

Manipulating Political Stock Markets: A Field Experiment and a Century of Observational Data^{*}

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October 2006

Preliminary

Abstract

Political stock markets have a long history in the United States. Organized prediction markets for Presidential elections have operated on Wall Street (1880-1944), the Iowa Electronic Market (1988-present), and *TradeSports* (2001-present). Proponents claim such markets efficiently aggregate information and provide forecasts superior to polls. An important counterclaim is that such markets may be subject to manipulation by interested parties. We analyze this argument by studying alleged and actual speculative attacks—large trades, uninformed by fundamentals, intended to change prices—in these three markets. We first investigate the speculative attacks on TradeSports market in 2004 when a single trader made a series of large investments in an apparent attempt to make one candidate appear stronger. Next we examine the historical Wall Street markets where political operatives from the contending parties actively and openly bet on city, state and national races; the record is rife with accusations that parties tried to boost their candidates through investments and wash or phantom bets. Finally we report the results of a field experiment involving a series of planned, random investments—accounting for two percent of total market volume—in the Iowa Electronic Market in 2000. In every speculative attack that we study there were measurable initial changes in prices. However, these were quickly undone and prices returned close to their previous levels. We find little evidence that political stock markets can be systematically manipulated beyond short time periods.

^{*}We thank Tim Groseclose, Robin Hanson, Donald Luskin, Tom Mroz, Sergio Parreiras, Marco Ottaviani, Charles Plott, David Primo, Mark Stegeman, Justin Wolfers, participants at the DIMACS Workshop on Markets as Predictive Devices, the 2005 International Symposium on Forecasting, London Business School Information and Prediction Markets Conference, 2006 NBER DAE Program Meeting, 2006 Prediction Markets Summit East, and workshops at Arizona, UNC, and Yale for assistance and comments. We are particularly grateful to TradeSports and Betefair for providing us with data from the 2004 Presidential Election market, Steve Cornwell of Intertops.com and Ken Kittlitz of the Foresight Exchange for providing us with data on the 2000 Presidential Election market, Bo Cowgill of Google for detailing that company's internal prediction markets, Joyce Berg for data from the IEM 2000 Presidential Election market, and Petra Moser for sharing her list of NYSE members.

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I. Introduction

Prediction markets trade contracts with payoffs explicitly linked to future events. An example is a binary option which pays a dollar on the outcome of a specific event, such as a candidate's victory or an on-time product launch. An efficient prediction market aggregates available information, yielding prices that are the best forecast of the event's probability. While the most well-know prediction markets involve sports, a growing number of on-line sites such as TradeSports, Betfair, and HedgeStreet have established futures markets on current events, economics, and weather. In political markets alone, one-hundred thousand participants will make over three million trades in 2006.

Prediction markets are currently the subject of intensive research in fields ranging from economics to political science to computer science (Berg, et al, 2005; Hanson, 1999; Pennock, 2004; Wolfers and Zitzewitz, 2004; Ledyard, 2005). There is also growing interest outside of academia. In the popular press, James Surowiecki (2004) has championed the *Wisdom of Crowds* while in the private sector, Abbott Labs, Corning, General Electric, Goldman Sachs, Google, Hewlett-Packard, Intel, Lilly, Microsoft, Siemens, and Yahoo! have begun running internal prediction markets. The hope is such markets can aid forecasting and improve decision-making in economic policy, corporate project selection, influenza vaccination and other areas.

However, several theoretical challenges to the efficiency and predictive power of these markets have been advanced. For example Manski (2005) questions the received wisdom that prices can be interpreted as probabilities. In his model, market prices only provide information about the wide interval in which mean beliefs over probabilities lie. The work has generated several responses including Wolfers and Zitzewitz (2005), Gjerstad (2005), and Ottaviani and Sørensen (2005).

Another, perhaps more damaging challenge to the forecasting ability of prediction markets is the possibility that small group of investors could deliberately distort or manipulate prices away from fundamentals for strategic purposes. Stiglitz (2003) criticized the proposed Policy Analysis Market, a heavily publicized futures market on Middle East economic and military events, on the grounds that it "could be subject to manipulation." This has also been a leading concern in internal corporate markets, with the organizer at Google noting that he "repeatedly encountered concern about the

potential for market manipulation from average employees as well as and senior leadership” (Cowgill, 2006). These fears might be warranted since one trader in the Google market later revealed he was attempting to manipulate prices. There have also been several charges of manipulation in online prediction markets. Such concerns will likely continue. As prediction markets become more visible, they will become an increasingly tempting target for interested parties who may attempt to strategically distort prices to influence real-world outcomes. And since insiders can participate (on-line sites like TradeSports do not explicitly ban insider trading and CFTC regulations permit insider trading in futures markets), it may be hard for other participants to simply disregard unexpected price changes.

This paper investigates the open empirical question of whether manipulation causes important distortions in actual prediction markets. For the purpose of this study, *fundamentals* are any information that influences the underlying value of the contract. A *speculative attack* is defined any trade, uninformed by fundamentals, intended to change prices. A (*successful*) *manipulation* is a speculative attack that achieves its objective of changing prices.¹

We analyze speculative attacks, both alleged and actual, in three political stock markets: the 2004 *TradeSports* market for President; the historical Wall Street betting markets for national, state, and city races; and the 2000 Iowa Electronic Market (IEM) for President. The cases we study involve large price jumps, with the initial price changes comparable to those in recent SEC stock market manipulation cases as summarized in Aggarwal and Wu (2005). Our empirical analysis ranges over a wide terrain, covering both observational data and field experiments, and evaluating evidence from both contemporary and historical prediction markets. We believe this breadth of approach substantially enhances the robustness of our findings.

¹A successful manipulation is usually not possible unless the trades influence the beliefs of other market participants. An investor’s *beliefs* are defined with respect to the fundamentals, as well as the future actions and beliefs of other investors.

Note that we focus on trade-based manipulation. It might also be possible to use rumors or incorrect information to drive prices from their true fundamentals.

It is interesting that there is no widely accepted definition of manipulation. Manipulation is not defined in the Commodity Exchange Act, and so the CFTC uses the rather tautological definition developed in the federal courts that a manipulation is an attempt to set a price “higher or lower than it would if it reflected the forces of supply and demand” (<http://www.cftc.gov>).

We find that these speculative attacks initially move prices, but these changes are quickly undone. The online 2004 *TradeSports* political stock market experienced two large price drops in the last months before the election. These drops were due to the large sales of a small group of traders who were purportedly aiming to steer the election to Kerry. While the price moves were large enough to warrant coverage in the *Wall Street Journal*, the effect was short lived and prices returned to their pre-attack level in less than an hour. The historical political markets operated in the late 19th and early 20th centuries, involved millions of dollars in wagers and had a respectable ability to predict the election winner. Political operatives often made large investments in these markets, and the record is filled with accusations that certain trades were executed to make a candidate appear stronger than he really was. Interested parties associated with both Democrats (Tammany Hall) and Republicans (Wall Street) had war-chests which they employed for large attacks in these markets, with the goal of influencing undecided voters during close contests. While these speculative attacks are associated with a price change, prices return to near their pre-attack level within days. The final set of evidence comes from a field experiment in the 2000 IEM presidential market. We made a series of random investments, totaling about two percent of the total trade volume, to simulate speculative attacks. Our experimental design exploited the fact that the IEM has two markets both linked to the same fundamental (candidate vote share). We varied our attacks between attacking a single market and simultaneously attacking both markets. The first case provides a natural control market, allowing us to test various hypotheses about market responses to speculative attacks. The second case might more accurately represent the trades of an insider possessing private information. These attacks led to large initial price changes, but prices typically reverted to their initial level in a few hours. In the case of single market attacks, prices in the control market did not markedly move following the attacks. In total our evidence suggests that manipulating political stock markets is difficult and expensive to do for more than a short period.

The paper has the following form. The next section investigates charges of manipulation in the 2004 *TradeSports* Market. The third section extends the analysis back one century by probing the role of manipulation in the large New York election betting markets, wagering on President, Governor, and Mayoral races between 1880 and

1944. The fourth section takes us from the position of passive outsider observers to active insiders by examining a field experiment involving a planned series of speculative attacks in the 2000 IEM Presidential markets. The final section summarizes our findings from this large and diverse set of data. The appendices include a section relating our concepts and methods to the existing literature.

II. *TradeSports* 2004 Presidential Market

a. Background

TradeSports operates several online prediction markets.² It ran the most influential market on the 2004 US Presidential election, which attracted more than \$15M in trade volume. Shares in the main election market paid a fixed amount if Bush won, and the prices were scaled between zero and a hundred to give the usual probability interpretation.

Shortly after 2:30 pm (EDT) on Friday, October 15, 2004, the *TradeSports* odds price on the re-election of President Bush began to fall precipitously. From a plateau of 54 points at 2:30 pm, the price dropped to 40 by 2:33 pm, bounced back to 50 and then dropped to just 10 points moments later. Thus prices fell by 44 points in just three minutes, suggesting that Bush went from a slight favorite to serious underdog. This sharp drop was the most dramatic of a series of trades that *National Review Online* blogger Donald Luskin soon charged were politically-motivated speculative attacks on Bush futures “to sway the election towards Kerry.”³ Some saw the hand of George Soros behind the October 15 plunge as well as earlier bear raids on Bush. Such rumors gained currency when a *TradeSports* press release, publicized in *Wall Street Journal* and *Time*,

²*TradeSports* markets are listed at <http://www.tradesports.com>. It is part of the Trade Exchange Network which provides an electronic matching service for trading futures on sports, entertainment, legal, and political events. The company, based in Dublin, Ireland, was founded in 2001. Its shares pay \$10 upon winning but are quoted between 0 and 100. When share prices are between 6 and 94, or exactly 0 or 100, then TradeSports charges a commission of 0.04 dollars (about 0.8 percent) per shared trades. Outside that range to the extremes the commission rate is 0.02.

³Donald Luskin, “Who’s Behind the Bush-Futures Attacks?” *National Review Online*, 18 Oct. 2004, 11:32 AM. http://www.nationalreview.com/nrof_luskin/luskin200410181132.asp. See also the 16 Oct. 2004 entry, “Bush Futures Being Manipulated” in Luskin’s own blog, *The Conspiracy to Keep You Poor and Stupid*, http://www.poorandstupid.com/2004_10_10_chronArchive.asp.

confirmed that the large trades of a single investor produced the October 15 price moves.⁴ The press release asserted “Bush contract has become the battle ground of wills between a cadre of large, well financed rogue traders seemingly bent on driving down the Bush re-election contract and a growing list of financial traders who think they can predict the outcome of this election.”

Figure 1 displays the price and volume during September and October when the purported manipulations occurred. In addition to the October 15 event, the other episode is a 13-point drop in the price of the “Bush Winner” contract over a fourteen minute period around 12 pm EDT on Monday, September 13. Figure 2 shows the manipulation events in greater focus (Time in the figures is reported in GMT or four hours later than EDT).

As a rule, the *TradeSports* market appears to quickly incorporate new information. For example, Bush shares fell over 5 points during the Presidential debate on October 8 (October 9 GMT) which many commentators later argued he lost. There is even stronger evidence in other *TradeSports* political markets. For example, John Kerry’s surprisingly poor performance in the Wisconsin primary in 2004 was announced 2/18/2004, 2:10 GMT on the *Drudge Report*. Kerry’s price in the Democratic nomination market fell from 90 to 85 within three minutes of the announcement, and declined another 10 points in the next twenty minutes. Similarly, Kerry’s purported affair with a former intern (announced 2/12/2004, 16:45 GMT on the *Drudge Report*) led Kerry shares to drop from 92 to 85 in three minutes and to decline a further 25 points in the next twenty minutes. The market also quickly realized this news was not too damaging, and Kerry shares stabilized in the mid-80’s in the next three hours. In total this evidence suggests that investors are actively monitoring the market, and that placid price periods are not simply due to investor inattention.

⁴“Bids and Offers,” *Wall Street Journal*, 22 Oct. 2004, p. C4; and “Let's Make This Vote Interesting, Shall We?” *Time*. 25 Oct. 2004.

b. Results

Through a special agreement with *TradeSports*, we have access to real-time trade data. These data include the quantity and price (though not identity of the traders) of every transaction from the 2004 Presidential market (the market was open from June 2003 through the election).

We use these trade-level data to analyze the two attacks described above, and our key results are presented in Table 1. The exact period of the trades is listed in the column headers, and the first four rows summarize the activity during the attacks. The price declines were far higher than was typically observed for such short periods. In the last three months of the market (September-November 2004), the average price range is 0.06 over three minute intervals (the length of the second attack) and is 0.25 over fifteen minute intervals (the length of the first attack). The price changes following the attacks, listed in Table 1, are an order of magnitude larger than any other price change over the market's lifetime. The volume is also heavy, with values that are several orders of magnitude larger than normal. Over the last three months of the market, the average volume per minute is 9.7 shares (or \$56.51) while the volume per minute is 491.9 shares in the first attack and 2208.0 shares in the second attack.

It seems unlikely that these episodes were instigated by unusual market conditions. While they did follow periods of slightly higher than average volume, the prior price volatility was relatively low. Prices changed by only 1.5 in the hour prior to attack 1, and not at all in the hour preceding attack 2.

Because volume data is available, we can investigate whether the attacks could have been immediately financially profitable. Row four of Table 1 calculates the net return if the manipulator immediately bought back the shares he had sold, using as data the observed prices following his trades. If a manipulator had no effect on the beliefs of other traders, prices would immediately return to their original level. The manipulator will have to buy back shares at the higher, pre-attack price and therefore take a loss. This is just what we see for attack 2, with the trader losing over ten percent of his investment. Attack 1, however, allows a four percent gain because prices did not immediately return to their initial level. This is an upper-bound estimate, because the trader would likely have to re-purchase some of his shares at a price exceeding the observed level (prices

were quickly increasing and some of the other purchasers would have executed their trades before him). Hence in practice even attack 1 would not likely be profitable.

We more precisely test this intuition using event study methodology (Campbell, Lo, and MacKinlay, 1997). Since there are no dividends in this market, the rate of return from buying a Bush contract at time $t-1$ and selling it the next period t is,

$$(1) \quad R_t \equiv (\text{price}_t - \text{price}_{t-1}) / (0.5(\text{price}_t + \text{price}_{t-1}))$$

where price_t is the price of the Bush contract.⁵ An advantage of using rates of return is that they are relatively comparable for all price levels. The cumulative return at time t of an investment made at time t_{\min} is,

$$(2) \quad CR_t \equiv \sum_{s \geq t_{\min}} R_s$$

The model in Appendix A shows that under some plausible assumptions CR_t is normally distributed with a variance $\sigma^2(t - t_{\min} + 1)^{-1}$, where σ^2 is the variance of R_t . This framework allows us to test whether the attacks had a statistically significant effect on prices at any moment. The attack has a significant effect at time t if zero lies outside the two standard error confidence interval around CR_t .

Figure 3 shows the cumulative return for the two attacks. A time period is defined as a minute, and time is normalized so the attack begins at $t=0$. The cumulative returns are calculated starting five minutes before the attack ($t=-5$), which allows for the possibility that the attacks were anticipated. The variance σ^2 is calculated from the observed dispersion in R_t during the hour before $t=-5$.⁶ The bottom part of Figure 3 shows the cumulative return for the 10/15 attack. CR_t is large and negative in the two minutes when the attack was executed. However CR_t is statistically indistinguishable from zero starting five minutes after the attack began or three minutes after the attack ended. For the 9/13 attack, the return remains negative and significant for a longer period of about forty-five minutes after the attack ends ($t=14$).⁷

⁵Using mean price in the denominator ensures that the return from a price jump will be comparable to the return if prices then revert to their initial level.

⁶This time period is referred to as the estimation window and is supposed to reflect the normal level of price volatility in the absence of unusual events. Our results are robust to alternative estimation windows.

⁷Two alternative formulations are considered (the specific numbers are omitted in the interest of brevity). First, we calculate the mean CR_t over the two attacks. This return is no longer statistically significant twenty-five minutes after the start of the attacks or about ten minutes after both attacks end. Second, we allow for a normal level of return. The adjusted “cumulative abnormal return” is calculated using two

It is also possible to evaluate whether the attacks influenced the long-run price dynamics. In omitted results, we estimate Chow tests of the form:

$$(3) \quad R_t = \alpha_1 + \beta_1 \times t + \alpha_2 \times I(\text{Post-attack})_t + \beta_2 \times t \times I(\text{Post-attack})_t + \varepsilon_t$$

where $I(\text{Post-attack})_t$ is an indicator for whether this time occurs after a attack. Using all trades over the last three months prior to the election, we cannot reject $H_0: \alpha_2, \beta_2 = 0$ for either of the attacks. This suggests that neither set of trades had a permanent effect on the rates of return.

In total these calculations confirm the visual inspection of the time series graphs. While the attacks involved extremely high volume and initially moved prices, the prices quickly returned to their prior level and were not financially profitable for the trader. This is consistent with the argument that attacks did not alter the price dynamics for this market.

Yet it is not possible to claim these attacks were failures. The speculative attacks could be considered successful from the perspective of gaining media attention. The second attack received widespread coverage in the press and involved an investment of only twenty-thousand dollars. In contrast, a full page advertisement in the *Wall Street Journal* (one of the papers covering the attack) would have cost two-hundred thousand dollars. If the motivation was a desire to shape press coverage and perhaps generate momentum for a candidate, then the attack was a success.

