panel B.[37] Note that the loadings for the

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[36] For example, P11 stands for the portfolio formed by the stocks with the smallest size and the lowest BTM ratio. While, P55 stands for the portfolio formed by the stocks with the biggest size and the highest BTM ratio.

[37] The risk factors in the conventional ICAPM are also estimated from the proposed state-space model but without including the sentiment factor.

AICAPM are all statistically significant at the 1% level. Given the statistical significance levels of the loadings, it is less likely that the second step results are subject to the “useless” factor problem described by Kan and Zhang (1999). Still, to formally test the null hypothesis of jointly zero coefficients on the three risk factors, I conduct the F-test in a seemingly unrelated regression (SUR) system for the 25 portfolios. The test strongly rejects the null hypothesis and show that loadings on the proposed risk factors are jointly significant, with the corresponding P-values being close to zero. The loadings on the sentiment factor unequivocally demonstrate that investor sentiment has a crucial role in explaining returns. In particular, the explanatory power of the sentiment factor is much higher for the extreme portfolios, the ones that the traditional models have difficulty in explaining. For instance, the average of absolute loadings on the sentiment factor for portfolios with the smallest stocks (P11, P12, P13, P14, and P15) is more than ten times as large as for portfolios formed by the biggest stocks (P51, P52, P53, P54, and P55). Also, compared to the ICAPM, the average adjusted R^2s (Avg.R^2) is higher for the AICAPM, while the average standard errors (Avg. *s(u)*) is lower. It should be noted that much of the improvement of the AICAPM is from the portfolios where the sentiment factor displays stronger explanatory power. Overall, these results suggest that the risk factors in the ICAPM alone cannot fully capture the return variation over time.

B. Cross-Sectional Regressions

The second step in the 2-pass regression procedure is to relate the average excess returns of the test assets to their risk exposures estimated from the time-series regressions. Thus, I cross-sectionally regress the sample mean of monthly excess returns on the estimated factor loadings as in the equation:

$$\overline{R_\iota} = \lambda_i^1\widehat{\beta_\iota^1} + \lambda_i^2\widehat{\beta_\iota^2} + \lambda_i^3\widehat{\beta_\iota^3} + e_i \tag{9}$$

where $\overline{R_\iota}$ is the mean excess return on portfolio i $(i = P11, \dots, P55)$, $\widehat{\beta_\iota^J s}$ are the estimated loadings on the three risk factors $(j = 1,2, and\ 3)$ from the time-series regressions the first pass, λ_is denote the coefficients to be estimated as factor risk premiums, and e_i is the residual term that measures the pricing error of the AICAPM for portfolio i.

Panel C of Table 2 reports the estimated factor risk premium $(PREM)$ and pricing errors (es). The levels of the risk premiums for the three proposed risk factors are -0.100%-0.194% and is statistically significant at any conventional level. The significant price of risk associated with the proposed risk factors suggests that the 3 factors in the AICAPM are indeed important determinants of average returns. The monthly risk premiums for the ICAPM in Panel D, on the other hand, show that after excluding the sentiment factor, the size of the premium for the market return in the ICAPM (.122%) is about three times larger than what is in the AICAPM (0.042%), and the premium for the factor of change in investment opportunity set becomes statistically insignificant.

Panel C of Table 3 also indicates that, in general, the pricing errors (es) of the AICAPM are much smaller (especially in the extreme portfolios) compared to those of the ICAPM reported in Panel D. It follows that the average absolute error (AAE) is down by almost 50% from 16.50 basis points (bp) to 11.40 bp per month, and the sum of the squared errors (SSE) decreases from 1.351 to 0.638. Notably, the decrease in pricing errors mainly occurs in the corner portfolios. For example, the pricing error in the growth portfolio (P31) for the AICAPM is only 0.029% per month, while its counterpart is -0.322% in the ICAPM. The reduction in the pricing errors is mainly because of the explanatory power of the loading on the sentiment factor. Given the incremental role of the sentiment factor, it is evident that the AICAPM outperforms the ICAPM.

Overall, the above analyses reveal that the proposed risk factors in the AICAPM are a vital component in asset pricing. The asset pricing tests show that the superior explanatory power of the AICAPM stems from the fact that the loadings on the traditional risk factors in the ICAPM alone do not fully incorporate all the relevant information. Once the bias is adjusted by including the psychological factor into the model, the AICAPM can better explain expected returns than the ICAPM.

