Manipulating Political Stock Markets: A Field Experiment and a Century of Observational Data[*]

Paul W. Rhode[**]
Univ. of Arizona and NBER

Koleman S. Strumpf
Univ. of Kansas School of Business

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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 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 bets. Next 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. Finally, we 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. In the cases studied here, the speculative attack initially moved prices, but these changes 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.

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[**]Corresponding author. McClelland Hall Room 401NN. Department of Economics. Univ. of Arizona. Tucson, AZ 85718. email: pwrhode@email.arizona.edu

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. Prediction markets on current events, economic outcomes, and even the weather have become increasing common as the internet has opened access to a growing number of on-line sites such as TradeSports, Betfair, and HedgeStreet.. In political prediction markets alone, one-hundred thousand participants conducted 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* and in the private sector, Abbott Labs, Corning, General Electric, Goldman Sachs, Google, Hewlett-Packard, Intel, Lilly, Microsoft, Siemens, and Yahoo! have set up 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 the strategic purpose influencing the expectations and actions of others. 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 senior leadership" (Cowgill, 2006). These fears might be warranted because one trader at Google market later revealed he did attempt to manipulate prices. On-line such as TradeSports or the Hollywood Stock Exchange do not explicitly ban insider traders and CFTC regulations permit such trading in future markets.

Manipulation is an inherent danger for prediction markets because the potential payoffs can far outweigh any financial losses. This is because the information collected in such markets may help shape decisions about real-world outcomes (For example, voters may be unwilling to support a candidate who is faring poorly in a political prediction market). Parties with an interest in the outcome have an incentive, whenever possible, to move the odds prices in their preferred direction. And such changes can be accomplished with a small investment relative to the consequence of the decision– compare the transaction volume in the 2004 *TradeSports* presidential market (millions of dollar) with the size of the federal budget (trillions of dollars).[1] As prediction markets become more visible, they will become an increasingly tempting target for manipulators. Even if such attempts become common they could still have lasting effect on prices, since investors still must weight the possibility that a large price change is the result of an insider trader.

This paper investigates the open empirical question of whether manipulation causes important distortions in actual prediction markets. Unfortunately, the finance literature does not provide detailed guidance on how to perform this analysis. First, academic papers define the concept of manipulation in different and inconsistent ways (see Appendix B).[2] 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

[1]Moral hazard may also be a problem. If the stakes in prediction market rise above the direct rewards from the decisions (in, for example, political races or product launch), insiders gain an incentive to act in untoward ways to influence the outcome (by throwing the races or sabotaging the launch and retiring with their winnings).

[2]These differences probably stem from the lack of a statutory definition of manipulation. For example the Commodity Exchange Act does not define manipulation, 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`).

speculative attack that achieves its objective of changing prices.[3] Second, most papers utilize the decisions of regulatory agencies (such as the SEC, CFTC, or Congressional Committees) to define when a manipulation attempt has occurred. Since there is no regulatory authority for political stock markets, we had to identify the manipulations ourselves. A third difficulty arises from differences between prediction markets and more traditional derivative markets which are studied in most analyses of market manipulation. In the case of financial futures, a standard technique is to look for squeezes or corners in the underlying deliverable asset (Pirrong, 1993, 2004). With financial options, one can look for deviations from the Black-Scholes equilibrium relationship for prices of the option and underlying asset. There are no underlying assets in political stock markets, and so manipulation can only be detected using data from the prediction market alone.

We analyze speculative attacks, both alleged and actual, in three political stock markets: the historical Wall Street betting markets for national, state, and city races; the 2000 Iowa Electronic Market (IEM) for President; and the 2004 *TradeSports* market 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.

We find that these speculative attacks initially move prices, but these changes are quickly undone. We first consider the historical political markets which 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

[3]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.

influencing undecided voters and turnout. While these speculative attacks are associated with a price change, prices return to near their pre-attack level within days. The second 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. The final case we analyze is the online 2004 *TradeSports* political stock market which experienced two large price drops for Bush 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. In total our evidence suggests that manipulating political stock markets is difficult and expensive to do for more than a short period.

It is important to note that we are focusing on "trade-based" manipulation rather than "information-based" manipulation such as the dissemination of false or misleading information to manipulate securities prices. A potential criticism of our approach is that real-world manipulators might rely mainly on information-based manipulation, or perhaps even combine the two approaches and support large trades with the simultaneous release of information (perhaps false) which justifies the resulting price movements. We do not believe that rumor-spreading could be successfully employed in political stock markets.[4] Nonetheless, we test this possibility using postings in the TradeSports

[4]First, it is not clear why traders would listen to such cheap-talk communications. And if they do, traders holding shares on the other side of the manipulator will have incentive to release false information to contradict the original communication. Second, it is difficult for traders to communicate with one another in some prediction markets such as the IEM. Third, the empirical evidence suggests that when

Politics/Current Events forum, http://forum.tradesports.com. Among the thousands of messages from 2004, 174 advocated a specific action (buy, sell, or hold) in the Presidential market we study. Appendix C. shows that these postings are often in the opposite direction predicted by the criticism (e.g. they suggest trading against the speculative attacks we study), are often in conflict with one another, and have little predictive power for future prices or volume. These results support our decision to not include information-based manipulation in our experimental design or empirical analysis.

The paper has the following form. The next section begins our analysis 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 third 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 fourth section investigates charges of manipulation in the 2004 *TradeSports* Market. 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 and an analysis of information-based manipulation.

II. The New York Betting Market, 1880-1944

a. Context

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

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communication is possible in financial markets that it has little impact on the direction of future prices (Antweiler and Frank, 2004 who study Internet stock message boards).

The structure of these markets evolved over time.[5] Although it was on the borderline of legality, election betting 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 and national 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 1 assembles estimates from selected newspapers of the sums wagered in the New York market from 1884 to 1928, converted to year 2000 purchasing power.[6]. 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 100:39:37.[7] That is, there was a large drop off between national and state elections, but only a small further decline

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[5]Moving 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.

[6] 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.

[7] 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.

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. Newspaper stories may have served to advertise the political affiliation of the bettors as well as to confirm the existence of the wagers.[8] 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'."[9] 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 -- in the close 1916 contest. In cases where there is a decisive winner, we also show that the betting markets correctly forecast the next president as early as four months prior to the election. The ability of the betting market to aggregate information is 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."[10] The odds were "generally considered the *best forecasters* of Presidential elections (emphasis ours)," as well as "good indicators of probable results in

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[8] 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.
[9] *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.
[10] *Wall Street Journal*, 27 July 1920, p. 11.

gubernatorial and Mayoralty results."[11] Rhode and Strumpf (2006) provides further details on the predictive capacity of these markets in all three types of elections.[12]

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 charged that Al Smith's backers were using election wagers as "indirect propaganda."[13] But Tammany was not alone in possessing a betting war chest. In other years, charges circulated that Republican brokers on Wall Street, were financing speculative attacks. The *New York Times* on 28 Oct. 1904 reported the GOP was manipulating the Presidential betting odds in favor of T. Roosevelt. 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."[14]

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.

[11] *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,

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

[13] *New York Times*, 17 Oct. 1926, p. XX10.

[14] *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 *Atlanta Constitution*, *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*, *Washington Post*, and *Washington Star*. Our sample currently includes 4302 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 odds price per candidate per day from each newspaper article.[15] 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 (1884-1937).

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 *TradeSport*s 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

[15] 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.

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 are withdrawn when the offer is accepted. In this exercise, we have employed both computer keywords searches using Proquest.com historical newspapers 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. Figure 2 gives an example of the manipulation charges as well as the names, dates, and amount of larger bets.

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 aversely 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 1 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,

$$(1) \qquad Demprice_{it} = \sum_s \alpha_s I(t{=}s)I(DemM) + \sum_s \beta_s I(t{=}s)I(RepM) + \sum_s \gamma_s I(t{=}s)I(DemWB) + \sum_s \delta_s I(t{=}s)I(RepWB) + \nu_i + \varepsilon_{it}$$

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 (ν_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 3-5, which shows the movements in the "Democrat" odds prices as well as the error bounds.

Figure 3 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 4 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 5 shows the price effects of manipulations on the Democrat odds prices where Democrat and Republican manipulations are both included (in equation (1) 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 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.

III. Iowa Electronic Market (IEM): Field Experiment

a. Background

The IEM is a real-money online futures market operated by the University of Iowa (`http://www.biz.uiowa.edu/iem`). It is currently the sole legal U.S. site 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).

This paper focuses 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 one who as 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 6 charts the gyrations of the IEM WTA contract on the night of 7 November 2000 and morning of 8 November. 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 Bush price 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.[16] 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 anonymity of trades also helps to lend credence to our trades. Because the order book and all trades are anonymous, there is no way for traders to realize that all this activity is the result of a single individual. Hence a trader observing the market cannot discount the possibility that the price spike reflects some new information which many

[16] The 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.

others (but not him) know. To further this illusion, we follow each of our trades with a limit order near the new price level as we describe in more detail below.