III. The New York Betting Market, 1880-1944

a. Context

A second arena where we can explore the potential impact of manipulation is the large market for election betting centered in New York City between 1880 and 1944 (Rhode and Strumpf, 2004; 2006). Participants could wager not only on national races but also on state and local elections. The New York betting odds received substantial media coverage in the era before scientific polls. These historical markets are of special

definitions of normal return: the mean return over the three days prior to the manipulation and the mean return over the prior hour. The cumulative values are quite similar those reported in Figure 3.

interest because partisans, including Democratic and Republican party operatives, actively and publicly traded. Accusations of manipulation and bluffing were rife.

The structure of these markets evolved over time.⁸ Although election betting was at times illegal, it was open conducted, well publicized, and employed standardized contracts, typically involving Winner-Take-All futures. The centers of election betting activity included the New York Stock Exchange, the Curb Market on Broad Street and the uptown hotels, the Hoffman House, Metropole, and the Fifth Avenue. The standard practice over much of the period was for a betting commissioner to hold the stakes (or signed agreements) of both parties and charge a five percent commission on the winnings. Our information about these markets comes from articles in the major New York newspapers (described below), which provided nearly daily quotes from early October until Election Day.

Compared with modern prediction markets, the betting volume in the historical New York market was huge. Figure 4 assembles estimates from selected newspapers of the sums wagered in the New York market from 1884 to 1928.⁹ All of the dollars are converted to year 2000 purchasing power. The betting volume varied depending on whether the race was for President, Governor, or Mayor, the closeness of the contests, enthusiasm for the candidates, and the legal environment. The period of greatest sustained activity was between 1897 and 1906. But the clear peak was the 1916 Wilson-Hughes peak, when \$158 million (2000 dollars) wagered in the organized New York markets. This was more than twice the total spending on the election campaigns in that year and ten times the volume in the 2004 *TradeSports* market. The betting volume tended to be much higher in Presidential years than in years when the NY Governor ran alone or the New York City Mayor was up for election. The ratios were on the order of

⁸Moving out of pool rooms in the 1880s, activity centered on the Curb Exchange and the major Broadway hotels until the mid-1910s. In the 1920s and 1930s, specialist firms of betting commissioners, operating out of offices in the financial district, took over the trade. These firms were variously viewed as brokerages, bucket shops, or bookie joints. *New York Times*, 10 Nov. 1906, p. 1; 29 May 1924, p. 21; 4 Nov. 1924, p. 2; *Wall Street Journal*, 29 Sept. 1924, p. 13. *New York Times*, 9 Nov. 1916, p. 3. For the long tradition of election betting, see *New York Herald Tribune*, 2 Nov. 1940, p. 23.

⁹ The reported totals in most instances represent the volume of money changing hands rather than the total amount staked. 1928 is taken as the end because quotations regarding volume become scarcer in the 1930s, not because activity appeared in that decade. Scattered evidence indicates volume in 1932 and 1936 was higher than at the end of the 1920s.

100:39:37.¹⁰ That is, there was a large drop off between national and state elections, but only a small further decline for city races. The average bet volume for the twenty-five elections appearing in the figure was roughly \$22 million (in 2000 purchasing power). As a point of contrast, activity on the IEM for the 1988-2000 elections has been orders of magnitude smaller, with trading volumes that never exceeded \$0.15 million in any one election (see Berg, et al, 2003).

During the heyday of election betting in the late 1890s and early 1900s, the names and four-figure stakes of bettors filled the pages of New York's daily newspapers. Thus, in contrast to the electronic markets of today, these activities were not anonymous. Such published stories may have served to advertise the political affiliation of the bettors as well as to confirm the existence of the wagers.¹¹ Tammany Hall, the NYC Democratic machine, was also reputed to have a special war chest to finance its wagering.

The Wall Street betting markets were widely recognized for their remarkable ability to predict election outcomes. As the *New York Times* put it, the "old axiom in the financial district [is] that Wall Street betting odds are 'never wrong'."¹² We show in Rhode and Strumpf (2004) that in the fifteen presidential elections between 1884 and 1940, the betting market underdog in mid-October won only once (the only exception being the extremely close 1916 contest). In cases where there is a decisive winner, we also show that the betting markets correctly select the next president as much as four months prior to the election. The ability of the betting market to aggregate information is all the more remarkable given the absence of scientific polls before the mid-1930s. The *Wall Street Journal* contended that the accuracy of betting odds held not only for "national elections but applies equally to state and local races."¹³ The odds were "generally considered the *best forecasters* of Presidential elections (emphasis ours)," as

¹⁰ It was estimated that in Presidential years, about two-thirds of the bets were placed on the Presidential races and the remainder on Governor and local races. *New York Times*, 3 Nov. 1924 p. 2. Election betting markets existed across the nation over most of this period, but New York City was the center of activity until the Second World War.

¹¹ Politicians as a matter of loyalty could be expected to bet publicly for their party's candidate, even when they did not favor them. For example, in 1900, Richard Croker made highly publicized bets in favor of William Jennings Bryan against his own preferences. *New York Times*, 5 Nov 1916.

¹² *New York Times*, 28 Sept 1924, p. E1. See also 30 Oct. 1916, p. 4; 7 Nov 1916, p. 1; 7 Oct 1924, p. 18; 6 Nov 1928, p. 46, 8 Nov. 1932 p. 33; 2 Nov. 1936, p. 20.

¹³ *Wall Street Journal*, 27 July 1920, p. 11.

well as “good indicators of probable results in gubernatorial and Mayoralty results.”¹⁴ Rhode and Strumpf (2006) provides further details on the predictive capacity of these markets in all three types of elections.¹⁵

Contrary to these assessments were the frequent assertions that active partisan involvement, especially by Tammany Hall, systematically distorted the betting odds and, at times, speculative attacks attempted to change the momentum of the races and influence voter turnout. As one example, in closing days of 1926 race for the NY Governor, the campaign of Republican Ogden Mills vocally charged that Al Smith’s backers were resorting to the old Tammany trick of using election wagers as “indirect propaganda.”¹⁶ But Tammany was not alone in possessing a betting war chest. Republicans, especially those on Wall Street, purportedly organized funds to finance speculative attacks. The *New York Times* on 28 Oct. 1904 charged the GOP of manipulating the betting odds in favor of T. Roosevelt in the Presidential race. The historical record is rife with such charges, most levied against partisans supporting the favorite. As an example, in 1916, Democrats charged “the money was being sent to Wall Street to force the betting odds to Wilson’s disadvantage, for the effect of wider odds would have, especially on up-State farmers, who in the past have been influenced by wagers reported here from below Fulton street. ‘Already,’ one prominent Democrat said, ‘we are hearing that many up-State farmers are struggling between their conscience and fear that Hughes will be elected and it might be found out that they voted for Wilson.’”¹⁷

While there are a variety of reasons for the partisans entry into the political betting markets, the primary goal was to sway public opinion. As we describe below, most of the purported manipulation attempts were made shortly before the election and almost always in close races where small changes in public opinion could swing the outcome.

¹⁴ *Wall Street Journal*, 17 Aug. 1925, p. 5. See also 27 July 1920, p. 11; 29 Sept. 1924, p. 13. The 1925 article added the betting odds were less accurate guide for offices below Mayor because less attention was devoted to studies the contests for minor offices and little money was wagered,

¹⁵ We show that the markets were not fully efficient and suffered from long-shot bias, a typical shortcoming of prediction markets.

¹⁶ *New York Times*, 17 Oct. 1926, p. XX10.

¹⁷ *Washington Post* 5 Nov. 1916 p. 1.

b. Our Data and Analysis of Manipulation

To analyze how manipulation affected the information-aggregation properties of the New York betting markets, we have collected a large dataset of betting odds on the presidential, gubernatorial, and mayoral races over the 1880s to the 1940s. Our sample is drawn from the *Brooklyn Eagle*, *Chicago Tribune*, *Christian Science Monitor*, *Los Angeles Times*, *New York American*, *New York Daily News*, *New York Evening Journal*, *New York Herald*, *New York Sun*, *New York Times*, *New York Tribune*, *New York World*, *St. Louis Post Dispatch*, *Wall Street Journal*, and the *Washington Post*. Our sample currently includes 3701 daily odds prices for 142 candidate-race-year triplets (that is, a given candidate running for a given office in a given year). The unit of observation is one daily odds price from each newspaper article.¹⁸ The sample covers 52 contests: 16 Presidential elections (1880-1944); 22 Gubernatorial elections (which basically occur biennially from 1888 to 1936), and 14 Mayoral races (1890-1937).

We investigate whether purported speculative attacks, or more correctly episodes associated public charges of manipulations, induced long-lasting prices movements unwarranted by the fundamentals. Given the available information about the activities of the market agents, we can not state whether intentional manipulation actually occurred, only what happened during an episode in which manipulation was publicly charged in one of the major newspapers. In this historical investigation, we are in the same position as being outside observers as in the 2004 *TradeSports* episodes. One difference is that we are sure in the historical markets that partisans were actively involved.

To identify the relevant events, we have surveyed the leading New York daily newspapers (with special emphasis on the *Times*) and classified the “manipulation” stories into three categories: (a) charges of intentional manipulation with investors betting to drive odds prices away from the levels justified by fundamentals; (b) charges of wash bets, that is, of bets made between confederates at non-market odds for publicity purposes; and (c) charges of bluffs, that is, offers to make bets at non-market odds which

¹⁸ That is, we may have several different observations on a candidate’s odds price on a given day from different newspapers (or much more rarely, from different articles in the same paper.) If a single article reports several wagers, we average to derive that day’s single observation. We have made no attempt to eliminate duplication resulting from multiple publications of the same article in different newspapers, as might happen if a wire service ran a story on the state of NY betting markets. We have been careful, however, to date the odds price to the day the betting took place rather than the day of the article and to focus on actual bets rather than mere offers.

are withdrawn when the offer is accepted. In this exercise, we have employed both computer keywords searches using Proquest.com (of the *New York Times*, *Wall Street Journal*, *Washington Post*, *Los Angeles Times*, and *Christian Science Monitor*) and extensive reviews of thousands of printed newspaper stories by the authors. We record the direction of the “manipulation” (i.e. in favor of the Republican’s or Democrat’s odds) but not the sources of the activities or of the charges. In 1916, for example, stories circulated charging a politically unaffiliated financial agent of manipulating the Presidential odds for purposes of influencing asset prices. Charges were advanced by participants in the betting markets, those in related financial markets, by newspaper writers, as well as the supporters of the electoral campaigns involved.

One might think that all such charges were “cheap talk” and that they would be as ubiquitous as stories of partisan involvement or stories of voting fraud. But there were not. Charges of intentional manipulation occur on only about 2 percent of days with reported betting odds. One reason that charges were not made more frequently is that the election cycles represented repeated games and the making unsubstantiated charges of manipulation would adversely affect one’s reputation and the creditability of one’s future charges.

Our investigation finds there were 46 charges of manipulation/wash sale/bluffing events during our sample period. There were 19 charges of full-blown manipulation of the odds, with 11 alleged manipulations in favor of the Democrats and 8 in favor of the GOP. 11 of these alleged manipulations involved presidential races with the other 8 on state and local races. All of the alleged manipulations were made shortly before the election: the average manipulation occurs 7.8 days before the election and the median is 4 days before the election (that is, during the last weekend of the campaign). Only six manipulations occurred over a week before the election. Manipulations are typically made to benefit a candidate who is the favorite (his odds are greater than half), and all GOP manipulation are made when their candidate has a lead. Manipulations also tend to occur when the markets forecast a close election (the odds are near half), though there are several exceptions.

Among the 27 charges of wash sales or bluffs, 5 were in favor of the GOP and 22 in favor the Democrats. (Of these minor charges regarding the Democrat odds, almost all

were bluff betting, the so-called “Old Tammany Trick.”) Most of the alleged wash sales or bluffs occurred in the month before Election Day--the mean was about 8.9 days before voting began. One accusation was 103 days before Election Day; the median event was 5 days, that is, in the final week of the campaign.

Given the nature of the historical data, we must make several adjustments to the event-study methodology employed above. First, our historical observations are of lower (at best daily) frequency but from multiple sources. Our data will be the daily odds prices quoted in the available newspapers. Second, the alleged historical manipulations do not all occur for a single candidate nor do they all push in the same direction. Our approach will to investigate the separate effects of the Republican and Democratic “attacks” on the “Democrat’s price.” Given data availability and a desire to avoid duplication, we will use the price quotes for the favored candidate in each race. Where the favorite is the Democrat, their prices will be used directly; where the favorite is not the Democrat, we will define the “Democrat’s price” as one minus the favorite’s price. Only in the three-way 1924 race does this procedure create any problems (because odds on the Democrat were not always reported). Third, to control for differences across the races, we include election-specific dummy variables. Fourth, given that many of the events occur close to the election (often the weekend before), we will define the window as extending 5 days after the alleged manipulation. We will begin the window one week before. (We treat new manipulations occurring within the window as separate events.)

One further note about timing: A purported attack is typically dated to occur one day before the newspaper allegation is published. This places it in line with the odds published on that day. As will become apparent, the price moves associated with an allegation may precede publication by more than one day. We cannot rule out the possibility that a genuine information shock drove the price movements. It is important to note, however, that the story containing the allegations was written before the prices of the current day were revealed.

Our analysis examines these effects for the Presidential race and for all races combined. Table 2 reports the regression results measuring the impacts of manipulations and wash sales/bluffs on the “Democrat” odds price. For each election i and date t we estimate an equation of the form,

$$(4) \quad \text{Demprice}_{it} = \sum_s \alpha_s I(t=s) I(\text{DemM}) + \sum_s \beta_s I(t=s) I(\text{RepM}) + \sum_s \gamma_s I(t=s) I(\text{DemWB}) + \sum_s \delta_s I(t=s) I(\text{RepWB}) + v_i + \varepsilon_{it}$$

We estimate the impact of a Democratic manipulation s days away from the action (α_s), the impact of a Republican manipulation (β_s), the impact of a Democratic wash/ bluff (γ_s), and the impact of a Republican wash/bluff (δ_s), all while controlling for election fixed effects (v_i). We consider these impacts roughly a week before and after each event ($-7 \leq s \leq 5$). The wash sales and bluffs prove to have little or no meaningful effect on prices, consistent with interpreting such charges as “cheap talk.” As a consequence, we will focus on the impact of manipulation events. These impacts may be more easily visualized by examining Figures 5-7, which shows the movements in the “Democrat” odds prices as well as the error bounds.

Figure 5 shows estimates for manipulation in the Presidential election market. The effects associated with a charge of a “Republican attack” on the President market may be described as follows. The Democrat price over the week before the attack was trending down. In the day of the event, the price fell 0.02. Over the next day, prices reverted back into the range prevailing in the previous week. The effects associated with a charge of “Democrat attack” in the Presidential market were somewhat different. Prices were far more volatile in the period before the charges. Over the day of the alleged attack and the next day, prices jumped about 0.12. But they fall back down sharply on day two and then trend into the range prevailing over the week before the attack.

Figure 6 examines attacks in all races. Combining the races increases the sample, especially of Democratic manipulations. The pattern for Republican attacks in all races is similar to that in Presidential races. Prices were low but stable up until the day before the charge, then jump down on the day of the “attack” before bouncing right back up. The pattern for Democrat attacks is smoother than for the Presidential races alone. There is a more moderate rise from the day of “attack” through day 3. Prices begin to trend down in days 4 and 5 but remain above the range prevailing during the week before. This suggests manipulation in local races had greater long term effects.

Figure 7 shows the price effects of manipulations on the Democrat odds prices where Democrat and Republican manipulations are both included (in equation (4) above, the α and β terms are combined and the Republican manipulations are multiplied by -1).

The regression results for the presidential races are sharper than those above (these estimates are omitted). The day of the manipulation witnesses nearly a 0.035 jump up in the Democrat odds prices. But prices quickly revert and by day two are within the range of the pre-manipulation period. Prices then begin to rise again. For all races, the manipulations were associated with a much smaller increase, less than 0.02. Prices drift down by the days two and three before again beginning to rise. Nothing in these patterns suggests that manipulation events led to large, irreversible changes in prices.

As a summary, our analysis of the historical record indicates that: (1) A large political betting market could operate despite (or perhaps because of) the active participation of partisans. The market betting odds possessed considerable predictive power and; (2) public charges of manipulations were not associated with large permanent changes in the odds prices.

Our analysis of manipulation in the *TradeSports* futures and the historical New York betting markets is limited because we are in the position of outside observers. We do not know the motivations of the investors who are affecting the price shifts. A field experiment conducting in the Iowa Electronic Market (IEM) in 2000, however, offers us the unique perspective of being insiders with knowledge about the timing and magnitude of a series of trades being made for reasons unrelated to changes in the fundamentals.

IV. Iowa Electronic Market (IEM): Field Experiment

a. Background

The IEM is a real-money, online futures market operated by the Henry B. Tippie College at the University of Iowa (<http://www.biz.uiowa.edu/iem>). It is currently the sole legal site in the US to trade in political information futures using real money. Its operations differ from either *TradeSports* or the New York betting markets because participants are limited to relatively modest stakes (\$5 to \$500). The IEM's clientele tends to be a select group: highly educated, young, predominately male, employed with academic or research job (Oliven and Rietz, 2004). Despite these constraints, the IEM political stock markets have performed quite well. They typically forecast better than polls, and they pass many tests of market efficiency (Berg, Nelson, and Rietz, 2003).