2.6.2. Competing with the Fama and French (1993) 3-factor (FF3) Model

One concern in the above analyses is that the better performance of the AICAPM over the traditional ICAPM may be primarily driven by the additional risk factor, D^{SENT}, used in the model. To address this issue, another competing model that also has three risk factors is considered in the study. The Fama and French (1993) 3-factor (FF3) model has been one of the most popular benchmarks in the modern empirical asset pricing literature. Also using 3 risk factors, MKT, SMB and HML, the FF3 has been found to be able to explain most of the cross-sectional variation in the average returns of portfolios sorted by the size and BTM.

For comparison purposes, I again apply the 2-pass regression procedure to the FF3 model using the same 25 portfolios as the test assets. The adjusted R^2s from the time-series regressions and the pricing errors (es) from the cross-sectional regressions are reported in Table 3. As can be seen that, on average, the adjusted R^2s are lower and the standard errors are higher for the FF3 model. However, the average absolute error (AAE) and the sum of squared errors (SSE) are nearly identical for both models. On balance, the in-sample test results seem to suggest that the AICAPM somewhat outperforms the benchmark model (the FF3 model). It should be recognized that the better pricing ability of the AICAPM over the FF3 mainly occurs in the extreme portfolios such as the portfolios made of the stocks with the smallest market capitalization. The same portfolios are more likely to be affected by investor sentiment.

2.7. Out-of-Sample Tests

In the previous section, I have shown that my AICAPM outperforms the ICAPM as well as the FF3 model, and all the proposed risk factors play a crucial role in explaining returns. However, these results are in the context of in-sample tests. From the perspective of investors, however, being able to obtain more accurate forecasts is very important in a variety of setting. In this section, therefore, I focus on the performance of my AICAPM in the out-of-sample context. Specifically, I make pair-wise comparisons of the accuracy in 1-step-ahead forecasts. In comparing the accuracy of the forecasts, I first use the following two competing models: 1) AICAPM, 2) ICAPM. Given the concern that the better performance of the AICAPM may be achieved by including an additional factor, I also consider a 3-factor model as follows: 3) FF3.

I again use the 25 size-and BTM-sorted portfolios as test assets. For this purpose, the first 273 months (1965:07-1988:03) of my whole sample period (546 months: 1965:07-2010:12) are used as training period in order to estimate the first set of model parameters. The first 1-step-ahead forecast is the computed for April 1988 using the estimated model parameters. The 1-step-ahead forecasts for the remaining 272 months (1988:05-2010:012) are also computed based on the model parameters estimated using the relevant data from the 273-month rolling windows, resulting in the total 273 forecasts (1988:04-2010:12) for each model.

For pair-wise comparisons between the competing models, the average of differentials in the mean squared forecast errors (MSFEs), $\bar{d}$, is computed as $\bar{d} = (\frac{1}{T})\sum_t^T\left[u_{1,t}^2 - u_{2,t}^2\right]$, where $u_{i,t}$ is time t forecast error of model i (i.e.,$u_{i,t} = R_{i,t} - \hat{R}_{i,t|t-1}$, where $\hat{R}_{i,t|t-1}$ is the forecast of excess returns $R_{i,t}$ at time t) and T is the total month number of the forecasts (273). In a comparison pair, AICAPM versus ICAPM, for instance, $u_{1,t}$ is the forecast error of the AICAPM and $u_{2,t}$ is the forecast error of the ICAPM. Following Simin (2008), I compute DM-STAT based on Diebold and Mariano (1995) to test the null hypothesis of $H_o\colon \bar{d} = 0$. This test statistic is defined as

$$\text{DM-STAT} = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{T}}} \qquad (10)$$

where $\hat{f}_d\,(0)$ is a consistent spectral density of $\left[u_{1,t}^2 - u_{2,t}^2\right]$ at frequency 0 and $2\pi/T$ is the length of time required for the process to repeat a full cycle. To examine if the average of $\bar{d}s$ is 0, we also conduct the overall *t*-test for each of the pairs using $\bar{d}s$ obtained from the 25 portfolios.