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.[17] 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 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.[18] The last hypothesis suggests it is difficult to successfully manipulate these markets.

Table 2 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,

$$\text{price}^{WTA}{}_t{}^* = \sigma_{vt}{}^{-1}\times\text{price}^{VS}{}_t{}^* \quad (2)$$

where "*" indicates an inverse normal transformation and is σ_{vt} is a measure of uncertainty t periods before the election.[19] If the attacks alter market beliefs, than when only one market is attacked prices in the unaltered market (the control market) should

[17]The 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).

[18]It 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.

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

Democrats (R^2=0.74): $\text{price}^{WTA}{}_t{}^* = -0.012 + 40.188\times\text{price}^{VS}{}_t{}^*\times(T\text{-}t)^{-0.5}$

Republicans (R^2=0.71): $\text{price}^{WTA}{}_t{}^* = 0.018 + 38.910\times\text{price}^{VS}{}_t{}^*\times(T\text{-}t)^{-0.5}$.

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

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 3 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 contact 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 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 3 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 3. 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 7 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 3). 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 Australian bookmaking firm.[20] Two advantages of the Centrebet data are: (i) the market is isolated from the IEM (there were no U.S. bettors in 2000), so persistent differences in the prices are possible; (ii) our trades occur during business hours in Australia, when both the bookmaker and the predominantly Australian bettors are likely to be actively monitoring the market. The Centrebet market was open for the three weeks prior to the election and overlaps with our last three trades. The Centrebet contract was based on the Electoral College winner, which is roughly comparable to the IEM WTA contract which is based on popular votes. We matched each of our IEM WTA price observation in the three weeks prior to the election to the contemporaneous Centrebet price and estimated the following regression,

$$\text{(3)} \quad \underset{}{IEMprice_t} = \underset{(0.01)}{1.360}*CentrebetPrice_t - \underset{(0.07)}{1.460}*CentrebetPrice_t*I(ManipPeriod) + \underset{(0.04)}{0.672}*I(ManipPeriod)$$

$$N=1140,\ R^2=0.88$$

where I(Manip) is an indicator that we are trading this contract at time t, robust standard errors are listed in parenthesis, and a constant is also estimated.[21] The first parameter estimate suggests that the two markets generally track each other, and near the one-for-one level we might expect. But the second parameter is negative and almost exactly offsetting this which indicates the two markets are no longer in synch during times when we trade. To the extent that the Centrebet market is always linked to fundamentals, these estimates are inconsistent with the claim that our trades track information innovations.

[20]Bookmakers set and continuously revise odds on events, with the goal of attaining equal bet volume on all sides of the event. This is in contrast to the markets studied in this paper, in which investors themselves set prices.

[21]We consider the manipulation window to be the entire hour after our first trade. The results are robust to longer or shorter windows. Note that for the GOP WTA the indicator is zero throughout the 10/23 and 10/28 trades, since there were not trades of this contract.

*****TO ADD:**

(i) regressions based on Foresight Exchange and Intertops odds

(ii) comparison with polls: CHOW test of structural break after manipulation***

The data for our analysis was collected from trader accounts, which provide basic statistics on each asset at any time: last, bid, ask, high, low. The main IEM web page updated the information every 15 minutes while the trader screen was updated in real-time. We collected data from the trader screen for several hours before, during, and after 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.

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

(4) $$R_t \equiv (price_t - price_{t-1})/price_t$$

where $price_t$ is the price of the contract. 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,

(5) $$CR_t \equiv \sum_{s \geq tmin} R_s$$

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.

For each trade we calculate the CR using the formula in equation (5), 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 8 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 9 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 3), 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 9.

Figure 10 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 11 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 12 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 (2). Prices in the non-attacked control market should not move if market beliefs are unchanged. The top panel in Figure 12 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 seem the returns are still positive in the attack market.

The bottom panel of Figure 12 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 (2) 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,

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

where $price^{Normal}{}_t$ is the normal price. In analogy to equation (5), the cumulative abnormal return at time t of an investment made at time t_{min} is,

(7) $$CAR_t \equiv \sum_{s \geq tmin} (R_s - R_s^{Normal})$$

The bottom if Figure 12 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 8.[22] 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 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

[22]The comparison is even clearer when the attack market CR is graphed for single market attacks.

trading. Finally, we turn to the large bear raids which occurred in the 2004 presidential market at *TradeSports*.

IV. *TradeSports* 2004 Presidential Market

a. Background

TradeSports operates several online prediction markets.[23] 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, a series of thirty trades in less than a second dropped the price to 48 at 2:31 pm. After stabilizing for two minutes, another rapid set of trades led prices to tumble to 10 at 2:33 pm. 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."[24] Reports circulated that George Soros was 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*, confirmed that the large trades of a single investor produced the October 15 price moves.[25] 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

[23] *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.

[24] Donald 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 blog, `http://www.poorandstupid.com/2004_10_10_chronArchive.asp`.

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

contract and a growing list of financial traders who think they can predict the outcome of this election."

Figure 13 displays the price and volume during September and October when the purported manipulations occurred. In addition to the October 15 episode, the price of the "Bush Winner" contract also experienced a a 13-point drop duringa fourteen minute period around 12 pm EDT on Monday, September 13. Figure 14 shows the manipulation events in greater focus (Time in the figures is reported in GMT or four hours later than EDT).

As a rule, *TradeSports* markets appears to quickly incorporate new information. 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. Even private information is rapidly incorporated into *TradeSports* prices. For example, in the 2006 market covering the resignation of Harvard's president the price spiked up to nearly 100 twelve hours prior to the official announcement (and six hours before the *Wall Street Journal* posting), reflecting the trades of insiders.

In total this evidence suggests that investors are actively monitoring the market, and that placid price periods are not simply due to investor inattention.

*****TO ADD:**

regressions based on Betfair data (in sync with TradeSports EXCEPT during manipulation period) ***

b. Results

Through a special agreement. *TradeSports* has provided us with access to real-time trade data on the quantity and price (though not identity of the traders) of every transaction for the 2004 Presidential market from its opening in June 2003 to the election day.

We use these trade-level data to analyze the two attacks described above, summarizing our key results Table 4. 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 was 0.06 over three minute intervals (the length of the second attack) and was 0.25 over fifteen minute intervals (the length of the first attack). The price changes following the attacks, listed in Table 4, were an order of magnitude larger than any other price change over the market's lifetime. The volume was also heavy: 491.9 shares traded per minute durin in the first attack and 2208.0 shares in the second attack compared with an average volume of 9.7 shares (or $56.51) per minute over the last three months of the market's operation.

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 4 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 the event study methodology introduced in the last section. We again calculate the rate of return (R_t), the cumulative return (CR_t) and the two standard error confidence interval around it to test for statistical significance.[26] Figure 15 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 bottom part of Figure 15 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).[27]

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.

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[26] One difference is that we use the following formula to calculate the rate of return,

$$R_t \equiv (price_t - price_{t-1})/(0.5(price_t + price_{t-1}))$$

Using 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. This is important here given the rapid price spikes.

To generate the standard error of CR_t using the formulae in the Appendix, the variance σ^2 is calculated from the observed dispersion in R_t during the hour before t=-5. This 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

[27] Two 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 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 15.

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:

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

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: α_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.

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, at least, if the goal was to attract 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 may have been a success.

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. We are aware of a half-dozen attempts to manipulate TradeSports markets in the last year (including multiple attacks on the TradeSports 2008 Presidential markets), and further back there were attempts to manipulate political markets at BetFair, in Germany (Hansen, et al, 2004) and in a non-US market which prefers to remain unnamed. Yet in each case 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.

Appendix

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

where VoteShare_t is the latent support at day *t*, VoteShare_{t-1} is the latent support on the prior day, and $\varepsilon_t \sim \mathbf{N}(0,\sigma_t^2)$ 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 $\Phi(.)$ 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) $\text{VoteShare}_T^* = \text{VoteShare}_t^* + \nu_t$

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

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

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

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

(A4) $\text{VoteShare}_T^* = \sigma_{\nu t} \times (\Pr(\text{Win})|\Omega_t)^* + \nu_t$.