In this paper we focus on the IEM markets on the 2000 presidential election. These markets had \$0.167 million in trading volume and had about one thousand active investors. In the IEM presidential markets, there were two forms of contracts: Winner-Take-All (WTA) and vote share (VS) contracts. Both assets were available for the Democratic candidate (DEM), the Republican (GOP), and the Reform party (REF). The VS contract was akin to a point-spread wager in sports betting and paid conditional on the size of the candidate's plurality of the vote. The IEM WTA contract was like a win-loss contract in sports betting but with one important difference. It paid off for the candidate who received the largest absolute vote, not the candidate who was actually elected president.

This created much confusion on election night 2000 when the popular vote went for Gore but the Electoral College vote was projected for Bush. Figure 8 charts the gyrations of the IEM WTA contract on the night of 7 Nov. 2000 and morning of 8 Nov. According to the IEM definitions, Gore won the 2000 contest for both the VS and WTA contracts. Yet when the major networks proclaimed that Bush had won the Electoral College at 1:20AM CST, the price of his shares rose to near a dollar. At this point it was already apparent that Bush was going to lose the popular vote (he was slightly behind in the VS market at midnight of 11/8), and he fell behind in the official aggregate vote tallies between 3:30 and 4:20AM CST. At this point, there was little uncertainty with regard to the IEM contracts and yet the prices were the exact opposite of where they should be. This is consistent with traders incorrectly believing the WTA contract was based on the Electoral College. The market slowly reversed itself and (the day after the election) the correct price was offered.

The definition of the IEM WTA contract differs from the analogous contracts prevailing in the historical markets and in the *TradeSports* 2004 presidential futures markets, both of which were linked to the Electoral College winner. The IEM markets have the useful analytical feature that both the VS and WTA prices are linked directly to the same fundamental variable, the final vote share. As we describe below, this implies there exists an equilibrium relationship between the prices under efficient markets and that one price may serve as a control for the other.

b. Experiment

During the summer and fall 2000, one of the authors engaged in a series of controlled uninformative trades in the IEM presidential markets. The trades sought to mimic the behavior of an insider with private information and followed a formalized protocol.¹⁹ The trades involved randomly investing real money in one or both of the WTA and VS contracts, with the side -- DEM or GOP --determined based on hundredth digit of Dow day before. Our goal was to test whether other investors recognized these were uninformed speculative attacks (sending prices back to their initial level), or rather they believed they were due to news shocks (and so prices did not revert).

There were 11 planned trades, roughly 10 days apart, starting 110 days before the election. The trades were typically executed in 15-30 minutes in a trading window time starting at either 8 pm or 11:15pm CDT/CST. The late evening schedule was selected to increase the chance that the trades shift beliefs and lead a long-term change in prices. The first reason for this is that information was less widely distributed during these times than earlier in the day. It would be difficult for an investor to refute that a price change was due to a news shock, which at these hours might not be widely reported and known only by the individual making the trades. A second reason is that late in the day volume is relatively light, and few traders are likely to be actively monitoring the market. Prices may stay distorted until the next morning when more traders come online. Thus the experimental design leans towards finding evidence of manipulation.

The experiment was designed to exploit the existence of the two IEM presidential markets. Some investments were in one market only and others were in the two simultaneously. The idea was that a trader with fresh inside information would likely invest in both markets whereas, perhaps, a non-financially motivated trader might invest just in one.²⁰ The two markets also help us distinguish between three leading hypotheses about the market response: (i) the markets are not actively monitored; (ii) the attacks change beliefs and markets are monitored; (iii) the attacks do not change beliefs and

¹⁹The procedures are codified in official trade strategy document, *iowa.strategy.2b.doc*, which is available on the author's web page. There was also an outside board which received this document prior to the execution of any trades.

²⁰The one exception is an event which creates greater uncertainty but does not favor one candidate or the other. In this case the price of the favorite should decline in the WTA market but not the VS (see the model in the Appendix A).

markets are monitored. The second hypothesis indicates successful manipulations are possible and likely indicate that investors believe that our attacks were due to a change in fundamentals.²¹ The last hypothesis suggests it is difficult to successfully manipulate these markets.

Table 3 summarizes the predictions of the three hypotheses. The first row indicates that price movements allow us to distinguish between the hypotheses using simply a one-market attack. Since the VS and WTA markets are linked to the same fundamental (final vote shares), under efficient markets there should be an equilibrium relationship between the markets. Appendix Section A shows this relationship is,

$$(5) \quad \text{price}_t^{\text{WTA}*} = \sigma_{vt}^{-1} \times \text{price}_t^{\text{VS}*}$$

where “*” indicates an inverse normal transformation and is σ_{vt} is a measure of uncertainty t periods before the election.²² If the attacks alter market beliefs, than when only one market is attacked prices in the unaltered market (the control market) should also move. If beliefs are altered (or if markets not monitored) than the control market should be unaffected. The second row summarizes the predictions for a two-market attack. While this case does not provide a clean test, it is still interesting since as we mentioned it may more realistically depict the investment of an insider with private information.

Table 4 shows that the dates of the trades and the details of each investment. The experimental design involved three types of trades: investing in the WTA contract alone; in the VS contract alone; and in both the WTA and VS contracts. The investments were made as follows. For WTA contracts, if it was randomly determined (by the Dow) to buy GOP, then an initial investment of \$160 was used to purchase this contract at market

²¹It is also possible that investors believe that other participants will change their behavior. For example, there may be a “Soros effect” where investors believe the trades were made by a single speculator who will continue to invest and himself sustain a price change. But this is not likely in the IEM, since there is a \$500 limits on investments.

²²Under a simplifying presumption in the law of motion of news shocks, $\sigma_{vt}=(t-T)^{0.5}$, where T is the period with the election Using daily closing price data from the 2000 IEM, we estimate the following relationships,

$$\begin{aligned} \text{Democrats (R}^2=0.74\text{): } & \text{price}_t^{\text{WTA}*} = -0.012 + 40.188 \times \text{price}_t^{\text{VS}*} \times (T-t)^{-0.5} \\ \text{Republicans (R}^2=0.71\text{): } & \text{price}_t^{\text{WTA}*} = 0.018 + 38.910 \times \text{price}_t^{\text{VS}*} \times (T-t)^{-0.5}. \end{aligned}$$

Consistent with the theory the constants are not statistically significant. We also estimated analogous equations relating the VS price to the WTA price.

prices. (The strategy also allowed the alternative of buying the entire slate and shorting DEM if that was cheaper.) Following these trades supporting limit orders were placed for \$80 to buy GOP at \$.006 below last Ask and \$80 to sell DEM at \$.006 above last Bid. (These expired untraded in some cases.) If the trade involved a VS contract, the procedure was identical but for one-half the amount. The 10/28 trade was different in that all of our holdings were sold that day (\$566 in total).

Given the nature of the IEM, the size of these investments was large relative to total trade volume. The third to fifth columns of Table 4 list the dollar amount of each trade. An aggregate sum of \$3116 was wagered, which was about two percent of total IEM trade volume. The largest trade of a VS contract was 3.0 percent of the current market cap (listed in column 6) while that of the WTA contract was 2.7 percent. Note that the relative size of our fixed-sum trades declined over time as the market expanded. The individual trades were also large relative to daily trading volume. A typical trade represented 181 percent ($=\$120/\66) of average daily volume in the VS market and 28 percent ($=\$240/\870) in the WTA market.

The initial price changes after the trades were generally large, comparable to daily range of trading. The specific values, right before and right after the trades, are listed in the last three columns of Table 4. To provide perspective, the average *intraday* price range for DEM and GOP was 0.5¢ for the VS contracts and 3.8¢ for WTA and the average price range in hour before trades were about 0¢ for VS contracts and 0.5¢ for the WTA. The price changes 30 minutes after the controlled trades were 0.3¢ for the VS and 2.5¢ for the WTA. That is, the changes were much larger than in the prior hour and roughly sixty percent of the intraday range. As an example, Figure 9 illustrates the time path of prices following the 10/28 trades.

A potential concern is that majority of our trades happen to be in the same direction as prevailing price trends (see the last three columns of Table 4). It is therefore important to show that our trades are not, by chance, reflecting changes in fundamentals. One way to show this is to compare the IEM prices to those in other markets on the 2000 Presidential election. We have a complete list of price changes from Centrebet, an

the trades. Joyce Berg has kindly shared with us additional IEM price data to supplement this investigation.

c. Results

We aggregate the data from our eleven trades into fifteen-minute periods (the frequency at which the price screen is refreshed on the main IEM page). For prices we use the last traded price, and if there are multiple observations in the period we average these prices. When the attack called for shares to be sold, we take the negative of prices. This ensures the attacks are aligned, with each case seeking to increase prices.

For each trade we calculate the cumulative returns (CR) using the formula in equation (2), and start the calculation six periods (an hour and a half) prior to the start of each trade. We will focus on average CR's for various subsets of trades. To establish confidence intervals we calculate the volatility of prices prior to each trade. In particular we calculate a CR starting roughly a day before each trade and take the mean standard deviation across these CR's. Since Appendix A shows the mean CR's are normally distributed, the two standard deviation interval is roughly a ninety-five confidence band.

We begin the analysis by focusing on the markets that are attacked (rather than the control market). Figure 10 shows the average CR for the full set of eleven trades. The figure plots CR values and their associated confidence intervals for the first five hours after the trades. There is little trend in the return for the hour and a half prior to the attack ($t=0$), which suggests the trades were not reinforcing some pre-existing price trend. The CR increases by a statistically significant four percent in the first half hour (the typical time to fully execute a trade), reflecting the large change in prices associated with attacks. The CR begins to decline immediately following the end of the trade period, and half of the effect is undone within two hours (and the effect is no longer statistically different from zero). The CR returns to zero within twelve hours. The relatively rapid unwinding of the attacks is impressive given that they occur during low volume periods, as discussed earlier

Continuing to focus on the attacked market, we next consider various subsets of attacks. Figure 11 shows the average CR for the four WTA-only and three VS-only attacks. In the WTA trades the returns spike up even more sharply following the attack,

with a seven percent return in the first half hour. The mean CR stays at an elevated level for the first two hours, at which point there is a large reversion. The price increase is basically fully undone within five hours. The VS trades have a rather modest effect and prices initially increase less than one percent. The mean CR remains virtually unchanged for the next nine hours, reflecting the relatively low activity in this market (see the market caps listed in Table 4), at which point prices quickly return to their initial level. We do not read too much into this slow reversion, given the small levels involved and the lack of statistical significance evident in Figure 11.

Figure 12 presents the average CR for trials in the first or second half of the observation period (because the market cap tends to increase over time, this can also be thought of as trials in a small or large market). The early/small cap trials had a rather modest initial effect which entirely disappears within two and a half hours. Alternatively, the late/large cap trades result in a large 8 percent increase in the CR in the first half hour. There is some reversion over the next five hours, but the CR remains large (about four percent) and is statistically significant. The CR gradually falls in half over the next seven hours, and is completely undone twenty-four hours after the initial attack. This slower reversion in the later period is somewhat surprising, since the market cap is larger and presumably there are more investors monitoring prices. Given the confusion on election eve, perhaps the late arriving investors are less experienced and perhaps more susceptible to being fooled by these large trades.

Figure 13 shows two more sets of trials in which the CR slowly reverts to zero. When both markets are attacked, the positive CR effect levels off at about two percent for hours one to twelve (though the wide confidence bands are a caveat). The positive effect persists for about twenty-four hours. This makes sense, since we have already argued that an insider might prefer to trade in both markets if he really knew there was a change in the fundamentals. Hence market participants may lend more credence to these trials. The CR also does not revert for about a day when the trial involves a purchase of Democrats and/or a sale of Republicans. The explanation for this case is less obvious and may reflect some partisan sentiment. It is important to stress that the reversion speed is not simply due to differences in the initial response. The mean CR increases over four

percent for trials involving a single market attack or for trials with Democrat sales/Republican purchases, and yet the CR reverts much faster to zero (figures omitted).

Figure 14 presents results for the control market in single market attacks. Recall that the VS and WTA markets are based on the same fundamentals and are linked in equilibrium according to equation (5). Prices in the non-attacked control market should not move if market beliefs are unchanged. The top panel in Figure 14 is consistent with this hypothesis. While there is a small response in the half hour following the attacks in the other market, the price change is not statistically or economically significant (it increases a half percent). Moreover, the CR becomes negative (and still small) within forty-five minutes at which point we have already seen the returns are still positive in the attack market.

The bottom panel of Figure 14 provides a more direct test of the hypothesis that beliefs remain unchanged following our trades. While the previous figure considers the average response in the control market, it is more appropriate to see whether there is a greater response in trials which had a larger effect in the attack market. In particular we calculate the “abnormal return” in the control market given its equilibrium relationship to the attack market. Equation (5) provides a measure of the normal WTA price, and if it is inverted it yields the normal VS price. These can be used to calculate the normal rate of return at time t ,

$$(7) \quad R_t^{\text{Normal}} \equiv (\text{price}^{\text{Normal}}_t - \text{price}^{\text{Normal}}_{t-1}) / \text{price}^{\text{Normal}}_{t-1}$$

where $\text{price}^{\text{Normal}}_t$ is the normal price. In analogy to equation (2), the cumulative abnormal return at time t of an investment made at time t_{\min} is,

$$(8) \quad \text{CAR}_t \equiv \sum_{s \geq t_{\min}} (R_s - R_s^{\text{Normal}})$$

The bottom of Figure 14 shows that the CAR for the control market becomes negative right after the attacks and then starts to revert to zero. This pattern is the mirror image of the CR for the attacked market in Figure 10.²⁵ Taken together this means that prices in the control market do not move enough to offset the price increase in the attack market (though the two markets typically move in tandem as reflected by the CAR values near zero prior to the attacks). The experience in the control markets supports the notion that

²⁵The comparison is even clearer when the attack market CR is graphed for single market attacks.

investors realized that the attacks were non-informative and is consistent with the claim that the attacks did not move beliefs.

The field experiment involving the IEM 2000 election provides a unique opportunity to investigate the market responses to uninformative trading. Eleven large trades were made at times and in directions unrelated to changes in fundamentals and nine had a significant initial impact on the IEM prices. But over a short period of time, all of these attempted manipulations were largely undone by other traders. In total, these results suggest that the long-term market dynamics were not influenced by uninformative trading.

V. Conclusion

The promise of improving decision-making by tapping the “Wisdom of Crowds” through the use of prediction markets has attracted great interest in recent years. An important challenge to utilizing such markets is the possibility of manipulation and speculative attacks by partisan or large moneyed interests. To assess this challenge, the paper has analyzed alleged and actual speculative attacks—large trades, uninformed by fundamentals, intended to change prices—in three markets: the 2004 *TradeSports* market for President, the historical Wall Street betting markets, and the Iowa Electronic Market in 2000. In almost every speculative attack that we study there were measurable initial changes in prices. However, these were quickly undone and prices returned close to their previous levels. Our investigation of evidence from field experiments and contemporary as well as historical observational data suggests it is difficult and expensive to manipulate political stock markets beyond short periods. And the period appears to become shorter over time—from days (New York Markets) to hours (IEM) to minutes (*TradeSports*). This is in contrast to stock market speculations. Aggarwal and Wu (2005) show in cases where there was SEC manipulation prosecution, prices double in the year following the manipulation.

Our evidence is not unique. Accusations of manipulation are now common in political stock markets. Yet in every additional episode we could investigate—the 2006 *TradeSports* markets on Control of the U.S. House, Mexican presidency, the Republican Presidential Primary or the 2006 Betfair market on the Liberal Democrats leader—the

price changes were again short-lived. The manipulation attempts on the Google market were similarly unsuccessful. One of the most active and successful Google traders made several bets with the explicit goal of changing the beliefs of other participants. But the trader later noted his attempts were unsuccessful and that he “lost lots of money to people who really did have information and wouldn't let me manipulate the prices” (quoted from Cowgill, 2006).

Among the questions for future research are: do these results hold for other prediction markets? What are the key characteristics that ensure markets are not easily manipulated? We have shown that certain characteristics are not crucial, because there is variation across the markets we study. For example, having public or anonymous markets does not seem to matter. But there are other traits that are common to all of our markets: large and thick markets; small number of possible outcomes; and diversity of opinions. In identifying which are the essential characteristics we might gain a better understanding of why certain of these markets work so well at making accurate predictions.

Appendices

Section A: A Framework for Political Stock Markets

Winner-Take-All Market

The efficient markets test can be applied to time series data, e.g. daily contracts for the winner of the overall election. The key feature of such data is that the uncertainty should systematically decrease as we approach the election date. We present a model related to the analysis of futures markets in Samuelson (1965).