The results are reported in Table 4. Given my AICAPM is essentially an extended version of the ICAPM; I first compare the predictive ability of the AICAPM with that of the ICAPM. As panel A indicate, the average MSFE differentials ($\bar{d}s$) of the pair (AICAPM vs. ICAPM) are mostly negative, and many of them are statistically significant at the 1% level.

Moreover, the overall t-test shows that $\bar{d}$s are negative on average and statistically different from zero at the 1% level. This clearly indicates that the AICAPM does a better job than the ICAPM in the 1-step-ahead forecasts. Specifically, the better predictive ability of the AICAPM over the ICAPM occurs predominately in the portfolios formed by the smallest stocks. The portfolios are precisely the ones that are most sensitive to investor sentiment.

To address the issue of whether the better predictive power of the AICAPM over the ICAPM may be primarily driven by using an additional factor (D^{SENT}) in the model, the AICAPM is again compared with the FF-3 model. The results presented in Panel B show that $\bar{d}$s in many portfolios are negative (17 cases out of the 25 portfolios) and statistically significant at the 1% level. The overall t-test indicates the $\bar{d}s$ are negative on average and significant at the 1% percent level, demonstrating that my AICAPM provides more accurate forecasts than the FF3. As can be seen that the superior predictive ability of the AICAPM over the FF3 model occurs primarily for the portfolios formed by growth stocks. The same stocks that found to have greater exposure to the sentiment risk by earlier studies.

To sum up, the AICAPM outperforms both competing models in the out-of-sample tests. Results from the asset pricing analyses provide irrefutable evidence that the 3 proposed risk factors (D^{MKT}, $D^{\Delta OPP}$, and D^{SENT}) all play a critical role in describing and forecasting asset returns. I further conjecture that the better explanatory and predictive power of my proposed model can be largely accredited to the high explanatory and predictive power of the loading on the sentiment factor.

2.8. Conclusion

In the discussion of the relationship between the elections and the stock market returns in the United States, the role of investor sentiment is mostly ignored by existing research. In this study, I develop a dynamic factor model to study the relationships among presidential elections, investor sentiment, and stock market returns simultaneously. Results from the model unveil that there is a significant rising in market optimism in the election years prior to an election. More importantly, this pre-election improvement of investor sentiment found to account for a substantial share of the observed presidential election cycle effect in the U.S. stock market. However, data in the paper fail to find significant evidence that Democratic presidents install more optimism in the stock market. My result, on the other hand, does confirm that there was a market-wide panic during the height of the recent financial crisis.

Furthermore, with the extracted factors, I conduct asset pricing tests in both the in-sample context and out-of-sample context for the proposed model. The test results show that the risk factors in the model all are a crucial component in asset pricing and prediction. In particular, the high explanatory and predictive power of the loadings on the sentiment factor leads the AICAPM in the study to outperform other competing models such the ICAPM and the FF3 model in both the in-sample asset pricing tests and out-of-sample tests.

Figure 2.1 Portion of The Presidential Election Effect Relate to Sentiment Change