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) $\text{VoteShare}_T^* = \sigma_{\nu t} \times \text{price}_t^* + \nu_t$

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

(A6) $price_t = Pr(VoteShare_T^* > 0) \equiv Pr(Win)$

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) $price_t^* = ((T-t)/(T-t-1))^{0.5} \times price_{t-1}^* + \varepsilon_t$

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) $VoteShare_T^* = (s_1^2(T-t)+s_2^2)^{0.5} \times price_t^* + \nu_t$

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 ν_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 $VoteShare_T^*$, $price_t^* \approx 0$ (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') $price_t \approx 0.5(1-((T-t)/(T-t-1))^{0.5}) + ((T-t)/(T-t-1))^{0.5} \times price_{t-1} + e_t$

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

(A8') $VoteShare_T \approx 0.5(1-(\sigma_1^2(T-t)+\sigma_2^2)^{0.5}) + (s_1^2(T-t)+s_2^2)^{0.5} \times price_{t-1} + v_t$

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

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, $price^{VS}_t = E(VoteShare_T|\Omega_t)$. Using equation (A2) this means $price^{VS}_t =$

[28]To see this, suppose the contract price is set as, $price_t = a + Pr(Win)|\Omega$ 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, $VoteShare_T^* \approx 0$) yields,

$$VoteShare_T^* = -(a\sigma_{vt}/\phi(0)) + \sigma_{vt} \times price_t^* + \varepsilon_i$$

where $\phi(.)$ 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) $price_t^* = price^{VS}{}_t{}^*/\sigma_{vt}$.

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 (4), (5), and (7). Given the framework in this Appendix (and presuming $price_{t-1}^*$, $price^{VS}{}_{t-1}{}^* \in \Omega_t$), 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.[29] 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.[30] 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.[31]

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 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

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[29]Some 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.

[30] Hanson 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.

[31] While 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.

papers have documented the existence of trade-based manipulation in traditional financial markets.[32]

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).[33] 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.

Section C. Information-Based Manipulation

This Appendix investigates whether messages can be successfully used to influence prices, and so whether they could be an important component of an attempted manipulation. With this goal, we analyze the causes and consequences of postings on the TradeSports Politics/Current Events forum, `http://forum.tradesports.com`, during the 2004 Presidential election. This forum was the sole means by which traders in this market could communicate with one another during this period, and there were 3541 postings during the last year of the campaign (1/1/04-11/2/04). Among these posts, 80 advocated that other traders buy in the Bush election market, 63 advocated selling, and 31 advocated holding.[34] The data analysis will focus on these postings.

One interesting feature of these data is that there are often conflicting suggestions for which way to trade. For example, a post which suggests buying is followed by another post which suggests selling. To be specific postings advocating a trade come from 73 threads (a thread is a group of messages which follow a common topic and are

[32]The 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).

[33]While 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.

[34]To make this classification, we manually read through the 837 postings which contained a word potentially suggesting a trading action (the key words are: "buy", "sell", "hold", "buying", "selling", "holding", "short", "shorting", "long", "overpriced", "underpriced").

listed together on the forum). 41.1% of these threads have postings advocating conflicting positions. This percentage does not markedly change even if we restrict attention to threads whose first post suggests an action or to threads where the suggested action is specifically linked to new information.

These posting data can also be linked to periods with large price fluctuations. In particular we can see what postings were made following the two speculative attacks studied in the main text. While both of these involved a sharp price decline, most of the resulting messages suggested this was a *buying* opportunity. This is the opposite direction of what an information-based manipulator would suggest. To be more specific, five messages suggest the 13 October attack created a sell opportunity, and these postings were made within two hours of the start of the attack. One posting did suggest selling, but this was made the day after the attack. Similarly, there were five buy messages following the 15 October attack and two of these messages were made within an hour of the attack; there were three sell messages, though two of these were made three days after the attack. In total, most postings suggest trading against the speculative attacks.[35]

We can formalize these intuitive results. We are interested in whether the messages in themselves induce predictable movements in the price and volume. In some cases the messages reflect actual news events, and so we generate an indicator *NewsStory* for the top twenty-five news events during the campaign (this list is based on a review of news sites, and the timing is based on the hour when the story is first posted on The Drudge Report (http://www.drudgereportarchives.com/). We also considered a variety of other news measures, such as whether the posting links to a specific story, and find similar results.

Table C.1 shows the formal estimates. The top panel investigates the determinants of forum posts. We consider logits (is there a post this period?), poisson regressions (how many postings are there this period?), and Cox proportionate hazard (what is the likelihood of a posting, conditional on no postings since the last one?) models. In all cases the explanatory variables are the NewsStory indicator and the lagged change in mean price and the lagged change in shares traded over the last hour (we obtains similar estimates when we instead consider fifteen-minute or one-day lags, and also if we use different summaries of price and volume).

The results are consistent across the different approaches. In terms of explaining postings (the top panel of Table C.1), these are more likely when there was a price decline or low volume in the previous hour and also when there was a news story (the latter effect two effects however, are typically not statistically significant). The price effect is pronounced in explaining buy messages and largely absent in explaining sell messages. These results suggest that action-based behavior may have a strategic component, with suggestions to buy following price dips.

Of more interest is the impact of postings on future price and volume (the bottom panel of Table C.1). The number of messages—either the total, or buy and sell messages separately-- do not have a statistically significant effect. These effects are also not economically important. For example a buy posting in the previous hour increases price

[35] Consistent with this view are the postings related to a rapid and more long-lasting price change, the drop in Kerry's price in the primary market due to the Interngate story. There were many offsetting messages posted following the initial posting on the Drudge Report, and a roughly equal number of postings suggested buying and selling Kerry.

by about \$0.01 (prices range from \$0-\$100), which is only two percent of the standard deviation of hourly price change. Note also the prices tend to go up after a sell message, so the market is moving against the suggestion. Finally, notice that a new story an hour ago has a statistically significant effect on the change in price and volume. This reflects the adjustment to prices when the event occurs, e.g. volume is lower in the current hour compared to the hour when there is a news story. Omitting these news indicators has little effect on the estimates of the message parameters. In total, these results suggest that message board postings have little impact on the dynamics of the political stock market, and in particular have little predictive power with respect to future prices.

Table C.1: Messages Suggesting Buy/Sell/Hold Trades on the 2004 TradeSports Political Forum
An action-based message is one which advocates a specific trade (buy/sell/hold)

A. Predicting message frequency (Dependent variable = Posting)

	logit			poisson			Cox proportionate hazard		
	I(Message)	I(Buy)	I(Sell)	#(Message)	#(Buy)	#(Sell)	Message	Buy	Sell
ΔPrice$_{\text{last hour}}$	-0.499	-0.613	-0.244	-0.484	-0.589	-0.237	-0.208	-0.292	-0.097
	(0.09)	(0.09)	(0.21)	(0.07)	(0.08)	(0.21)	(0.05)	(0.06)	(0.06)
ΔVolume$_{\text{last hour}}$	-0.001	-0.001	-0.000	-0.001	-0.001	-0.000	-0.0003	-0.0004	-0.0001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.0002)	(0.0003)	(0.0002)
NewsStory	1.124	1.917	---	1.095	1.914	-13.884	0.170	1.073	-39.030
	(1.02)	(1.02)		(1.00)	(1.00)	(0.24)	(1.01)	(1.01)	(0.22)
constant	-5.233	-6.045	-6.187	-5.191	-6.019	-6.157	---	---	---
	(0.08)	(0.12)	(0.13))	(0.08)	(0.12)	(0.13)			
N	29550	29550	29490	29550	29550	29550	29549	29549	29549
logL	-1006.78	-519.04	-437.36	-1057.61	-537.11	-451.16	-1426.40	-653.85	-525.81
Dep. Var. mean	0.006	0.003	0.002	0.006	0.003	0.002	---	---	---

B. Consequences of Messages (Dependent variable = ΔPrice, ΔVolume)

	OLS ΔPrice			OLS ΔVolume		
I(Message)$_{\text{last hour}}$	0.104	---	---	11.476	---	---
	(0.13)			(23.88)		
I(Buy Message)$_{\text{last hour}}$	---	0.012	---	---	-15.145	---
		(0.126)			(44.55)	
I(Sell Message)$_{\text{last hour}}$	---	---	0.312	---	---	26.160
			(0.33)			(31.20)
NewsStory	-0.049	-0.047	-0.047	136.747	137.139	136.944
	(0.16)	(0.16)	(0.16)	(73.77)	(73.78)	(73.76)
NewsStory$_{\text{last hour}}$	-0.635	-0.636	-0.636	-173.816	-174.029	-173.880
	(0.11)	(0.11)	(0.11)	(60.16)	(60.16)	(60.16)
Constant	0.004	0.005	0.004	0.084	0.192	0.095
	(0.003)	(0.003)	(0.003)	(1.15)	(1.15)	(1.16)
N	29539	29539	29539	29539	29539	29539
R^2	0.003	0.002		0.002	0.002	0.002
Dep. Var. mean		0.004			0.076	
Dep. Var. std. dev.		0.589			200.21	

Analysis is based on 15 minute intervals over the period 1/1/04-11/2/04. Robust standard errors are in parentheses. NewsStory parameters are omitted when they perfectly predict the dependent variable in Panel A (the sample size is also reduced in these cases). All variables are defined in the text.

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Table 1: Impact of Manipulations and Wash Sales/Bluffs on Democratic Odds Price in Historical New York Markets

Dependent variable = Democrat odds price.