Suppose that time is discrete and in each period some news about the candidates arrives. For concreteness we focus on the Democrat's electoral prospects, and presume there is a latent level of Democrat support (two party vote share) each period. The Democrat's latent support evolves according to,

$$(A1) \quad \text{VoteShare}_t^* = \text{VoteShare}_{t-1}^* + \varepsilon_t$$

where VoteShare_t is the latent support at day t , VoteShare_{t-1} is the latent support on the prior day, and $\varepsilon_t \sim \mathcal{N}(0, \sigma_t^2)$ is the independent across time news shock. The zero mean implies the news does not systematically favor any candidate, while the independence assumption precludes trends in the news. The star superscript indicates an inverse normal transform, $x^* \equiv \Phi^{-1}(x)$ where $\Phi(\cdot)$ is the standard normal distribution function. This transform insures the range of the VoteShare variables is the entire real line like with the ε_t term. This equation can be iterated forward to yield,

$$(A2) \quad \text{VoteShare}_T^* = \text{VoteShare}_t^* + v_t$$

where T is the election day, VoteShare_T is the election day latent support (presumed to be the actual election outcome), and $v_t \equiv \varepsilon_t + \varepsilon_{t+1} + \dots + \varepsilon_T$.

Presuming that VoteShare_t is in the time t information set Ω_t , the best guess about the transformed election outcome is normally distributed, $\text{VoteShare}_T^* | \Omega_t \sim \mathcal{N}(\text{VoteShare}_t^*, \sigma_{v_t}^2)$ where $\sigma_{v_t}^2 \equiv \sigma_t^2 + \sigma_{t+1}^2 + \dots + \sigma_T^2$. This means the time t prediction about the Democrat's election probability is,

$$(A3) \quad \Pr(\text{Win}) | \Omega_t \equiv \Pr(\text{VoteShare}_T^* > 0) | \Omega_t = \Phi(\text{VoteShare}_t^* / \sigma_{v_t})$$

Inverting equation (A3) and using equation (A2) this can be re-written as,

$$(A4) \quad \text{VoteShare}_T^* = \sigma_{v_t} \times (\Pr(\text{Win}) | \Omega_t)^* + v_t$$

Under the efficient capital markets hypothesis, the price of a contract paying a unit if Democrat's win the election should equal $\Pr(\text{Win}) | \Omega_t$: $\text{price}_t = \Pr(\text{Win}) | \Omega_t$, where price_t is the market price (odds) of the contract. Substituting this into the equation gives,

$$(A5) \quad \text{VoteShare}_T^* = \sigma_{v_t} \times \text{price}_t^* + v_t$$

When equation (A5) is estimated, it is possible to interpret the constant term: a positive (negative) constant indicates that prices have indicates unfavorable (favorable) bias for

the Democrats.²⁶ A transformation of equation (A5) shows that the (efficient market) price at any time is the probability the candidate *actually* wins,

$$(A6) \quad \text{price}_t = \Pr(\text{VoteShare}_T^* > 0) \equiv \Pr(\text{Win})$$

Since equation (A6) is not conditioned on any information set, it can be directly tested using every observation. After grouping the data into price ranges, the proportion of candidates which eventually win should match the midpoint of the price range.

Imposing some additional structure on σ_{vt} give additional equations which can be estimated. The weak-form efficiency equation considers a time differenced version of (A5),

$$(A7) \quad \text{price}_t^* = ((T-t)/(T-t-1))^{0.5} \times \text{price}_{t-1}^* + \varepsilon_t$$

where we presume for simplicity that the standard errors are equal, $\sigma_s = \sigma \forall s$ (this is necessary to ensure the equation estimated in the text is concave in the parameters; a more general version is considered next). The semi-strong form efficiency equation is,

$$(A8) \quad \text{VoteShare}_T^* = (s_1^2(T-t) + s_2^2)^{0.5} \times \text{price}_t^* + v_t$$

where we presume $\sigma_s = s_1 \forall t \neq 0$ and $\sigma_T = s_2$ (so $\sigma_{vt} = (s_1^2(T-t) + s_2^2)^{0.5}$). In this more general error form, the s_1 term represents the time-varying uncertainty (presumed to be *a priori* identical across days), and s_2 is time-invariant uncertainty (say uncertainty about the voters' preferences). Notice that both of the equations (A6) and (A7) are estimable using observed data. Because we treat the s_i terms as parameters to be estimated, equation (A7) must be estimated using NLLS. Also, since v_t is heteroscedastic and autocorrelated, we use bootstrapped standard errors.

As an aside, notice that the main equations (A7) and (A8) also roughly hold in a linear form which omits the starred superscripts (the inverse normal transform). Suppose that the elections are competitive so $\text{VoteShare}_T^*, \text{price}_t^* \approx 0$ (the untransformed values are near one half). In this case a linear Taylor series is valid, and using the properties of the normal distribution we have the approximations,

$$(A7') \quad \text{price}_t \approx 0.5(1 - ((T-t)/(T-t-1))^{0.5}) + ((T-t)/(T-t-1))^{0.5} \times \text{price}_{t-1} + e_t$$

where $e_t \equiv \phi(0)\varepsilon_t$ with $\phi(\cdot)$ as the standard normal density and,

$$(A8') \quad \text{VoteShare}_T \approx 0.5(1 - (\sigma_1^2(T-t) + \sigma_2^2)^{0.5}) + (s_1^2(T-t) + s_2^2)^{0.5} \times \text{price}_{t-1} + v_t$$

where $v_t \equiv \phi(0)v_t$.

Vote Share Market

Equation (A2) gives the law of motion for vote shares. Under efficient markets a market for vote shares should be priced based on the best current estimate of the final vote totals, $\text{price}_{t=0}^{\text{VS}} = E(\text{VoteShare}_T | \Omega_t)$. Using equation (A2) this means $\text{price}_{t=0}^{\text{VS}} =$

²⁶To see this, suppose the contract price is set as, $\text{price}_t = a + \Pr(\text{Win}) | \Omega$ where $a > 0$ ($a < 0$) indicates favorable (unfavorable) bias for the Democrats and $a = 0$ indicates efficient markets. Substituting this into equation (A4) and taking a linear expansion (which is valid for a close election, $\text{VoteShare}_T^* \approx 0$) yields,

$$\text{VoteShare}_T^* = -(a\sigma_{vt} / \phi(0)) + \sigma_{vt} \times \text{price}_t^* + \varepsilon_t$$

where $\phi(\cdot)$ is the standard normal density. Since $\sigma > 0$, if the constant is positive (negative) then $a < 0$ ($a > 0$). If the constant is zero, then efficient markets holds.

VoteShare_t. This can be used to determine the relationship between efficient prices in a winner take all and vote share market. Applying equations (A2) and (A5) yields,

$$(A8) \quad \text{price}_t^* = \text{price}_t^{\text{VS}} / \sigma_{\text{vt}}.$$

Case Study Framework

Following Campbell, Lo and MacKinlay (1997), we consider the path of prices following a specific event which in this case is a (potential) speculative attack. Normalize time so that $t=0$ when the manipulation begins. Define the *estimation window* as some period $t \in [-T_1, 0)$ prior to the manipulation. This period will be used to calculate the typical volatility of prices. We are interested in the path in prices during the *post-event window*, $t \geq 0$.

In particular we are interested in the post-event window distribution for the rate of return, cumulative return, and cumulative abnormal return defined in equations (1), (2), (5), (7), and (8). Given the framework in this Appendix (and presuming price_{t-1}^* , $\text{price}_{t-1}^{\text{VS}} \in \Omega_t$), then $R_t | \Omega_t$, $CR_t | \Omega_t$, and $CAR_t | \Omega_t$ are normally distributed. The variances for any of these terms can be calculated from prices during the estimation window. Tests of statistical confidence can be readily generated using these values.

Section B. Definition of Manipulation and Existing Literature

This section begins by providing definitions. *Fundamentals* are any information that influences the underlying value of an asset. A *speculative attack* is defined any trade, uninformed by fundamentals, intended to change prices. A (*successful*) *manipulation* is a speculative attack that achieves its objective of changing prices. A successful manipulation is usually not possible unless the trades influence the beliefs of other market participants. (An investor's *beliefs* are defined with respect to the fundamentals, as well as the future actions and beliefs of other investors). Consider a large purchase, which will tend to increase the price. If the position is rapidly unwound, no share will sell for more than the initial price unless the beliefs underlying prices change. Alternatively if investors believe this purchase reflects more favorable fundamentals or will lead other investors to buy, then higher prices are possible. Models formalizing this intuition are discussed below.

Our definition of manipulation differs from others which focus on the goal of investor profits. The reason we focus on market prices stems from the richer set of motives for manipulating prediction markets. While profit-seeking is the main objective of manipulation in traditional financial markets, investors in prediction markets may be willing to accept losses if this has large and lasting effects on prices. These manipulators might be primarily interested in the feedback effect of such prices. For example, in political prediction markets an investor could sell shares to lower prices and signal a candidate has weakened. This might influence the choice of undecided voters, either directly or through the media. The manipulator also might be interested in other indirect effects, such as a spillover into other financial markets such as the NYSE. We are

agnostic on the exact incentives of the manipulating trader. As long as the manipulator's goal involves a long-term change in prices and there is no new information—a common feature of the objectives listed above-- the market response should be similar.²⁷ Our goal is to focus on how markets respond to these attacks. Still they suggest care is needed in the empirical work. For example, rather than focusing on volume-weighted prices (reflecting the typical price a manipulator might get) we might be more interested in a time-weighted price (since an extended period with unusual price might attract attention, even if trading is light).

Our work complements two related papers. Hanson, Oprea, and Porter (2006) find that manipulators are unable to influence the predictive capacity of prices in an experimental prediction market.²⁸ Camerer (1998) conducts a field experiment at the horse-track. At the track a wager on a horse pays-off only if that horse wins the race, so prices can be stated in terms of probabilities. The author simulates manipulation by placing and then removing a large wager on a specific horse. The final price on this horse is virtually identical to that of a control horse, which has similar characteristics but whose price was not manipulated. We built on his innovative work using both observational data and field experiments. The markets we study are sufficiently different to warrant further investigation. For example, the incentives for manipulators may be different, with profit-making paramount at the track and other objectives outlined earlier playing a role in the political market.²⁹

Manipulations are traditionally defined as attempt to profit from artificially changing stock prices. Allen and Gale (1992) divide manipulations into three categories: action-based (attempting to influence the fundamentals of the underlying asset), information-based (spreading false information), and trade-based (buying and selling shares). The first two are explicitly outlawed in the Securities and Exchange Act of 1934 and are not considered here. We evaluate several cases of trade-based manipulation, which involve large purchases or sales which are sometimes rapidly unwound in so-called pump-and-dumps. Allen and Gale (1992) show that the latter can potentially be profitable even in a rational expectations equilibrium, even without bubbles, if other investors believe the manipulator may instead be a well-informed insider. The key point

²⁷Some apparent speculative attacks may not be primarily designed to change prices. For example, a trader from another political market might seek to hedge his position (this is referred to as a lay-off bet) or might seek to learn the market's depth / resiliency. Still, these are costly activities and there are often far cheaper ways to obtain these objectives. For example a layoff bettor should try and spread his money across different markets to get the lowest purchase price, while the free TradeSports trading screen reports the top fifteen orders (both price and quantity) in the bid and ask queue.

²⁸Hanson and Opreas (2004) advance a theoretical model arguing that the activities of manipulators increase market accuracy by covering the cost of information acquisition by non-manipulators.

²⁹While our field experiment for the IEM Presidential contracts is similar to Camerer (1998), there are some key differences relating to timing and incentives. First, the track manipulations occurred far before the race started while a preponderance of the wagers is placed right before post time. Investments are more uniform in political stock markets, and the market is fairly thick even months before the election. Second, the payoff of a winning wager at the track is inversely related to the bet total on that horse. An insider has strong incentive to delay his wager until the last possible moment so as to not draw attention (and potentially additional bets) on his horse. Political stock market participants are more likely to infer that even our earliest price shocks were due to an insider, since there is no incentive to delay an investment (payoffs in these markets are fixed at the time of the wager). Third, our cases include markets where wagering is non-anonymous.

is that the price movements are believed to convey information, and it is the information asymmetry which is central to this and other models discussed later. Various empirical papers have documented the existence of trade-based manipulation in traditional financial markets.³⁰

A range of market microstructure models allows such investments to have long-term effects on prices. Rational investors may chase trends in prices, even when the underlying fundamentals are unchanged or only slightly perturbed. A survey of these dynamic models is presented in Brunnermeier (2001) and O'Hara (1995).³¹ Past prices and volume can help forecast future values when there is information asymmetry and investors are learning about one another's private information (Blume, Easley, and O'Hara, 1994). It is sometimes optimal for investors to herd, to repeat the last observed action. In this case bad news may not be fully reflected in current prices, and the herd may be fragile with a small shock leading to a large price change (Bikhchandani, Hirshleifer, and Welch, 1992; Bulow and Klemperer, 1994). Similarly, following Keynes' beauty contest interpretation of financial markets, investors may all collect the same kind of information and ignore others (Froot, Scharfstein, and Stein, 1992). There also may be multiple equilibria in which case large price changes can be triggered by a sunspot, an uninformative public information revelation, or small changes in fundamental parameters (Cass and Shell, 1983; Romer, 1993). And finally if noise traders or other non-rational agents are the marginal traders, investments not based on changing fundamentals can have long-term effects on prices.

A common theme from all of these models is that prices do not serve as a sufficient statistic for public information. This would call into question the predictive capacity of prediction market.

³⁰The more recent empirical evaluations have focused on stock pools during the 1920s (Mahoney, Jiang, Mei, 2005), "pump-and-dumps" of penny stocks (Aggarwal and Wu, 2005) or by brokers making personal trades (Khwaja and Mian, 2005), and cornering in futures markets (Merrick, Naik, and Yadav, 2005).

³¹While a bubble would allow prices to exceed an asset's fundamental value, rational bubbles are difficult to sustain when there is a known termination time as with prediction markets.

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Table 1: Analysis of TradeSports 2004 Presidential Election Speculative Attacks

	September 13: 15:59-16:13 GMT Attack 1	October 15: 18:31-18:33 GMT Attack 2
<i>Attack summary</i>		
length (minutes)	14	2
price change in previous hour	-1.5	0
price change	-12.8	-44.0
volume (shares)	6887	4416
volume (\$)	\$40,246.76	\$21,000.42
profits (upper bound)	\$1,634.94	-\$2,735.50

Note: The profitability calculation presumes that the manipulator immediately unwinds his position through re-purchasing the share he has sold (a “dump-and-pump”). This is the upper-bound of profits since it presumes he can sell at the observed market prices following his attack; his actual price will be lower if his orders are executed after the other traders buying shares.

Table 2: Impact of Manipulations and Wash Sales/Bluffs on Democratic Odds Price in Historical New York Markets

Dependent variable = Democrat odds price.

Party	Days	Presidential Races (mean dep var=0.415, std dev=0.208)				All Races (mean dep var=0.473, std dev=0.200)			
		Manipulation		Wash/Bluff		Manipulation		Wash/Bluff	
		Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
Republican	-7	0.0094	0.0096	0.0290	0.0138	0.0116	0.0090	-0.0008	0.0190
	-6	0.0013	0.0091	0.0037	0.0102	0.0094	0.0096	-0.0096	0.0141
	-5	0.0175	0.0106	0.0129	0.0107	0.0236	0.0111	-0.0038	0.0128
	-4	0.0014	0.0084	0.0091	0.0128	0.0042	0.0085	0.0144	0.0117
	-3	-0.0002	0.0077	-0.0058	0.0148	0.0029	0.0073	0.0021	0.0155
	-2	-0.0123	0.0079	-0.0202	0.0097	-0.0057	0.0075	-0.0122	0.0101
	-1	-0.0111	0.0084	-0.0286	0.0120	-0.0115	0.0078	-0.0095	0.0106
	0	-0.0306	0.0073	-0.0533	0.0077	-0.0284	0.0071	-0.0336	0.0098
	1	-0.0085	0.0089	-0.0348	0.0056	-0.0082	0.0089	-0.0107	0.0098
	2	-0.0081	0.0104	-0.0424	0.0135	-0.0101	0.0105	-0.0103	0.0144
	3	0.0140	0.0106	-0.0547	0.0098	0.0184	0.0109	-0.0390	0.0100
4	-0.0176	0.0111	-0.0329	0.0127	-0.0212	0.0109	-0.0297	0.0105	
5	-0.0193	0.0124	-0.0494	0.0114	-0.0213	0.0116	-0.0456	0.0131	
Democratic	-7	0.0834	0.0268	-0.0078	0.0114	0.0000	0.0234	-0.0150	0.0081
	-6	-0.0921	0.0065	-0.0117	0.0118	-0.0191	0.0133	-0.0247	0.0095
	-5	0.0391	0.0288	-0.0109	0.0069	0.0163	0.0164	-0.0216	0.0070
	-4	-0.0232	0.0255	-0.0143	0.0074	-0.0175	0.0108	-0.0188	0.0075
	-3	0.0093	0.0236	-0.0226	0.0065	-0.0143	0.0112	-0.0202	0.0055
	-2	0.0584	0.0197	-0.0171	0.0058	0.0024	0.0165	-0.0137	0.0057
	-1	-0.0163	0.0185	-0.0214	0.0058	-0.0087	0.0100	-0.0233	0.0059
	0	0.0594	0.0235	-0.0219	0.0052	0.0103	0.0112	-0.0181	0.0065
	1	0.1046	0.0256	-0.0120	0.0050	0.0439	0.0170	-0.0155	0.0056
	2	0.0420	0.0295	-0.0238	0.0064	0.0541	0.0160	-0.0287	0.0064
	3	0.0648	0.0241	-0.0359	0.0064	0.0606	0.0159	-0.0414	0.0089
4	0.0553	0.0228	-0.0194	0.0056	0.0574	0.0183	-0.0130	0.0062	
5	0.0222	0.0096	-0.0242	0.0064	0.0460	0.0132	-0.0122	0.0066	
Election									
Fixed Effects:				Yes				Yes	
No. of Obs.:				1235				2185	
R-squared:				0.942				0.926	

Notes: This table reports the results for two regressions measuring the impacts of manipulation events and wash or bluff bet events in: (1) presidential races and (2) all races. The standard errors are robust.