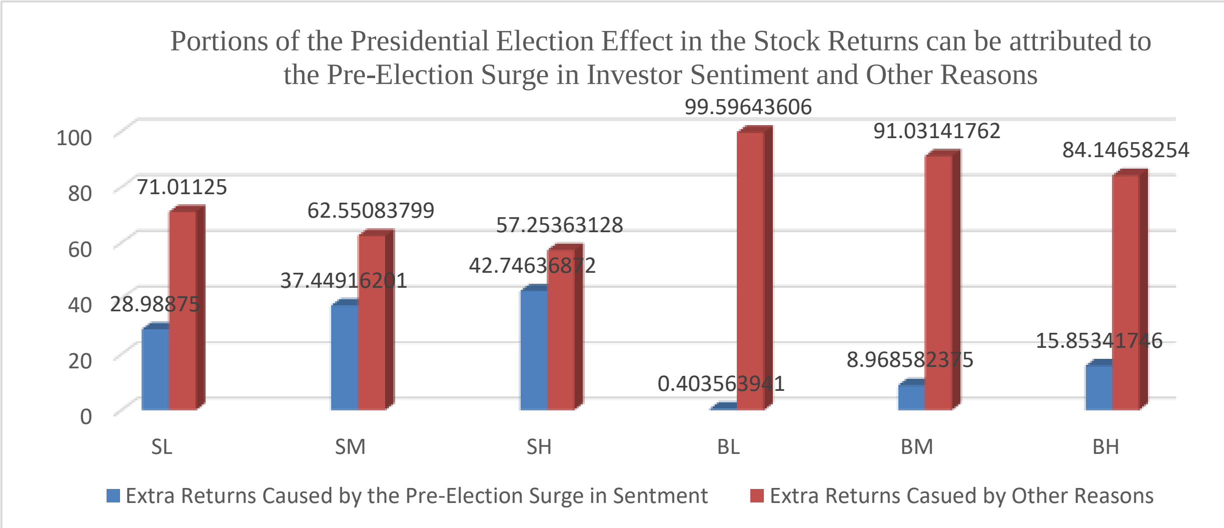

Figure 2.2 The Evolution of Investor Sentiment

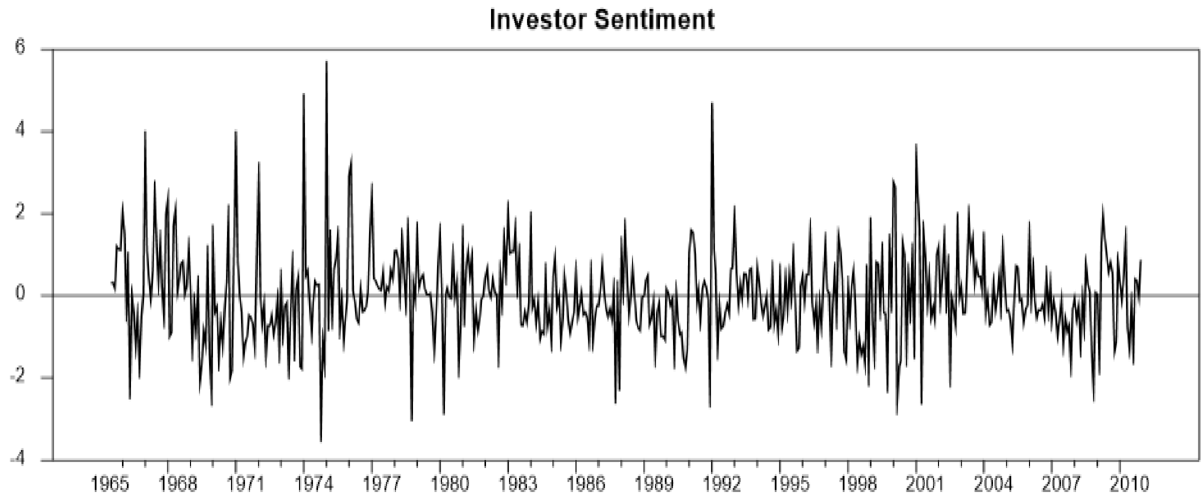

Table 2.1 Maximum Likelihood Estimates for the Model

Panel A of Table 1 reports the means of excess returns on the 6 initial test assets across parties and throughout presidential terms from 1965:07-2010:12. Panel B reports the maximum likelihood estimation of the parameters for the proposed model obtained using the Kalman filter.

Panel A. Descriptive Statistics about the 6 portfolios formed on Size and BTM

	REP	DEM	DEM-REP		HLF1	HLF2	HLF2-HLF
SL	-0.387	1.185	1.572	SL	-0.426	1.334	1.760
SM	0.286	1.326	1.040	SM	0.217	1.470	1.253
SH	0.585	1.619	1.034	SH	0.513	1.766	1.253
BL	-0.012	0.615	0.627	BL	-0.150	0.804	0.954
BM	0.090	0.306	0.216	BM	-0.020	0.763	0.783
BH	0.057	0.831	0.774	BH	-0.003	0.948	0.951