		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	
Party	Days	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 2: Hypotheses Regarding Market Participant Behavior

	Hypotheses		
	Markets are Not Monitored	Beliefs Change | Markets Monitored	Beliefs Unchanged | Markets Monitored
Attack Market M_1	(↑,0)	(↑,↑)	(↑↓,0)
Attack Markets M_1 and M_2	(↑,↑)	(↑,↑)	(↑↓,↑↓)

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

Table 3: Timing and Features of Investments in 2000 Presidential IEM

Manip Date	Market Attacked	Investment Democrat	Investment Republican	Investment Reform	Market Cap	Price Change Democrat	Price Change Republican	Price Change 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:

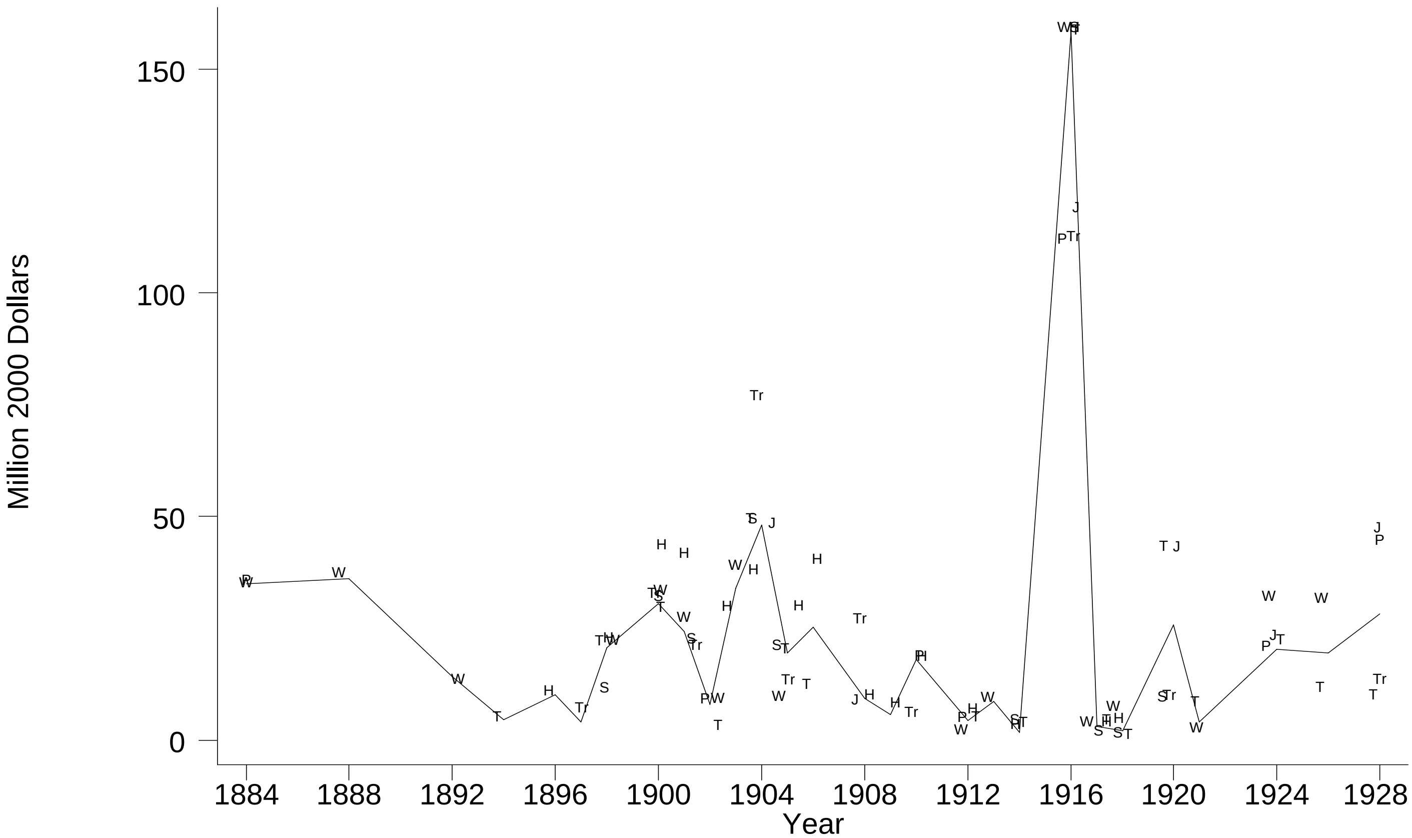
- In the investment column, a positive amount indicates a purchase and a negative amount indicates a sale.
- The market cap is the prevailing number of bundles (one share each of Democrat, Republican, Reform); a bundle can always be purchased or redeemed with the exchange at $1.
- The price change is 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.

Table 4: 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
Attack summary		
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.

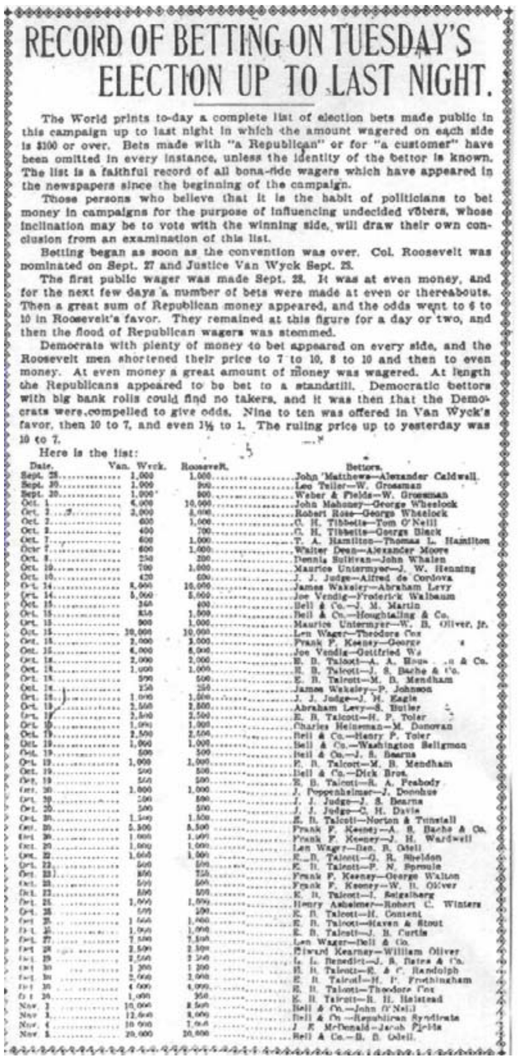
Figure 1: Estimated Volume in Historical New York Markets, 1884-1928



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

Figure 2: Newspaper Accounts of Historical New York Markets

A. Individual Bets (*NewYork World*, Nov. 1898)



RECORD OF BETTING ON TUESDAY'S ELECTION UP TO LAST NIGHT.

The World prints to-day a complete list of election bets made public in this campaign up to last night in which the amount wagered on each side is $100 or over. Bets made with "a Republican" or for "a customer" have been omitted in every instance, unless the identity of the bettor is known. The list is a faithful record of all bona-fide wagers which have appeared in the newspapers since the beginning of the campaign.

Those persons who believe that it is the habit of politicians to bet money in campaigns for the purpose of influencing undecided voters, whose inclination may be to vote with the winning side, will draw their own conclusion from an examination of this list.

Betting began as soon as the convention was over. Col. Roosevelt was nominated on Sept. 27 and Justice Van Wyck Sept. 28.

The first public wager was made Sept. 28. It was at even money, and for the next few days a number of bets were made at even or thereabouts. Then a great sum of Republican money appeared, and the odds went to 6 to 10 in Roosevelt's favor. They remained at this figure for a day or two, and then the flood of Republican wagers was stemmed.

Democrats with plenty of money to bet appeared on every side, and the Roosevelt men shortened their price to 7 to 10, 8 to 10 and then to even money. At even money a great amount of money was wagered. At length the Republicans appeared to be bet to a standstill. Democratic bettors with big bank rolls could find no takers, and it was then that the Democrats were compelled to give odds. Nine to ten was offered in Van Wyck's favor, then 10 to 7, and even 1½ to 1. The ruling price up to yesterday was 10 to 7.