Table 3: Hypotheses Regarding Market Participant Behavior

	Markets are Not Monitored	Hypotheses	
		Beliefs Change Markets Monitored	Beliefs Unchanged Markets Monitored
Attack Market M_1	($\uparrow, 0$)	(\uparrow, \uparrow)	($\uparrow \downarrow, 0$)
Attack Markets M_1 and M_2	(\uparrow, \uparrow)	(\uparrow, \uparrow)	($\uparrow \downarrow, \uparrow \downarrow$)

The cells are predicted responses in markets (M_1, M_2) following the speculative (purchase) attack listed in the left-most column. “ \uparrow ” indicates an increase in asset price, “0” indicates prices do not change, and “ $\uparrow \downarrow$ ” indicates an increase followed by decrease in asset price.

Table 4: Timing and Features of Investments in 2000 Presidential IEM

Manip Date	Market Attacked	Investment			Market Cap	Price Change		
		Democrat	Republican	Reform		Democrat	Republican	Reform
7/20	WTA	-\$108.86	\$119.72	\$0	\$8,544	-7.4¢ (-9.2¢)	0.9¢ (0.0¢)	---
7/30	VS	\$120.00	-\$19.60	\$0	\$4,717	0.0¢ (0.0¢)	0.0¢ (0.0¢)	---
8/10	WTA	\$80.30	-\$240.30	-\$1.07	\$16,679	0.2¢ (-0.3¢)	-1.2¢ (-0.2¢)	-0.1¢ (0.0¢)
	VS	\$38.96	-\$120.26	-\$5.33	\$5,003	0.0¢ (0.0¢)	-2.5¢ (0.0¢)	-0.9¢ (0.1¢)
8/28	WTA	\$0	-\$238.39	\$0	\$26,087	---	-1.2¢ (-0.7¢)	---
9/11	VS	\$14.17	-\$106.69	\$0	\$5,818	0.0¢ (-0.1¢)	-0.7¢ (-0.3¢)	---
9/20	WTA	-\$240.16	\$80.13	\$0	\$40,115	-0.5¢ (0.5¢)	0.0¢ (0.0¢)	---
	VS	-\$81.05	\$0	\$0	\$5,930	-0.7¢ (0.0¢)	---	---
10/3	WTA	\$77.92	-\$234.62	\$0	\$48,996	2.6¢ (1.5¢)	-5.4¢ (0.0¢)	---
10/14	VS	-\$40.18	\$97.20	\$0	\$8,206	0.0¢ (0.0¢)	1.0¢ (0.0¢)	---
10/23	WTA	\$152.95	\$0	\$0	\$62,504	3.1¢ (3.3¢)	---	---
	VS	\$17.14	-\$63.00	\$0	\$7,347	0.7¢ (-0.3¢)	-0.4¢ (0.0¢)	---
10/28	WTA	-\$340.38	\$0	\$0	\$68,828	-7.9¢ (-4.4¢)	---	---
	VS	-\$224.48	\$0	-\$1.32	\$7,266	-1.7¢ (0.0¢)	---	0.0¢ (0.0¢)
11/4	WTA	\$209.64	-\$42.61	\$0	\$71,521	6.5¢ (5.9¢)	-3.0¢ (-9.5¢)	---

Notes:

- In the investment column, a positive amount indicates a purchase and a negative amount indicates a sale.
- The market cap is the prevailing number of bundles (one share each of Democrat, Republican, Reform); a bundle can always be purchased or redeemed with the exchange at \$1.
- The price change is the change in purchase price just prior and just after the attacks (this is between a quarter to a half hour). The number in parentheses is the change for the three hours prior to the attacks.
- On 10/28 all current holding were sold.

Figure 1: TradeSports 2004 US Presidential Market (Sept-Oct 2004 only)

TradeSports 2004 Bush Contract

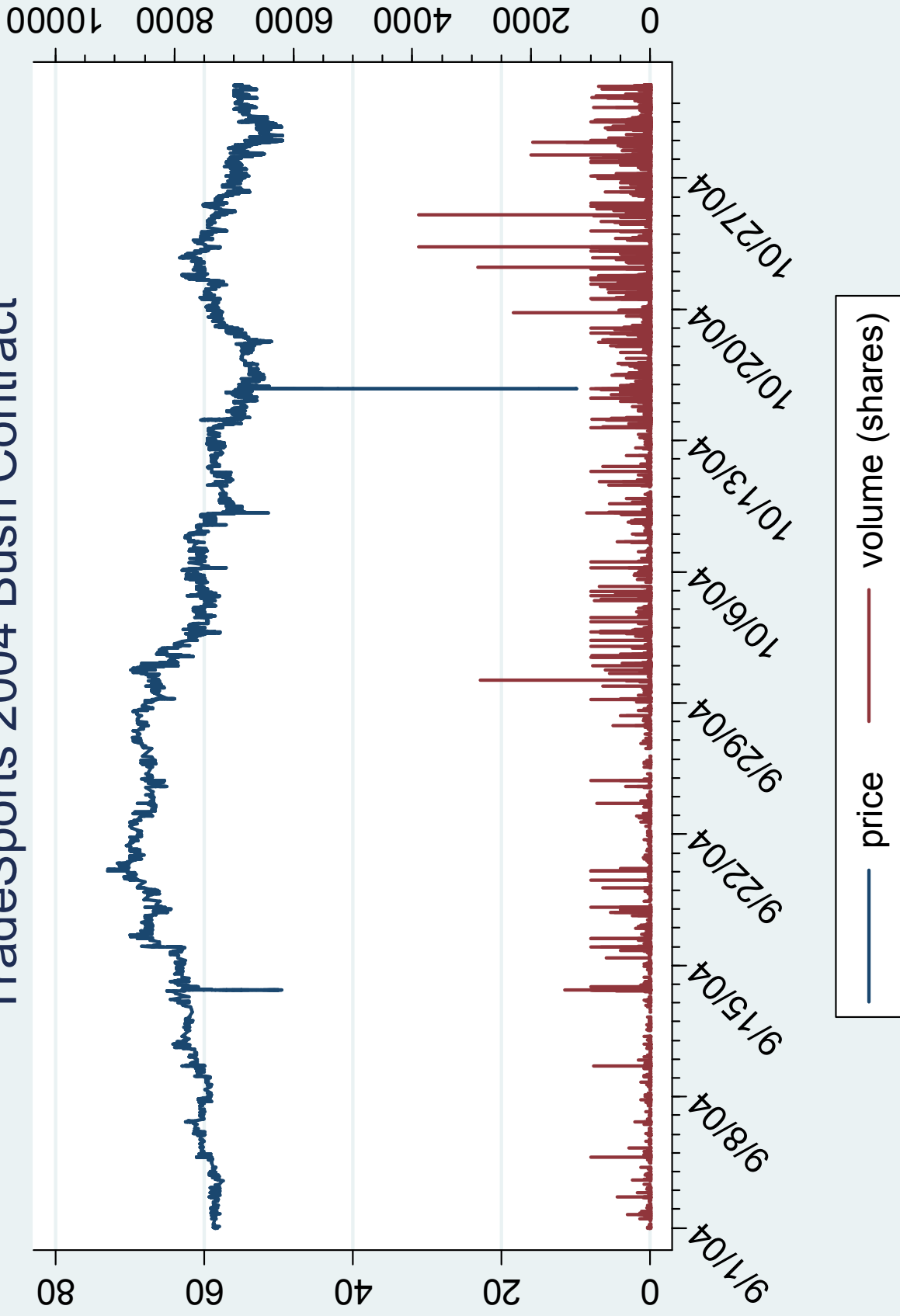


Figure 2 Speculative Attacks in *TradeSports* 2004

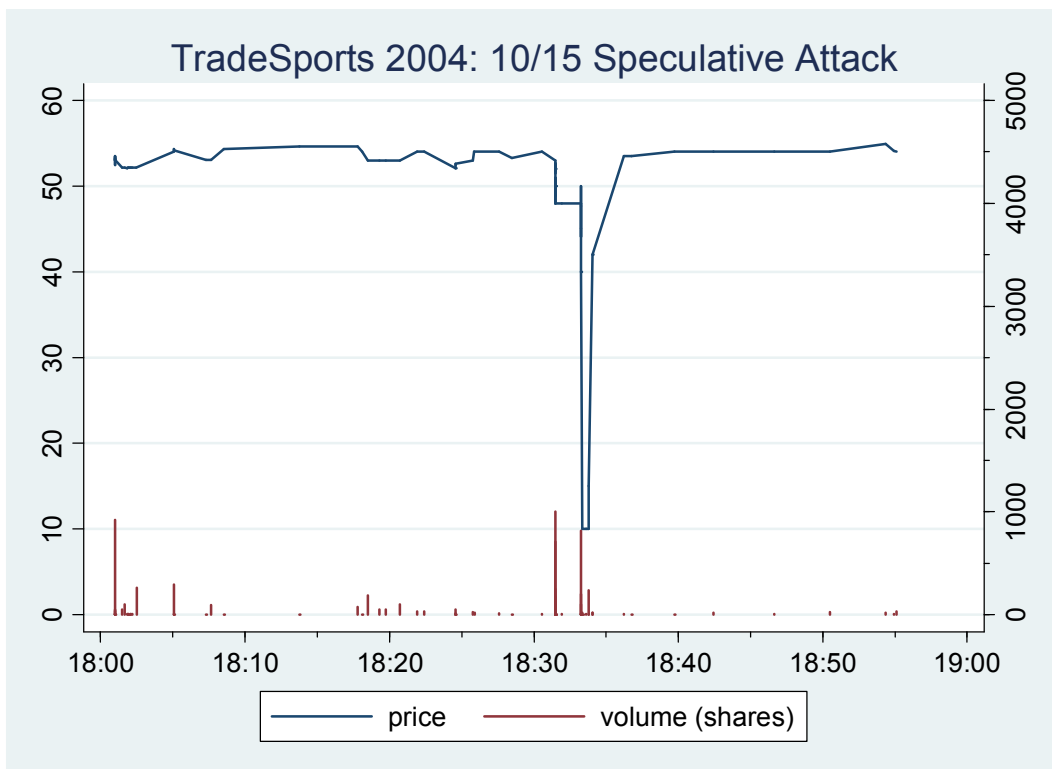
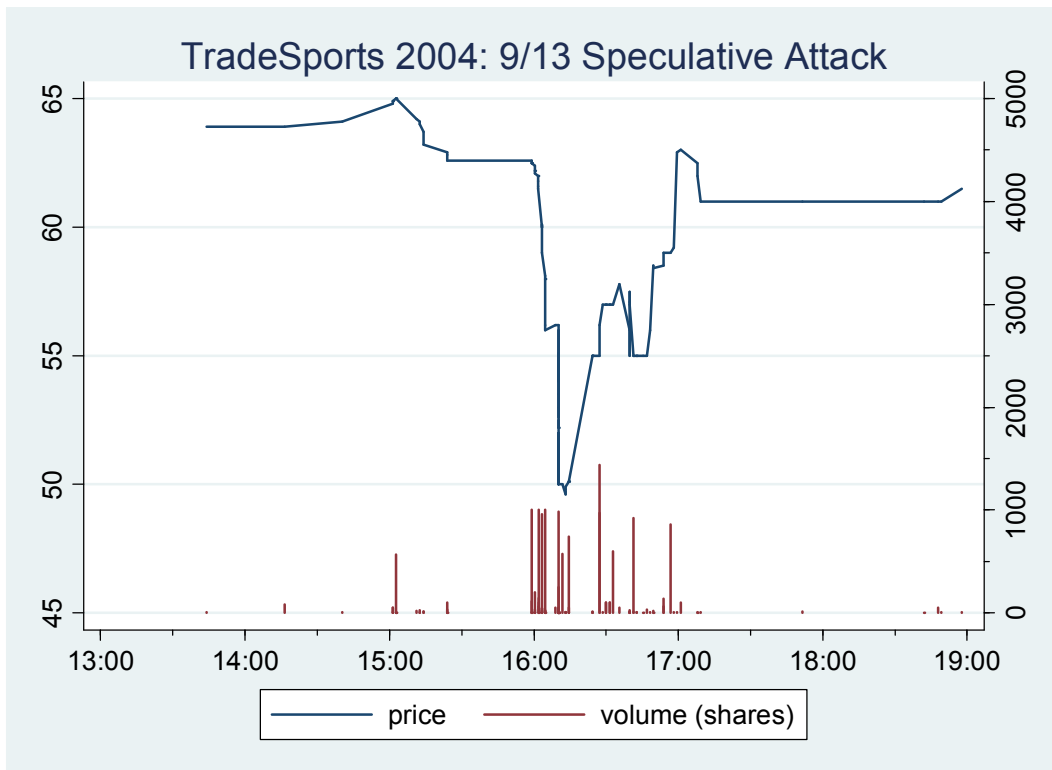