Panel B. Maximum Likelihood Estimates of the Parameters for the Model

	D^{MKT}		$D^{\Delta OPP}$		D^{SENT}		σ^2	
SL	6.916	***	2.430	***	3.313	***	1.961	***
SM	4.525	***	0.360	**	3.047	***	0.174	***
SH	3.863	***	0.068	*	3.478	***	1.364	***
BL	5.722	***	0.750	***	0.025		0.100	
BM	3.400	***	-1.641	***	0.456	***	0.423	***
BH	3.095	***	-2.045	***	0.979	***	1.579	***
R_M	4.200	***					1.057	***
Div.Yield			0.097	***			0.015	***
Term			-0.037	***			0.075	***
Default			-0.002				0.013	***
T-bill Rate			0.007	***			0.004	***
BW					-0.080	**	0.035	***
II					0.052	***	0.887	***
$\varnothing^{KMT}$	0.125	***	$\varnothing^{\Delta OPP}$	0.081	*	$\varnothing^{SENT}$	0.146	***
HLF2	0.154	**	DEMO	0.008		CRISIS	-0.716	***

*,** and *** indicate coefficients are significantly different from 0 at the 10%, 5% and 1% levels, respectively .

Table 2.2 Two-Pass Regression Results to Test the Augmented Intertemporal Capital Asset Pricing Model (AICAPM)

Panel A contains the 1st-step results that include the estimates of the factor loadings on the proposed risk factors and adjusted R^2 (Adj. R^2) for each of the 25 portfolios, and the averaged values of adjusted R^2 (Avg. R^2) and standard errors (Avg. $s(u)$) after running the time-series regressions. Panel B reports the time-series regression results from the ICAPM for comparison purpose.

Panel A Time-Series Regression Results for AICAPM							
Portfolios	D^{MKT}		$D^{\Delta OPP}$		D^{SENT}		Adj.R^2
P11	6.641	***	2.630	***	4.477	***	0.937
P12	5.723	***	1.333	***	4.150	***	0.971
P13	5.212	***	0.478	***	3.880	***	0.981
P14	4.648	***	0.167	***	3.731	**	0.973
P15	4.732	***	-0.044		4.178	***	0.943
P21	7.046	***	1.974	***	2.150	***	0.947
P22	5.904	***	0.255	**	2.177	***	0.947
P23	5.149	***	-0.633	***	2.042	***	0.933
P24	4.799	***	-1.078	***	2.013	***	0.928
P25	5.399	***	-1.403	***	2.629	***	0.912
P31	6.790	***	1.748	***	1.114	***	0.958
P32	5.520	***	-0.439	***	1.187	***	0.937
P33	4.898	***	-1.107	***	1.206	***	0.940
P34	4.559	***	-1.578	***	1.271	***	0.936
P35	5.127	***	-1.791	***	1.779	***	0.889
P41	6.113	***	1.239	***	0.165	***	0.977
P42	5.210	***	-1.032	***	0.409	***	0.945
P43	4.839	***	-1.643	***	0.642	***	0.956
P44	4.553	***	-1.825	***	0.769	***	0.939
P45	5.289	***	-2.123	***	1.345	***	0.877
P51	5.195	***	0.560	***	-0.669	***	0.957
P52	4.615	***	-1.024	***	-0.213	**	0.942
P53	4.195	***	-1.775	***	-0.103		0.935
P54	4.145	***	-2.238	***	0.284	***	0.920
P55	4.363	***	-2.049	***	0.476	***	0.777
F-TEST	>100	***	>100	***	>100	***	
Other Statistics							
Avg. R^2	0.934						
Avg. $s(u)$	1.525						

Panel B Time-Series Regression Results for ICAPM					
Portfolios	D^{MKT}		$D^{\Delta OPP}$		Adj.R^2
P11	6.692	***	4.439	***	0.851
P12	6.040	***	3.693	***	0.941
P13	5.696	***	3.128	***	0.977
P14	5.178	***	2.875	***	0.957
P15	5.367	***	3.003	***	0.895
P21	6.706	***	2.365	***	0.823
P22	6.036	***	1.609	***	0.932
P23	5.482	***	1.093	***	0.938
P24	5.222	***	0.827	***	0.918
P25	5.965	***	1.108	***	0.883
P31	6.260	***	1.471	***	0.786
P32	5.607	***	0.417	***	0.924
P33	5.175	***	0.098		0.945
P34	4.949	***	-0.086		0.92
P35	5.598	***	0.204	***	0.855
P41	5.521	***	0.450		0.77
P42	5.281	***	-0.561	***	0.94
P43	5.122	***	-0.727	***	0.965
P44	4.874	***	-0.649	***	0.921
P45	5.692	***	-0.273	*	0.83
P51	4.593	***	-0.519	***	0.736
P52	4.558	***	-1.025	***	0.919
P53	4.363	***	-1.355	***	0.94
P54	4.469	***	-1.225	***	0.888
P55	4.614	***	-0.968	***	0.736
F-TEST	>100	***	>100	***	
Other Statistics					
Avg. R^2	0.888				
Avg. $s(u)$	1.960				

*,** and *** indicate coefficients are significantly different from 0 at the 10%, 5% and 1% levels, respectively .