Here is the list:

Date.	Van. Wyck.	Roosevelt.	Bettors.
Sept. 28	1,000	1,000	John Matthews—Alexander Caldwell
Sept. 30	1,000	900	Leo Teller—W. Grossman
Sept. 30	1,000	900	Weber & Fields—W. Grossman
Oct. 1	6,000	10,000	John Mahoney—George Wheelock
Oct. 2	3,000	4,000	Robert Rose—George Wheelock
Oct. 2	600	1,000	C. H. Tibbetts—Tom O'Neill
Oct. 3	400	700	C. H. Tibbetts—George Black
Oct. 7	600	1,000	T. A. Hamilton—Thomas L. Hamilton
Oct. 7	600	1,000	Walter Dean—Alexander Moore
Oct. 8	250	200	Dennis Sullivan—John Whalen
Oct. 10	700	1,000	Maurice Untermyer—J. W. Henning
Oct. 10	420	600	J. J. Judge—Alfred de Cordova
Oct. 14	8,000	10,000	James Wakeley—Abraham Levy
Oct. 14	5,000	5,000	Joe Vendig—Frederick Walbaum
Oct. 15	340	400	Bell & Co.—J. M. Martin
Oct. 15	816	1,000	Bell & Co.—Houghtalling & Co.
Oct. 15	900	1,000	Maurice Untermyer—W. B. Oliver, Jr.
Oct. 15	10,000	10,000	Len Wager—Theodore Cox
Oct. 15	2,000	3,000	Frank F. Keeney—George [illegible]
Oct. 15	4,000	6,000	Joe Vendig—Gottfried W[illegible]
Oct. 18	2,000	2,000	E. B. Talcott—A. A. Hous[illegible] & Co.
Oct. 18	1,000	1,000	E. B. Talcott—J. S. Bache & Co.
Oct. 18	500	500	E. B. Talcott—M. B. Mendham
Oct. 18	250	250	James Wakeley—P. Johnson
Oct. 18	1,000	1,000	J. J. Judge—J. H. Eagle
Oct. 19	2,500	2,500	Abraham Levy—S. Butler
Oct. 19	2,500	2,500	E. B. Talcott—H. P. Toler
Oct. 19	1,000	1,000	Charles Heineman—M. Donovan
Oct. 19	2,500	2,500	Bell & Co.—Henry P. Toler
Oct. 19	1,000	1,000	Bell & Co.—Washington Seligman
Oct. 19	500	500	Bell & Co.—J. S. Bearns
Oct. 19	1,000	1,000	E. B. Talcott—M. B. Mendham
Oct. 19	500	500	Bell & Co.—Dick Bros.
Oct. 19	500	500	E. B. Talcott—R. A. Peabody
Oct. 20	1,000	1,000	J. Poppenheimer—J. Donohue
Oct. 20	500	500	J. J. Judge—J. S. Bearns
Oct. 20	500	500	J. J. Judge—C. H. Davis
Oct. 20	1,500	1,500	E. B. Talcott—Norton & Tunstall
Oct. 20	5,500	5,500	Frank F. Keeney—A. S. Bache & Co.
Oct. 20	1,000	1,000	Frank F. Keeney—J. H. Wardwell
Oct. 20	1,000	1,000	Len Wager—Dan. B. Odell
Oct. 22	1,000	1,000	E. B. Talcott—G. R. Sheldon
Oct. 22	500	500	E. B. Talcott—P. N. Sproule
Oct. 22	800	750	Frank F. Keeney—George Walton
Oct. 22	500	500	Frank F. Keeney—W. B. Oliver
Oct. 23	800	800	E. B. Talcott—I. Seligsberg
Oct. 25	1,000	1,000	Henry Asheimer—Robert C. Winters
Oct. 25	500	500	E. B. Talcott—H. Content
Oct. 25	1,000	1,000	E. B. Talcott—Haven & Stout
Oct. 26	1,000	1,000	E. B. Talcott—J. B. Curtis
Oct. 27	7,500	7,500	Len Wager—Bell & Co.
Oct. 28	2,500	2,500	Edward Kearney—William Oliver
Oct. 29	2,500	2,500	L. L. Benedict—J. B. Dates & Co.
Oct. 30	1,200	1,200	E. B. Talcott—E. & C. Randolph
Oct. 30	2,000	2,000	E. B. Talcott—H. P. Frothingham
Oct. 30	4,000	4,000	E. B. Talcott—Theodore Cox
Oct. 30	1,000	950	E. B. Talcott—R. H. Halstead
Nov. 2	10,000	8,500	Bell & Co.—John O'Neill
Nov. 3	12,000	8,000	Bell & Co.—Republican Syndicate
Nov. 4	10,000	7,000	J. F. McDonald—Jacob Fi[illegible]
Nov. 5	20,000	20,000	Bell & Co.—D. B. Odell

B. Charges of Manipulation (*New York Times*, 28 October 1904; 5 November 1916)

WALL STREET BETTING ODDS MANIPULATED

Methods Used by Brokers to Bring "Sure Thing" Profits.

HARD TO PLACE REAL WAGERS

Open Charge That Republican Campaign Funds Have Been Used to Hammer Odds Encounters No Denial.

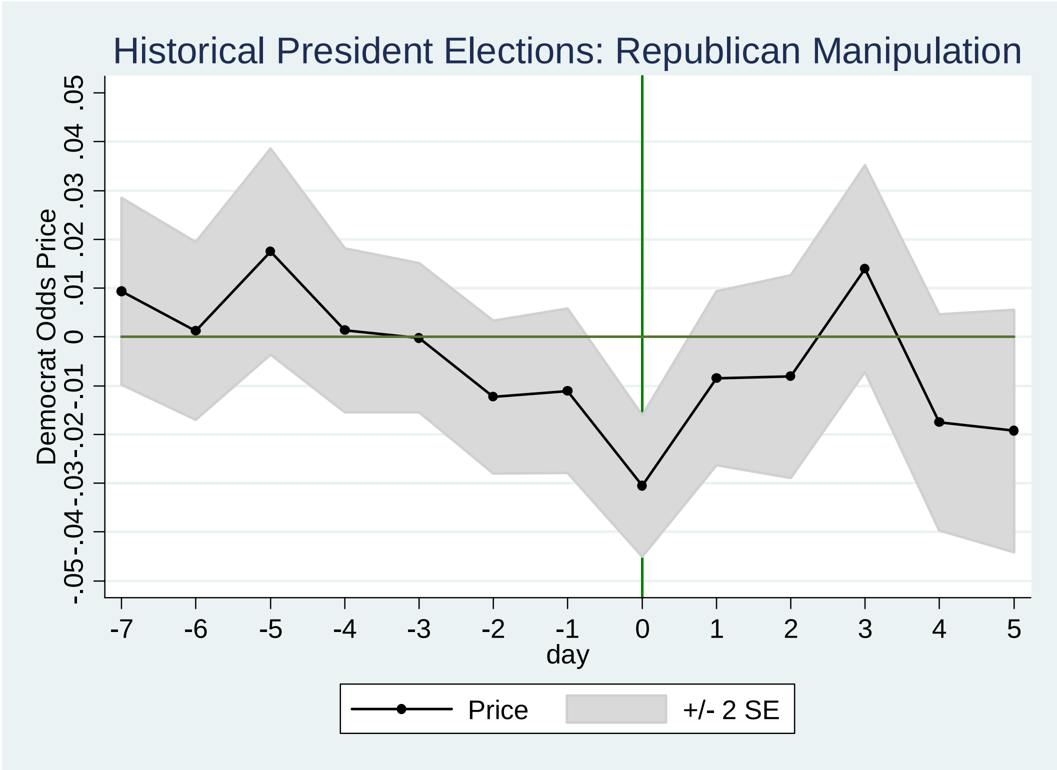
$5,000,000 BET HERE TO DATE ON ELECTION

Estimated That $1,000,000 More Will Be Wagered in Wall St. Tomorrow.

STILL 10 TO 7 ON HUGHES

Large Amounts of Money from the West Bet on Wilson—Talk of "Rigged" Odds.