Figure 3: Cumulative Returns during Speculative Attacks in *Tradesports* 2004

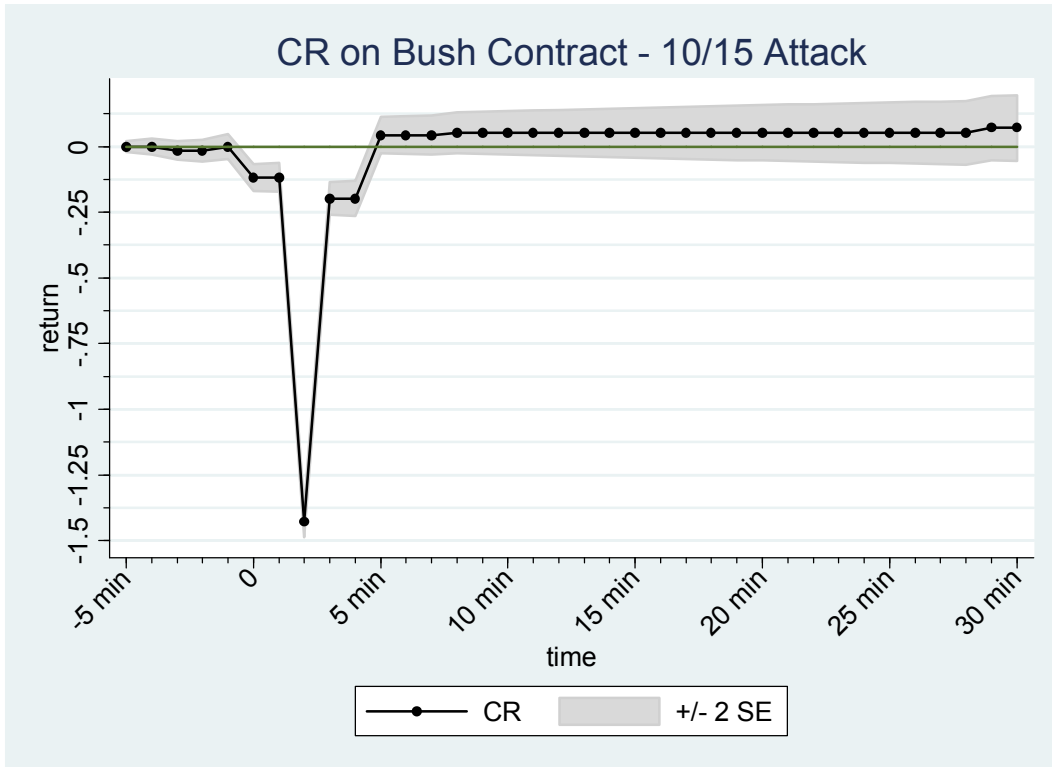
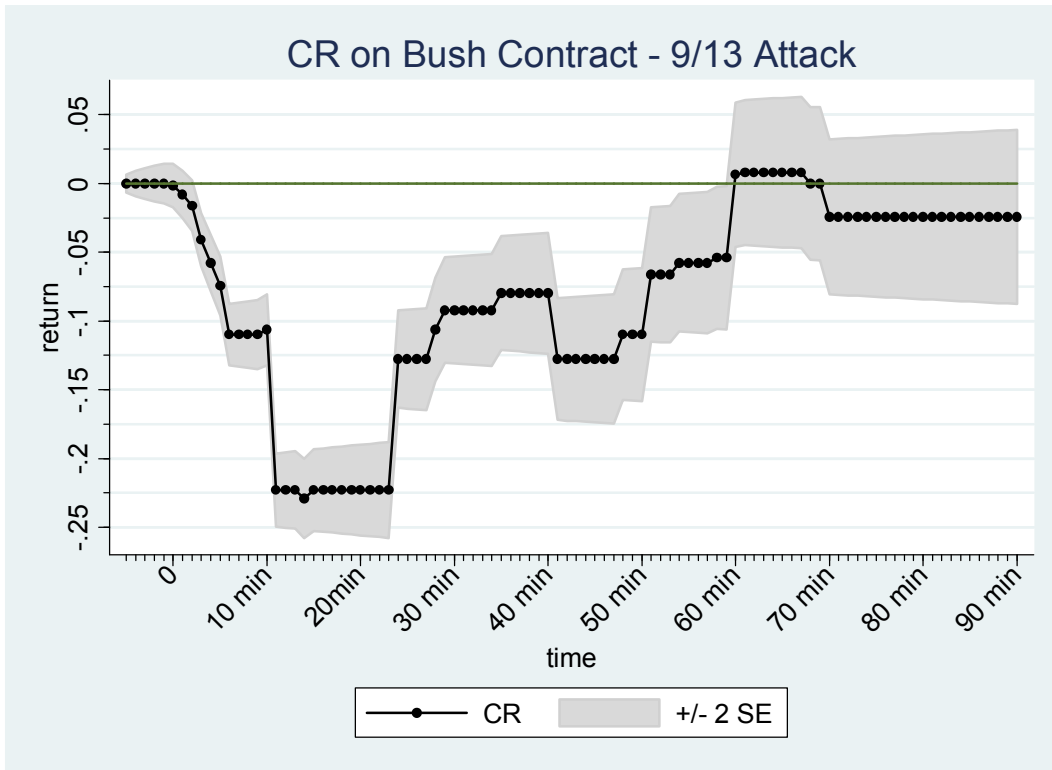
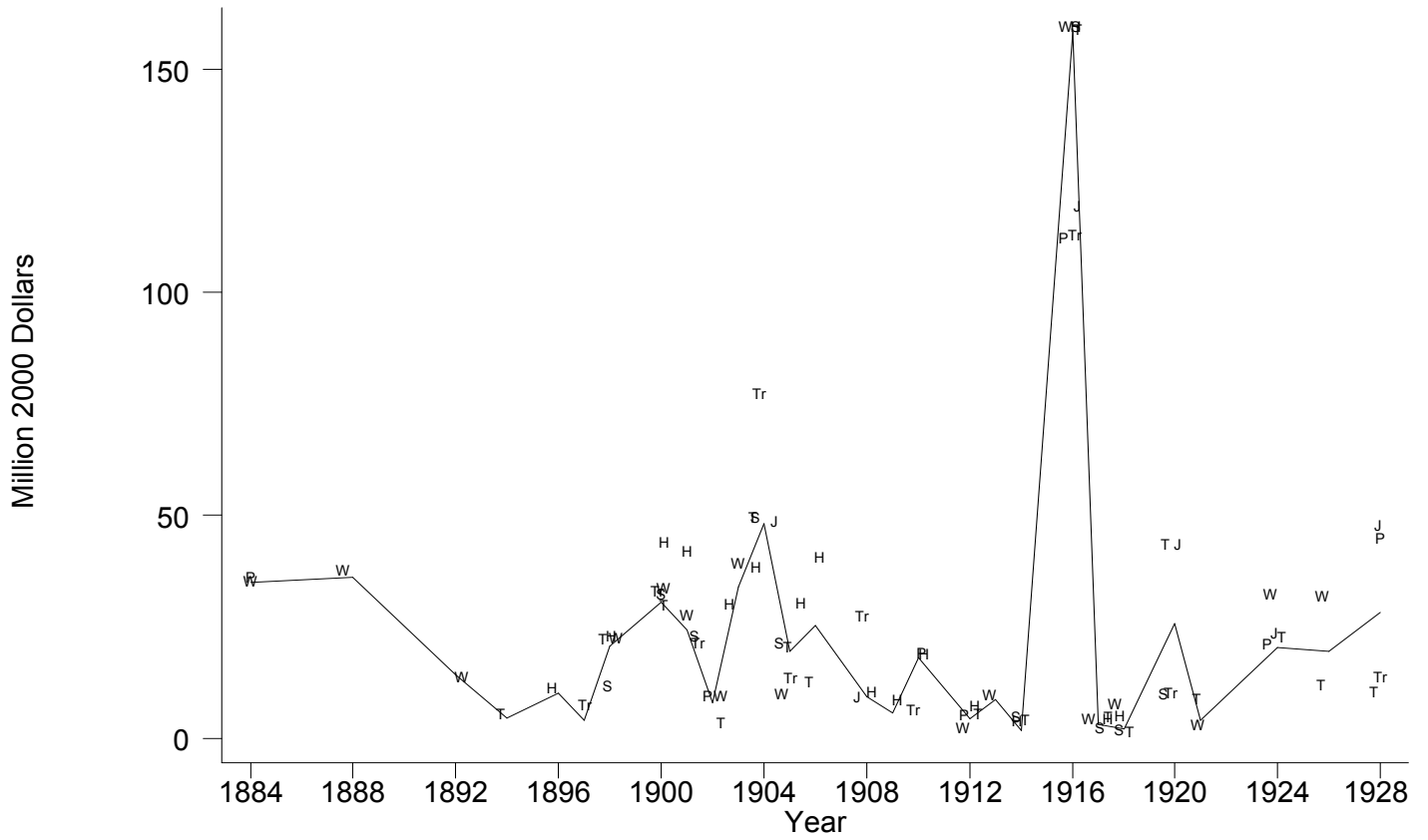


Figure 4: Estimated Volume in Historical New York Markets, 1884-1928



Key: J=Wall Street Journal; P= Wash. Post; H=NY Herald; S=NY Sun; T=NY Times; Tr=NY Tribune; W= NY World.

Figure 5 Manipulations in Presidential Races in Historical New York Markets

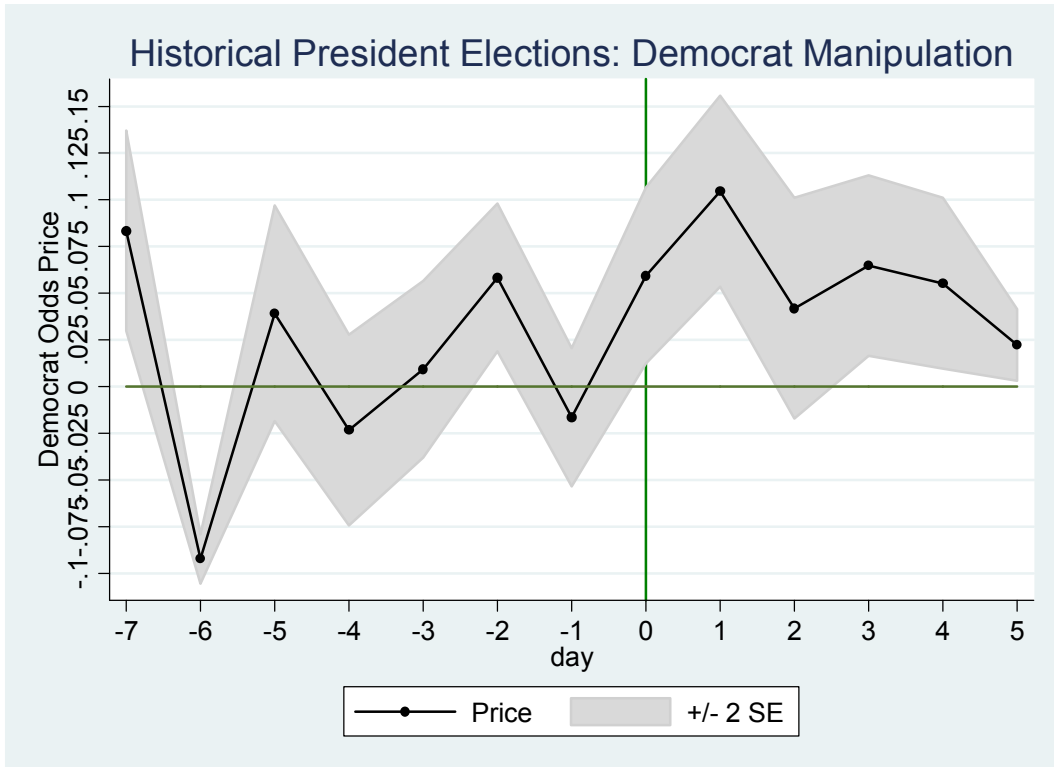
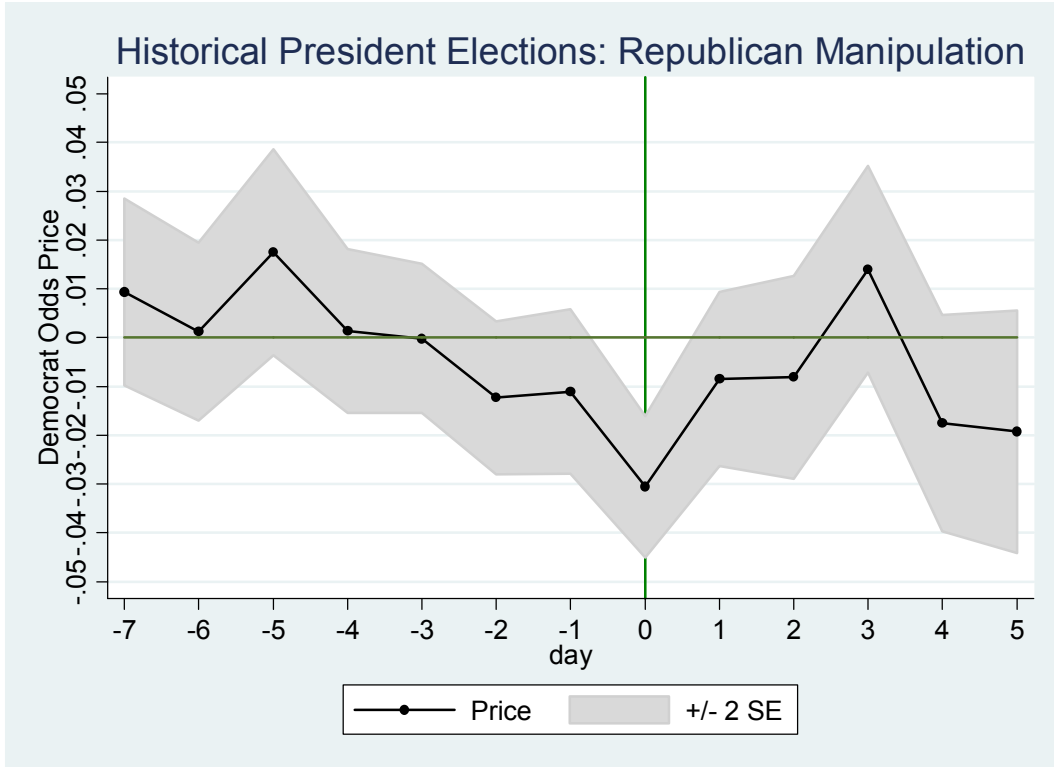


Figure 6 Manipulations in All Races in Historical New York Markets

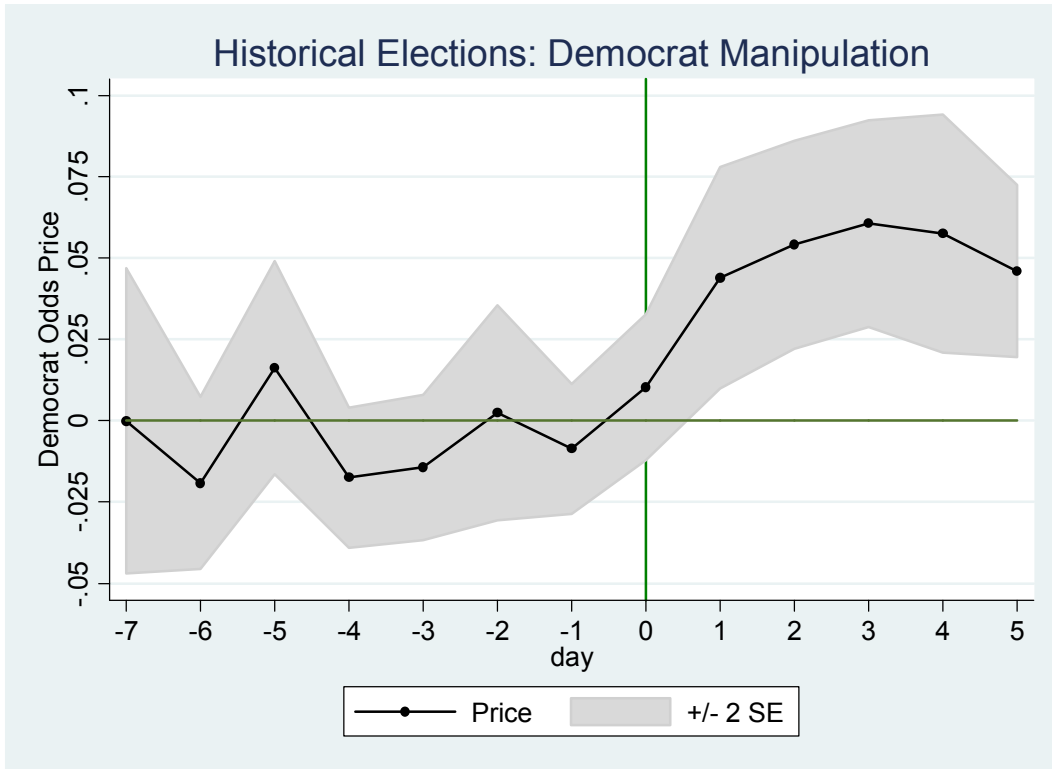
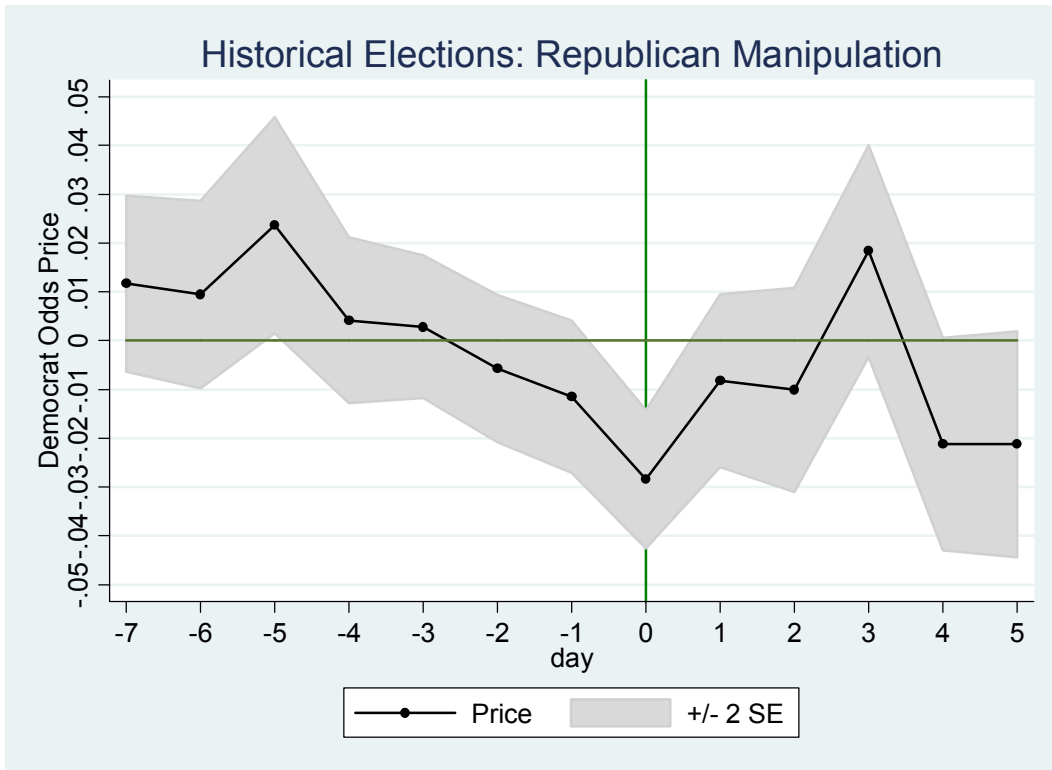