Table 2.2 (Continued)

Panel C contains the results from the 2nd step, which involves cross-sectionally regressing the sample mean of monthly excess returns on the estimated factor loadings from the 1st step. λ is the estimated factor premiums (PREM), and e is the residual term that measures the pricing error of the AICAPM. For comparison purpose, the cross-sectional regression results from the ICAPM are also reported in Panel D. AAE stands for the average absolute error, and SEE stands for the sum of squared errors.

Panel C Cross-Section Regression Results for AICAPM			
PREM(in %)	λ^{MKT}	$\lambda^{\Delta OPP}$	λ^{SENT}
	0.040 ***	-0.100 ***	0.194 ***
Portfolios	e(in %)		
P11	-0.426		
P12	-0.006		
P13	0.026		
P14	0.198		
P15	0.355		
P21	-0.183		
P22	0.010		
P23	0.070		
P24	0.011		
P25	-0.057		
P31	0.029		
P32	0.103		
P33	-0.040		
P34	0.038		
P35	0.143		
P41	0.250		
P42	-0.033		
P43	-0.078		
P44	-0.009		
P45	-0.113		
P51	0.197		
P52	0.043		
P53	-0.057		
P54	-0.282		
P55	-0.086		
Other Statistics			
AAE	0.114		
SEE	0.638		

Panel D Cross-Section Regression Results for ICAPM		
PREM (in %)	λ^{MKT}	$\lambda^{\Delta OPP}$
	0.1222 ***	0.050
Portfolios	e(in %)	
P11	-0.533	
P12	0.023	
λ P13	0.137	
P14	0.355	
P15	0.584	
P21	-0.469	
P22	-0.045	
P23	0.127	
P24	0.132	
P25	0.140	
P31	-0.322	
P32	0.047	
P33	0.005	
P34	0.157	
P35	0.314	
P41	-0.107	
P42	-0.082	
P43	-0.019	
P44	0.093	
P45	0.046	
P51	-0.128	
P52	-0.041	
P53	-0.029	
P54	-0.165	
P55	0.023	
Other Statistics		
AAE	0.165	
SEE	1.351	

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively .

Table 2.3 Two-Pass Regression Results for the Fama-French (1993) 3-Factor (FF3) Model

Panel A contains the 1st-step results that include the adjusted R^2 (Adj. R^2) for each of the 25 portfolios, and the averaged values of adjusted R^2 (Avg. R^2) and standard errors (Avg. $s(u)$) after running the time-series regressions. Panel C contains the results from the 2nd step, which involves cross-sectionally regressing the sample mean of monthly excess returns on the estimated factor loadings from the 1st step. e is the residual term that measures the pricing error of the FF3 model.

Panel A Time-Series Regression Results		Panel B Cross-Section Regression Results	
Portfolios	Adj. R^2	Portfolios	e(in %)
P11	0.804	P11	-0.366
P12	0.857	P12	0.039
P13	0.868	P13	0.081
P14	0.879	P14	0.225
P15	0.837	P15	0.384
P21	0.917	P21	-0.222
P22	0.924	P22	-0.020
P23	0.919	P23	0.035
P24	0.938	P24	-0.044
P25	0.937	P25	-0.143
P31	0.911	P31	-0.038
P32	0.902	P32	0.073
P33	0.898	P33	-0.058
P34	0.897	P34	0.013
P35	0.888	P35	0.079
P41	0.919	P41	0.210
P42	0.872	P42	-0.008
P43	0.865	P43	-0.042
P44	0.878	P44	0.007
P45	0.855	P45	-0.115
P51	0.939	P51	0.245
P52	0.903	P52	0.108
P53	0.872	P53	0.010
P54	0.882	P54	-0.224
P55	0.799	P55	-0.068
Other Statistics		Other Statistics	
Avg. R^2	0.886	AAE	0.114
Avg. $s(u)$	2.021	SSE	0.616

*,** and *** indicate coefficents are significantly different from 0 at the 10%, 5% and 1% levels, respectively .