Figure 3: Manipulations in Presidential Races in Historical New York Markets



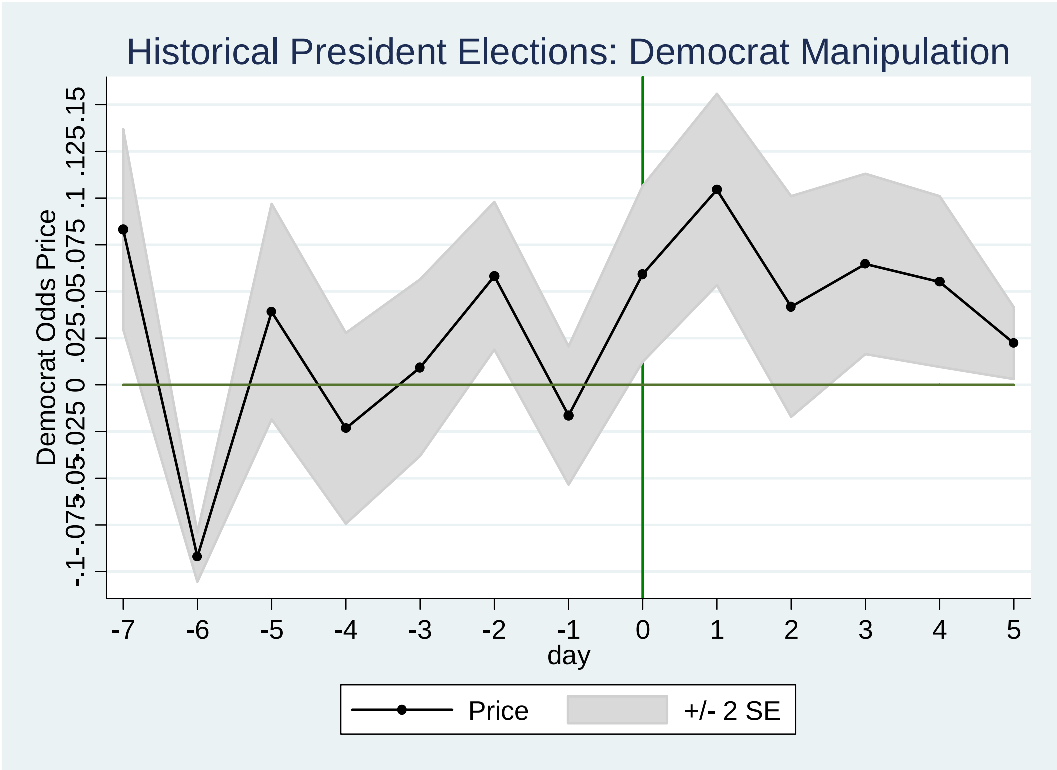
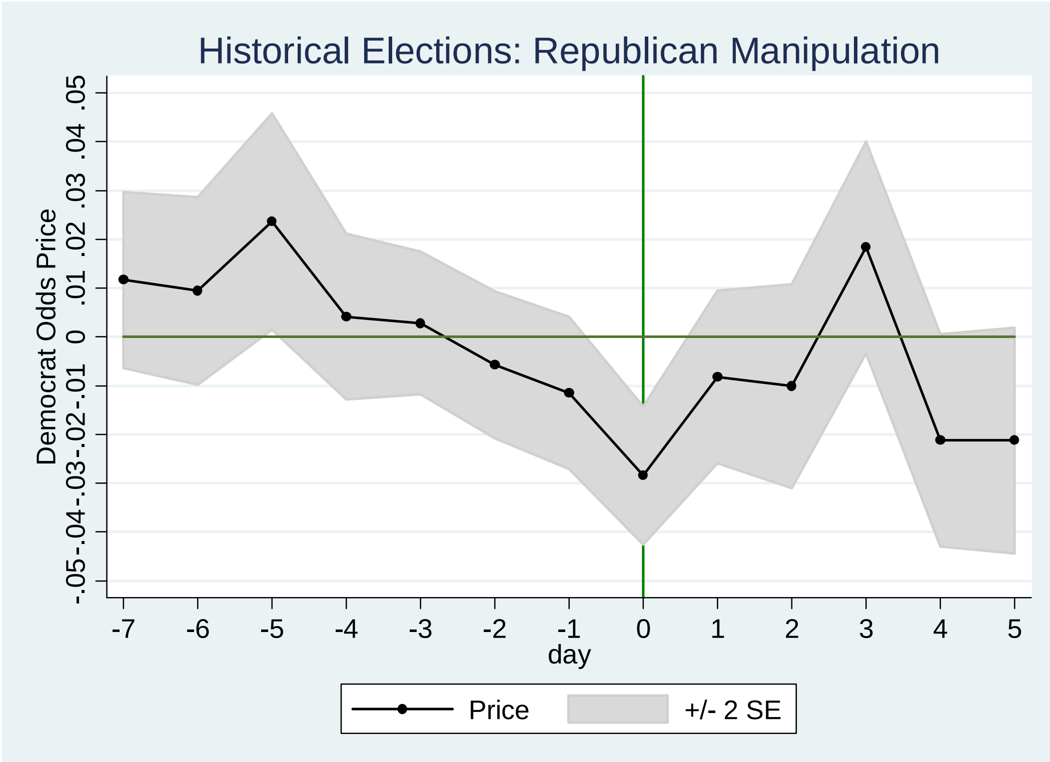


Figure 4: Manipulations in All Races in Historical New York Markets



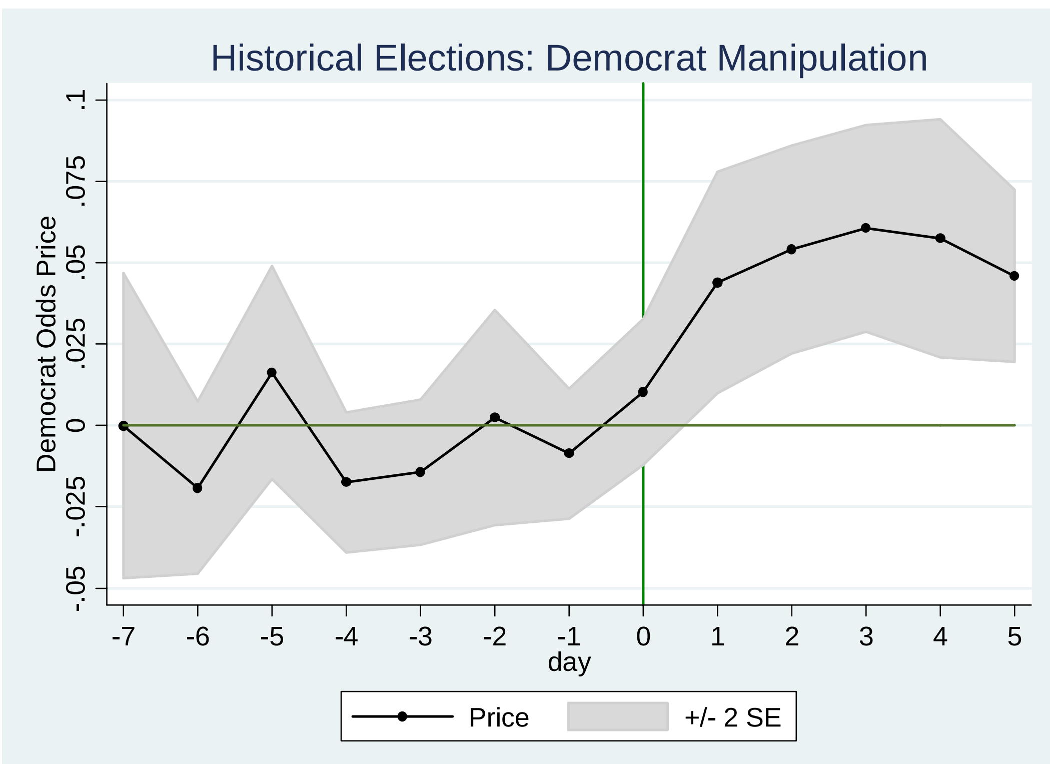
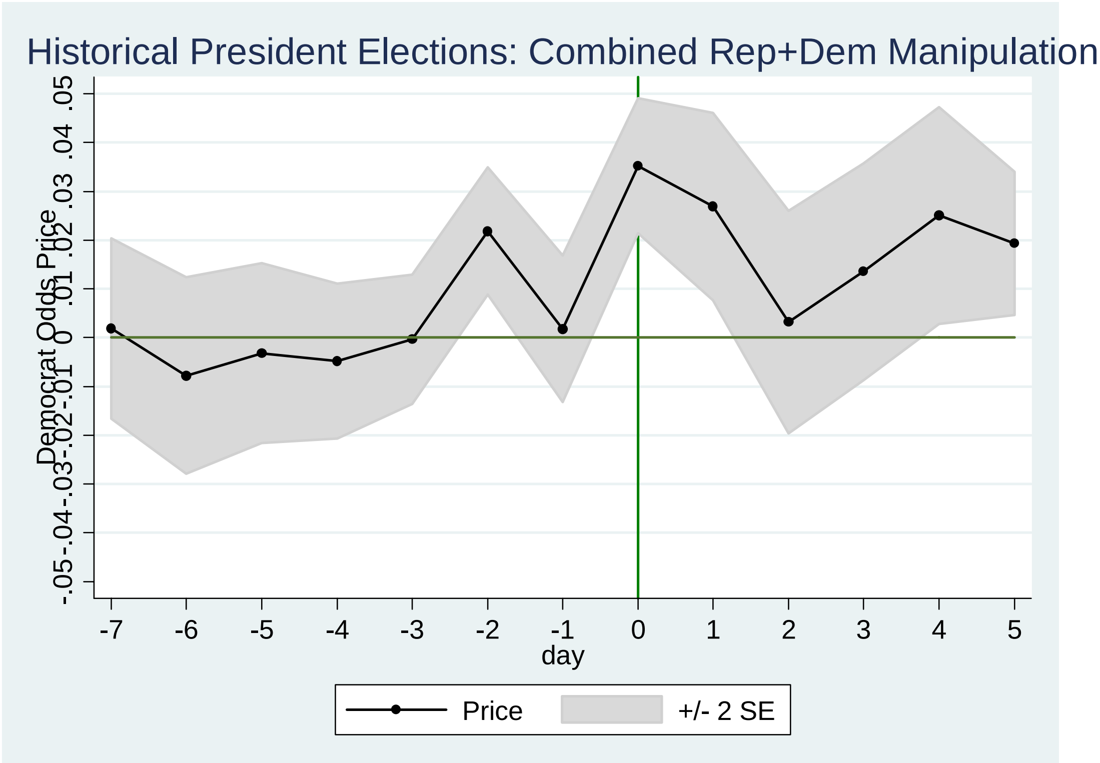