Figure 7 Results Combining Manipulations for Historical New York Markets

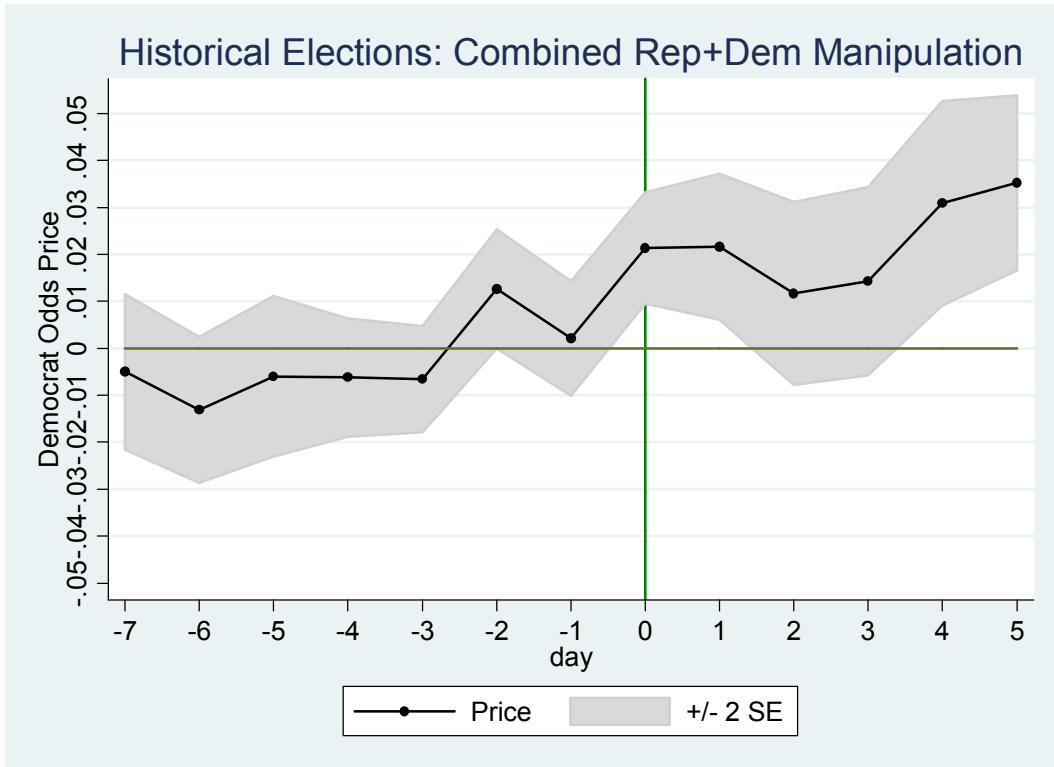
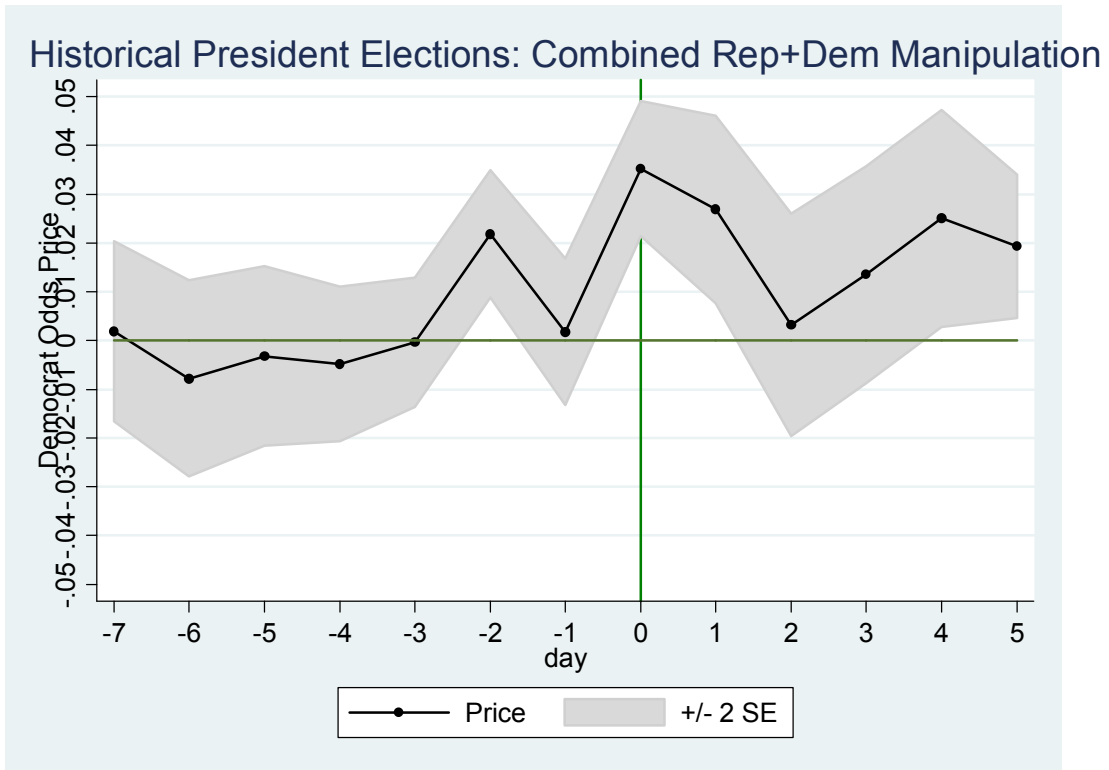


Figure 8: IEM 2000 WTA Market: Day After Election (CST)

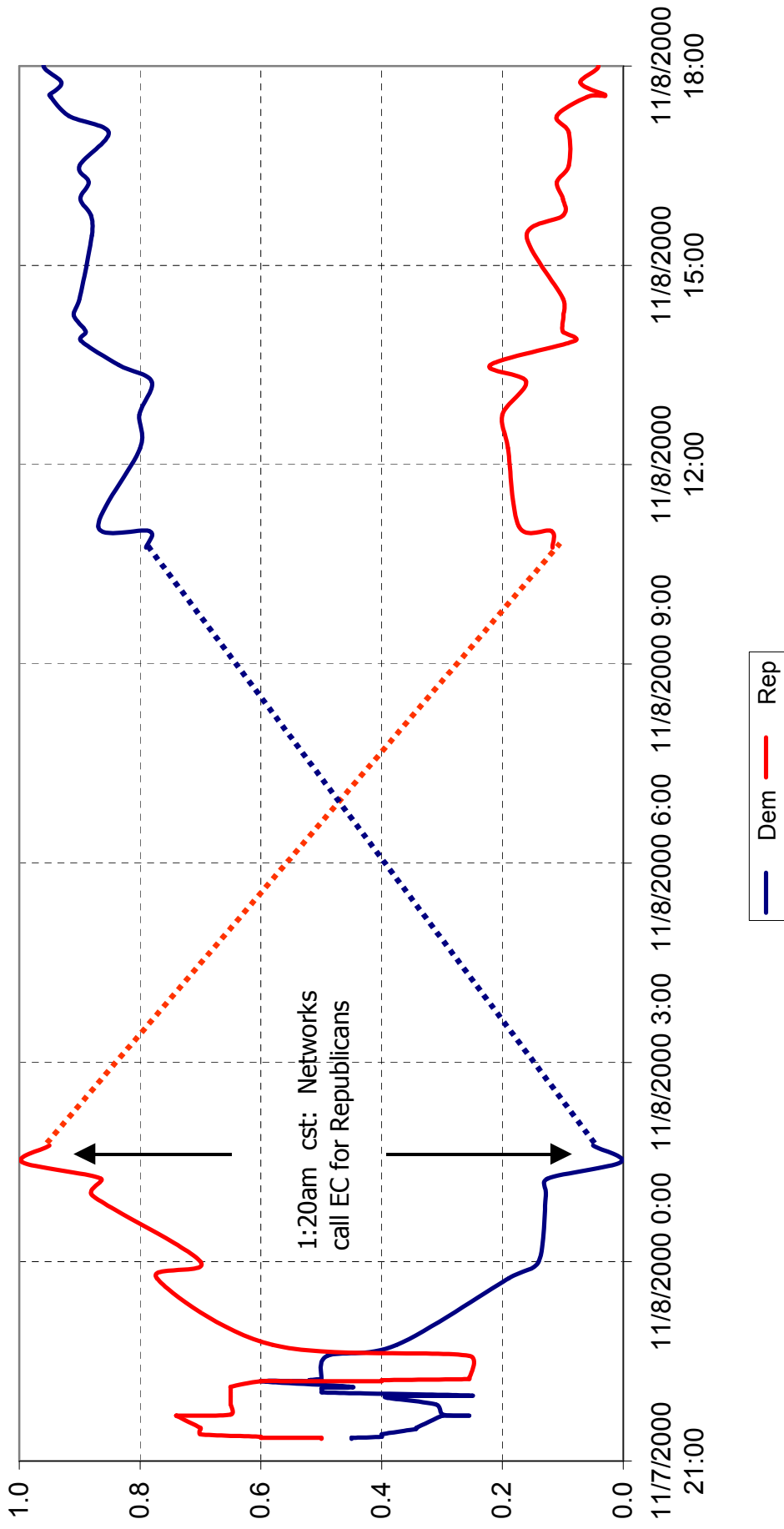


Figure 9: IEM 2000: 10/28/00 Trades (Sell Democrats in WTA+VS)

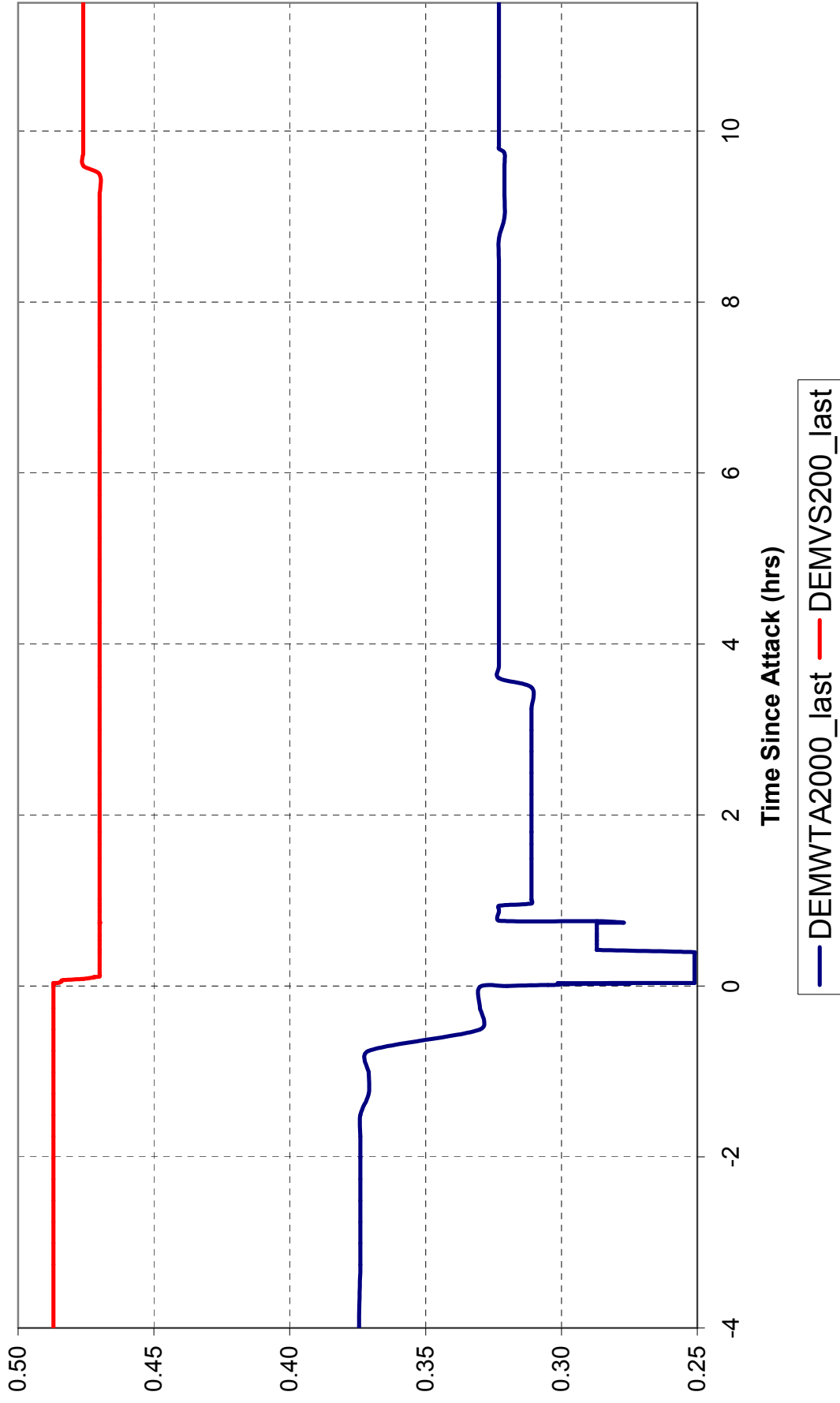


Figure 10: IEM 2000.

Mean CR in the Attacked Market over the Full Set of Trades (N=11)

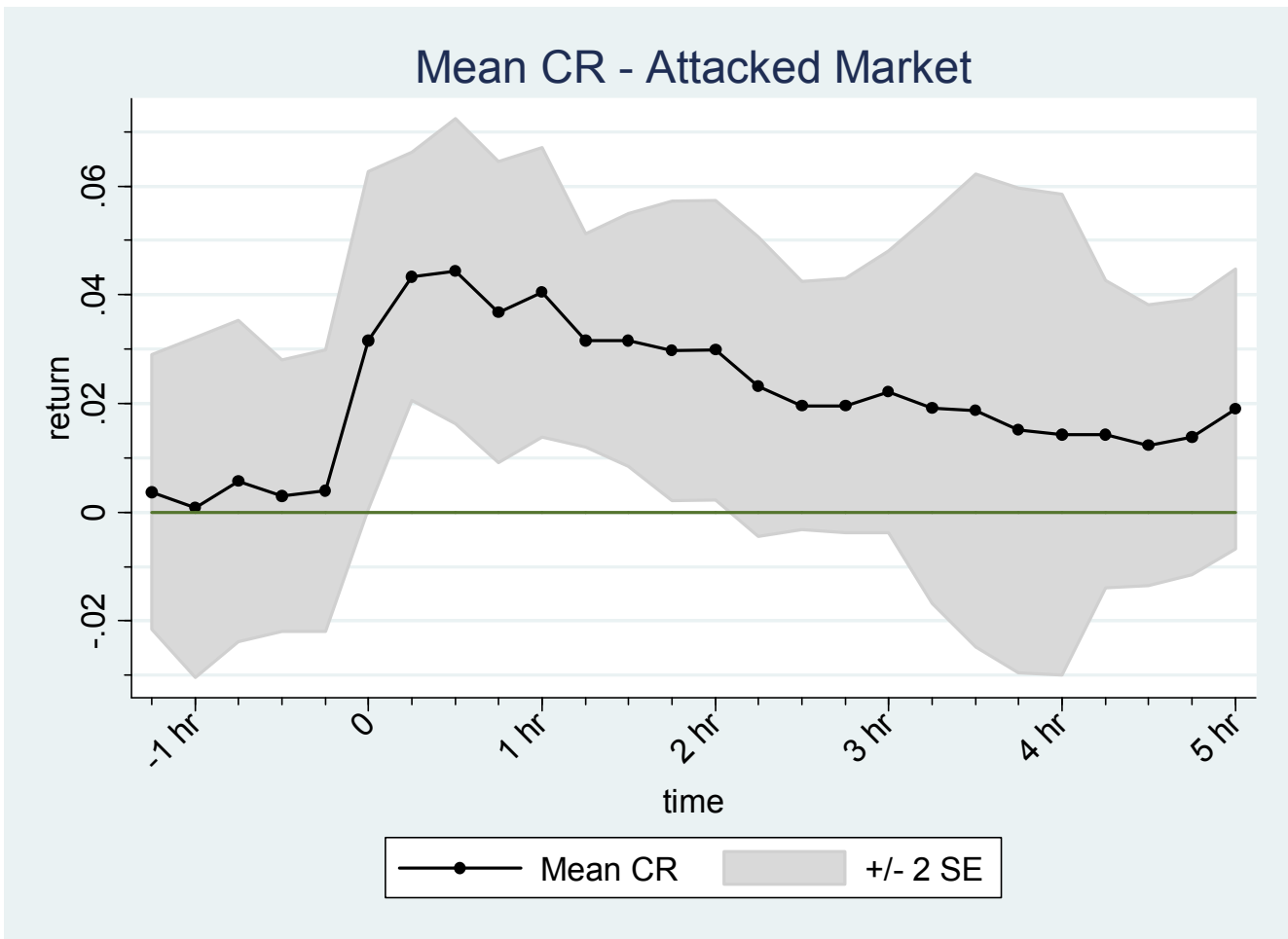
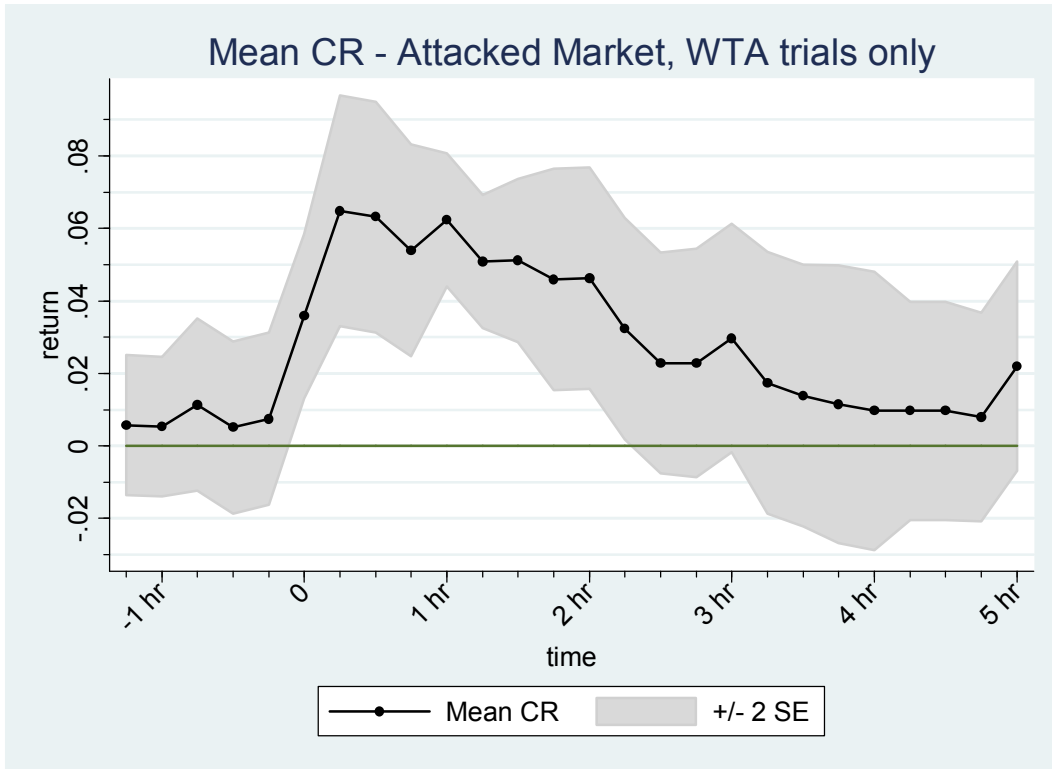