Table 2.4 Out-of-Sample Tests: Comparison of Accuracy in One-Step-Ahead Forecasts

This table presents the pair-wise comparison of the accuracy in 1-step-ahead forecast from the competing models using 25 portfolios sorted by size and BTM. The competing models are 1) AICAPM, 2) ICAPM, and 3) FF3 model. For pair-wise comparison between the competing models, the average of differentials in the mean squared forecast errors (MSFEs) is computed and DM-STAT is computed based on Diebold and Mariano (1995).

Average of Differentials in MSFEs $(\bar{d})$				
	Panel A		Panel B	
Portfolios	AICAPM vs. ICAPM		AICAPM vs. FF3	
P11	-17.988	***	-9.154	***
P12	-9.599	***	-2.581	***
P13	-7.030	***	-0.294	***
P14	-4.646	***	-0.737	***
P15	-6.836	***	-2.555	***
P21	-4.000	*	-9.730	***
P22	-1.670	**	-0.639	**
P23	-1.023		0.376	
P24	0.373		-0.193	*
P25	1.136		-1.333	***
P31	-4.473	**	-12.949	***
P32	-2.383	***	-0.448	**
P33	-2.192	***	0.170	
P34	-1.997	***	-0.351	
P35	-0.943		-1.210	***
P41	-3.445	***	-10.696	***
P42	-3.787	***	0.274	
P43	-4.435	***	0.268	
P44	-2.318	***	-0.271	***
P45	-1.352	*	-1.812	***
P51	-0.737	**	-7.345	***
P52	-1.713	***	-0.415	***
P53	-2.271	***	0.097	
P54	-1.712	***	-1.113	***
P55	0.782		-0.960	***
Panel B. Overall *T-Test*				
Mean	-3.370	***	-2.544	***

*,** and *** indicate coefficients are significantly different from 0 at the 10%, 5% and 1% levels, respectively .

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Appendix

The Kalman Filter as a Model of Conditional Expectations

At the beginning of month t, investors make prior assessments about the conditional means and variances of the unobserved factors (D_t) on the information set I_{t-1}, which have the following characteristics:

Property 1 (Producing a Forecast of D_t Based on I_{t-1}): In a conditional distribution $D_t \mid I_{t-1} \sim N(D_{t|t-1}, P_{t|t-1})$ and from Eq.(6),

1) A vector of the ex-ante (prior) expectations of the unobserved true factors (D_t) is given by $D_{t|t-1} = \Phi D_{t-1|t-1}$.

2) $P_{t|t-1} = \Phi P_{t-1|t-1}\Phi' + \Omega$ is a function of the population parameters (hence a constant matrix).

3) $D_{t|t-1}$ is the minimum mean squared error (MMSE) estimator of D_t with respect to $P_{t|t-1}$.

At the end of month t, investors make contemporaneous (real-time) assessments about the conditional means and variances of the unobserved factors as the data (R_t) are observed, leading to the following characteristics:

Property 2. Updating the Inference about D_t Based on I_t. In a conditional distribution $D_t \mid I_t \sim N(D_{t|t}, P_{t|t})$,

1) A vector of the ex-post (posterior) expectations of the true factors (Dt) is given by

$$D_{t|t} = D_{t|t-1} + K_t e_{t|t-1},$$

where $K_t \equiv P_{t|t-1}B'\Sigma_{t|t-1}^{-1}$ is the Kalman gain matrix (which is a function of the population parameters). In the Kalman gain matrix, $\Sigma_{t|t-1} \equiv (BP_{t|t-1}B' + \Delta)$ is the variance-covariance matrix of the forecast error, $e_{t|t-1} \equiv R_t - R_{t|t-1}$.

2) $P_{t|t} = P_{t|t-1} - K_t B P_{t|t-1}$ is a function of the population parameters (hence a constant matrix).

3) $D_{t|t}$ is the MMSE estimator of D_t with respect to $P_{t|t}$