Figure 5: Results Combining Manipulations for Historical New York Markets



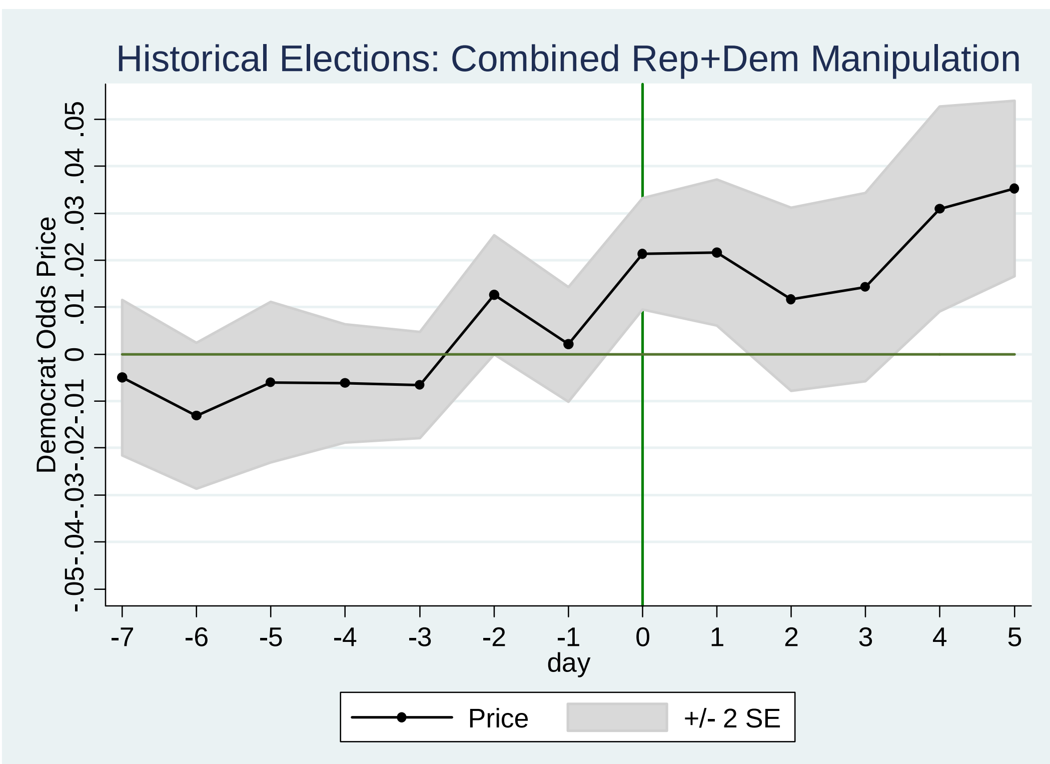


Figure 6: IEM 2000 WTA Market: Day After Election (CST)

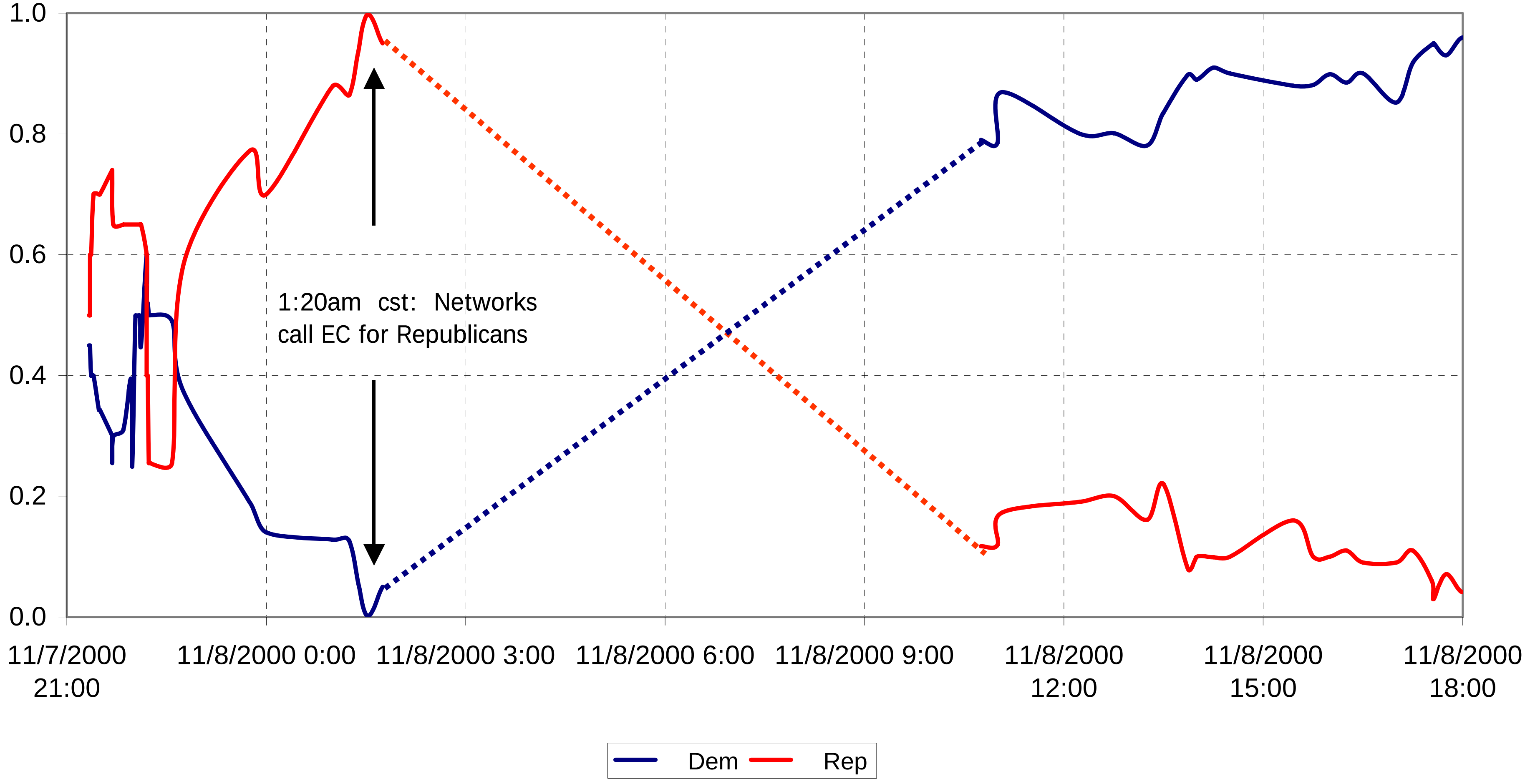


Figure 7: IEM 2000: 10/28/00 Trades (Sell Democrats in WTA+VS)