Figure 11: IEM 2000, by Market

(a) Mean CR in the Attacked Market for WTA-only Trades (N=4)



(b) Mean CR in the Attacked Market for VS-only Trades (N=3)

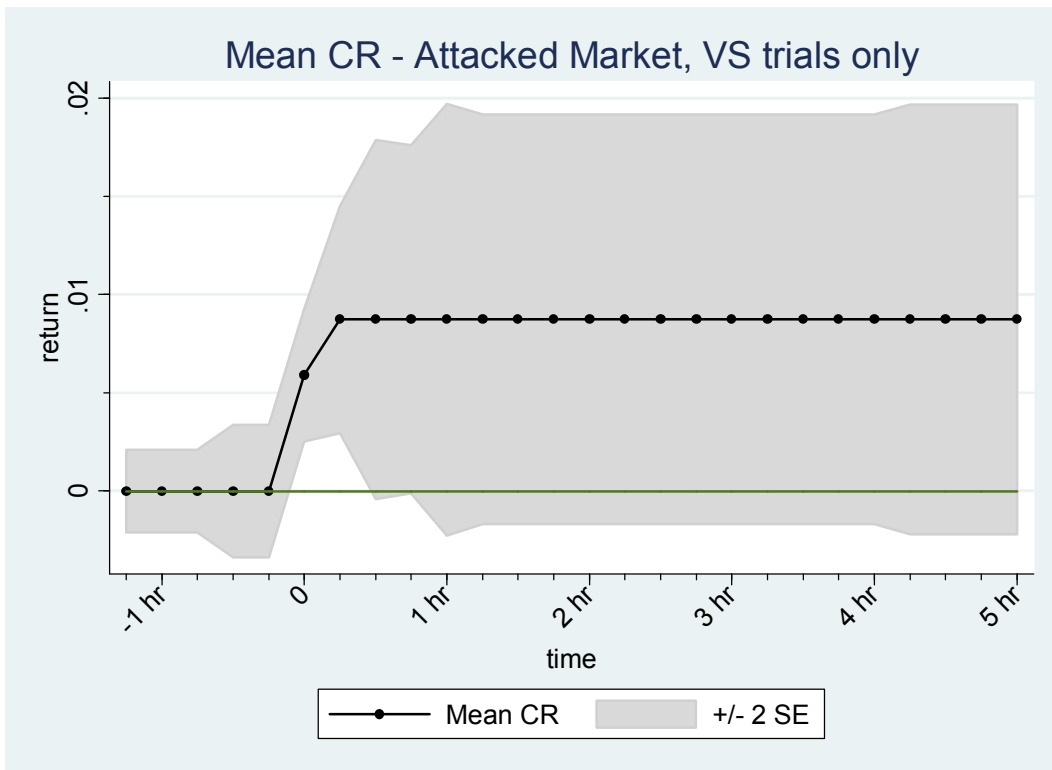
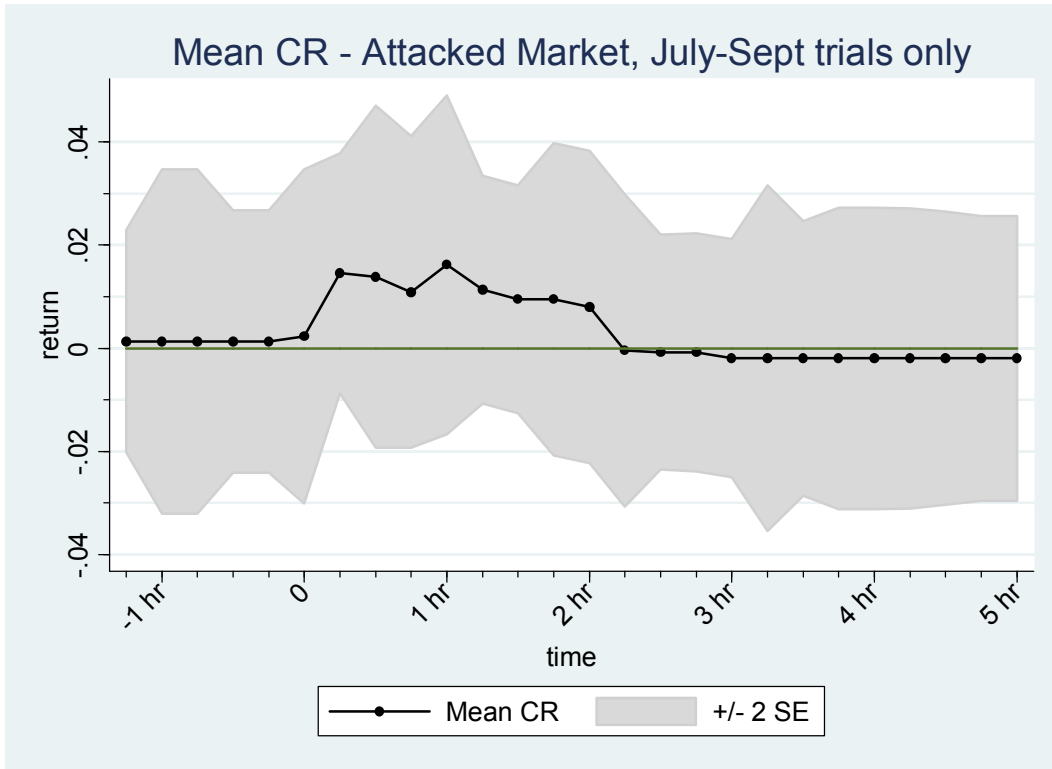


Figure 12: IEM 2000, by Time/Market Cap

(a) Mean CR in the Attacked Market for Early/Small Cap Trades (N=6)



(b) Mean CR in the Attacked Market for Late/Large Cap Trades (N=5)

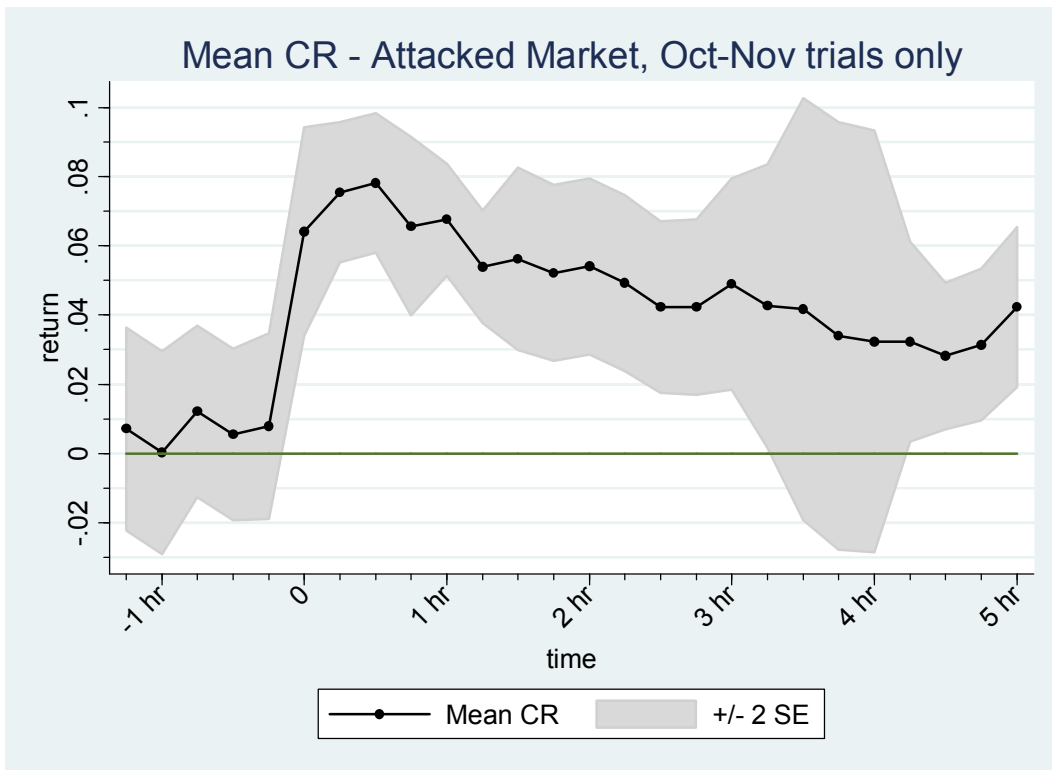
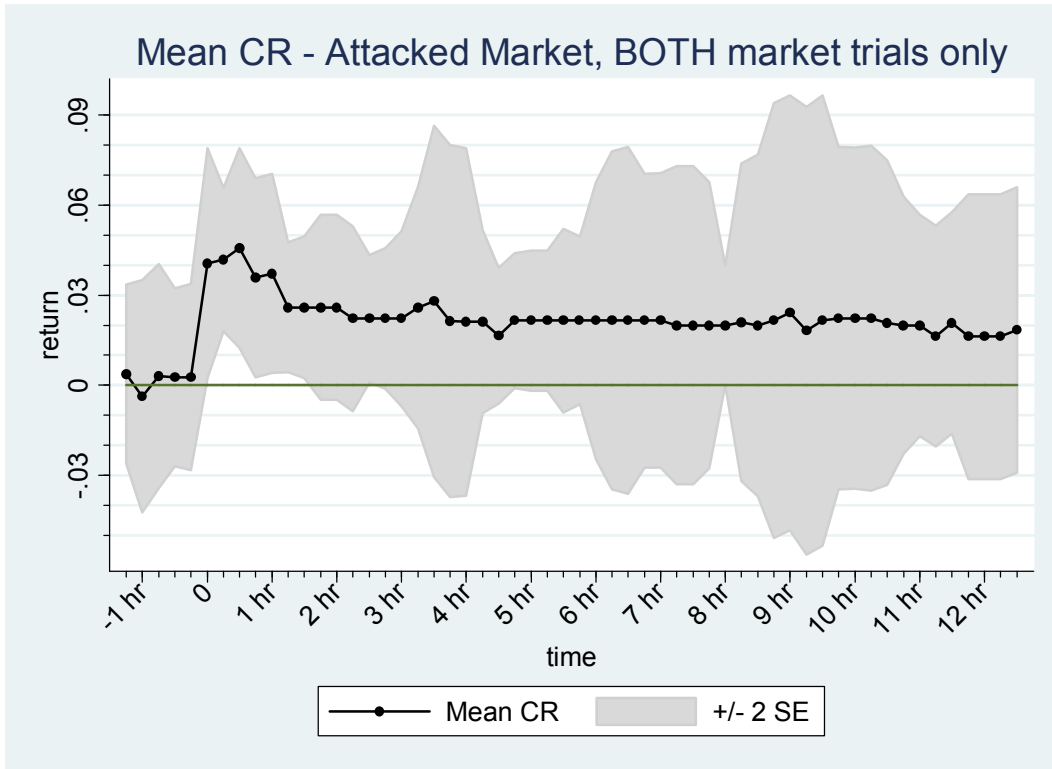


Figure 13: IEM 2000, Slow Reverting trials

(a) Mean CR in Two Market-Attacks (N=4)



(b) Mean CR in Trials with Democrat Purchases/Republican Sales (N=7)

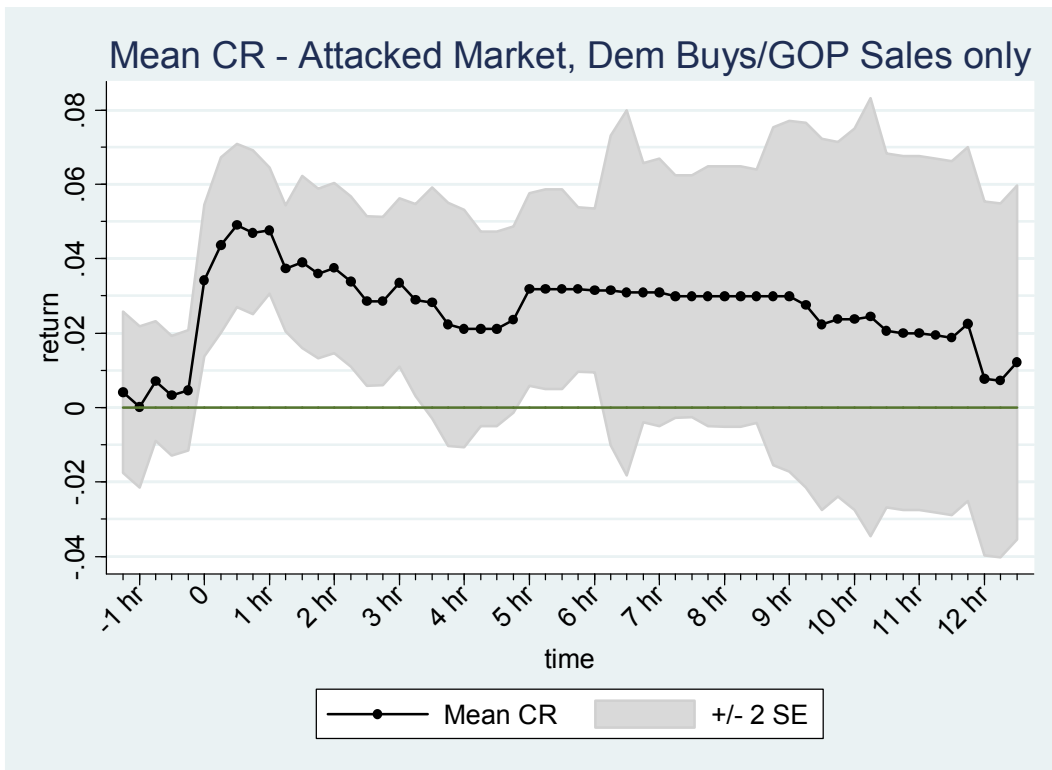
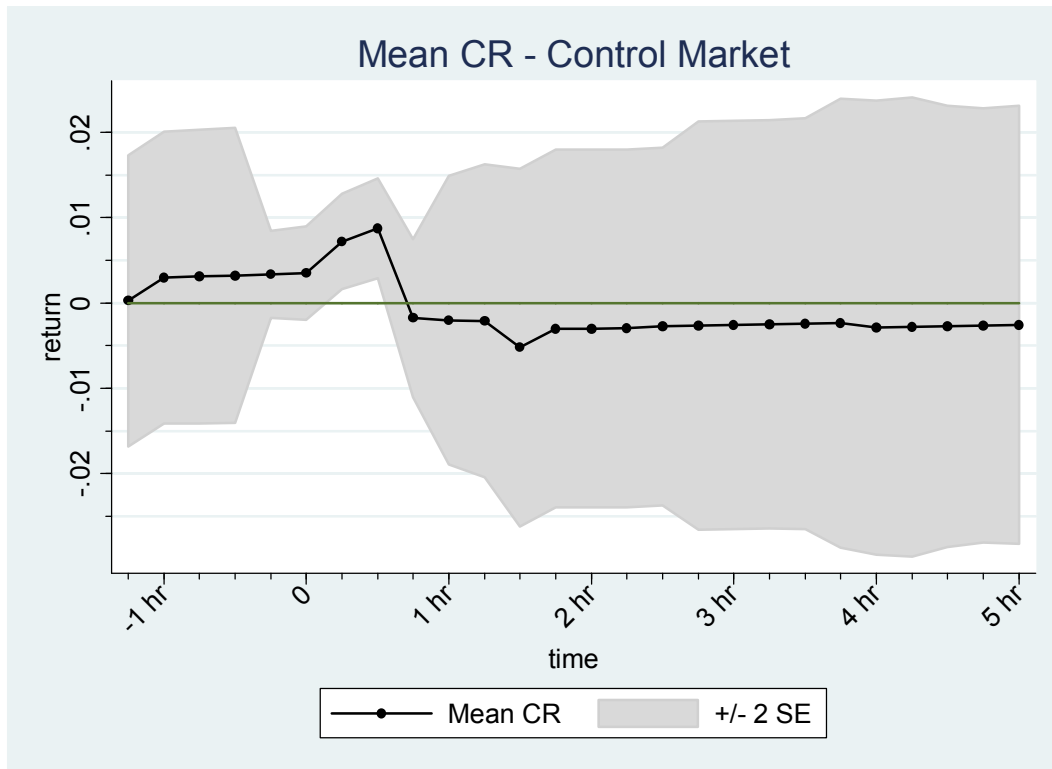


Figure 14: IEM 2000, Control Markets

(a) Mean CR (N=7)



(b) Mean CAR (N=7)