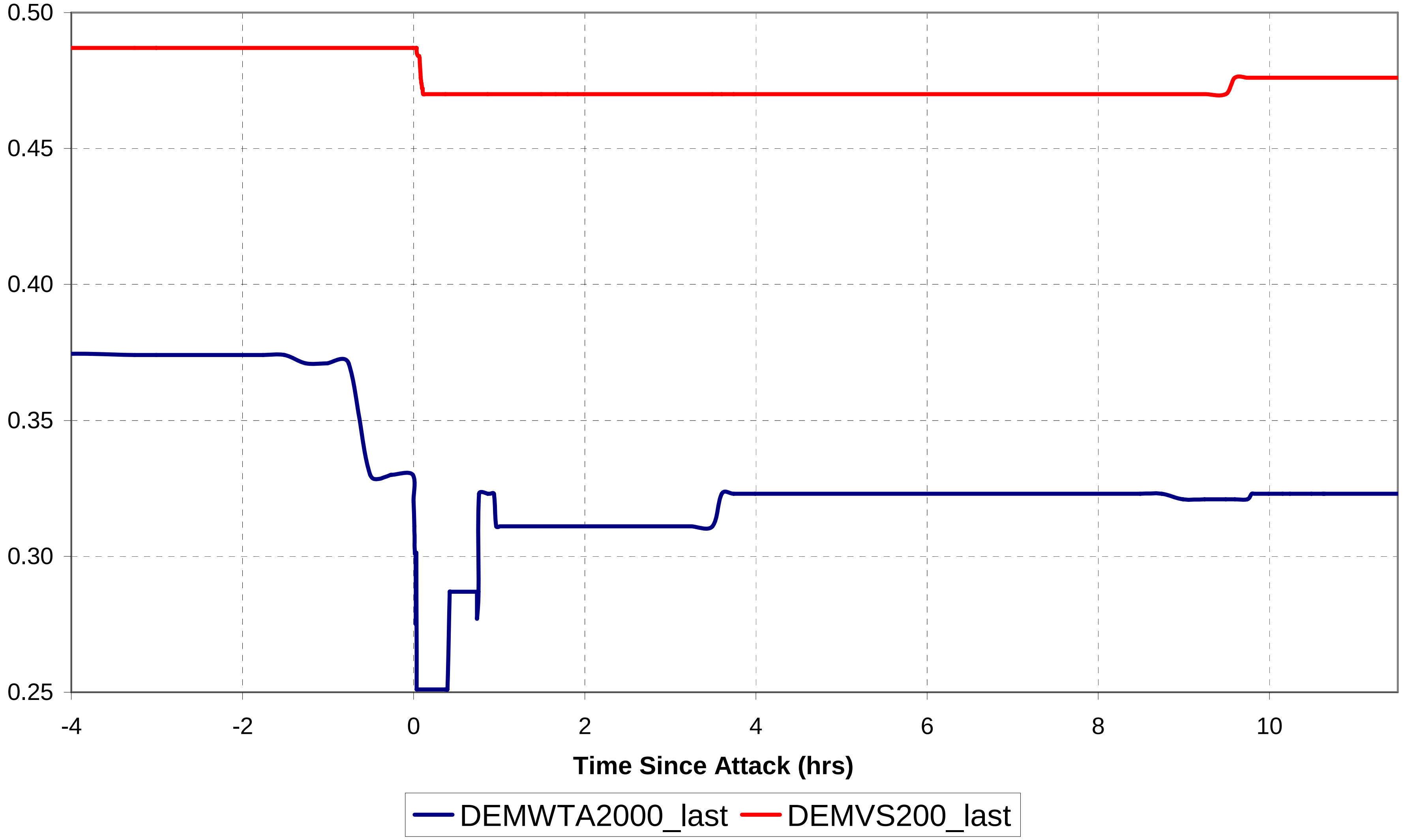


Figure 8: IEM 2000.
Mean CR in the Attacked Market over the Full Set of Trades (N=11)

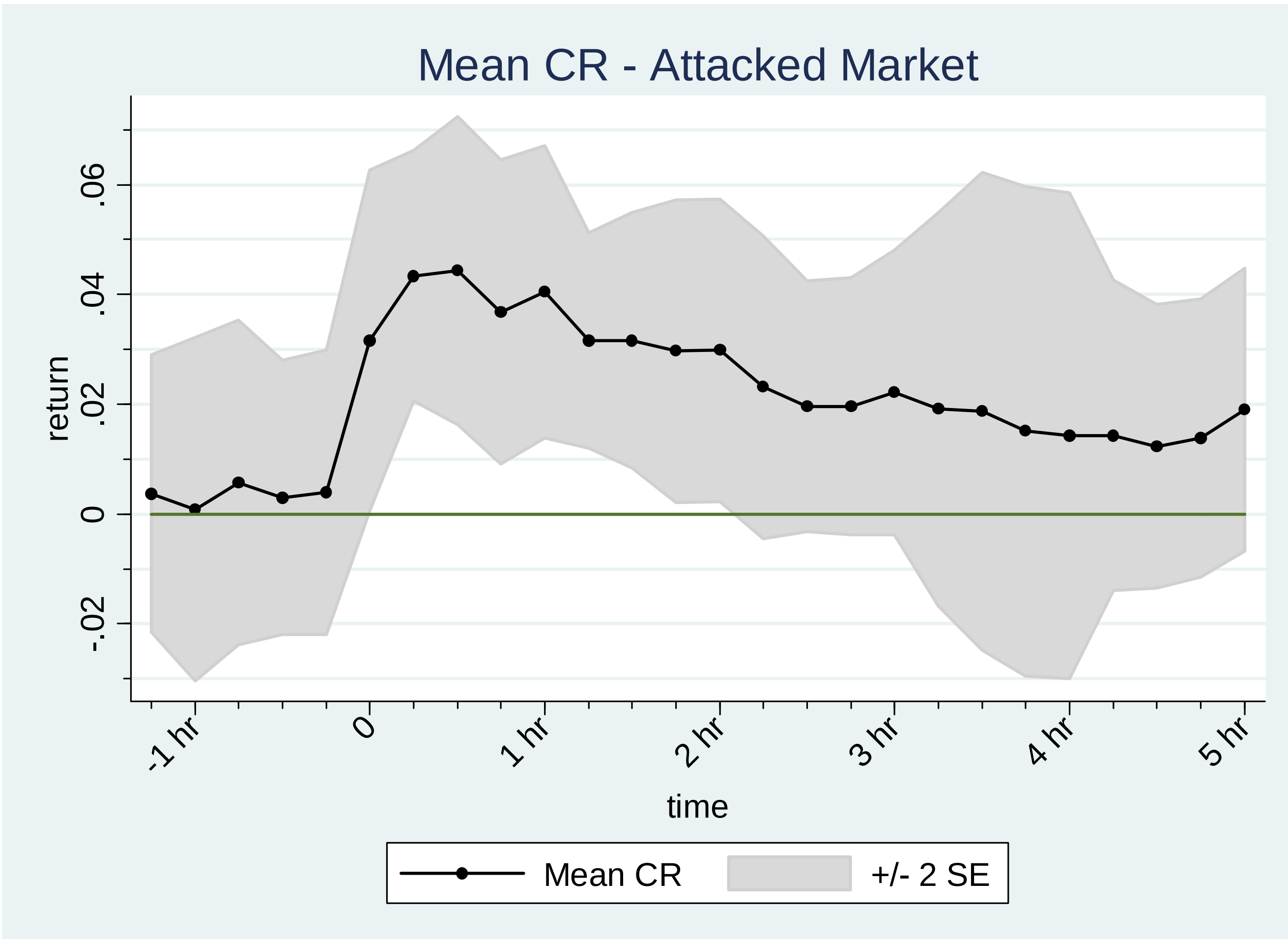
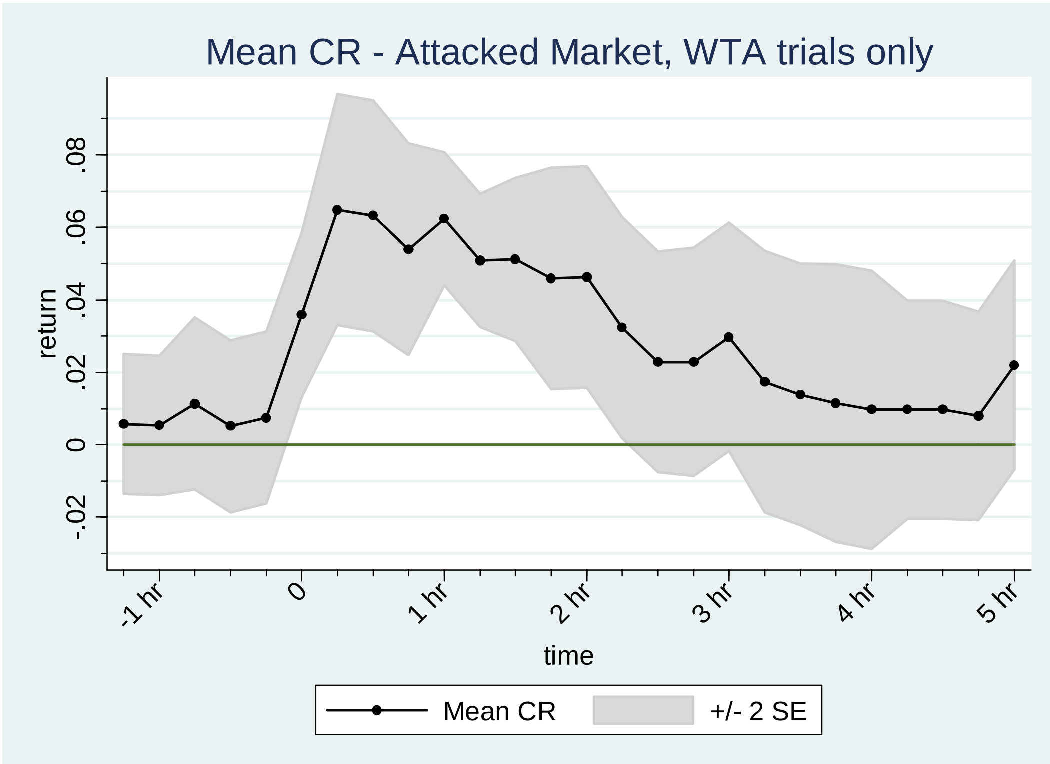


Figure 9: IEM 2000, by Market

(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)

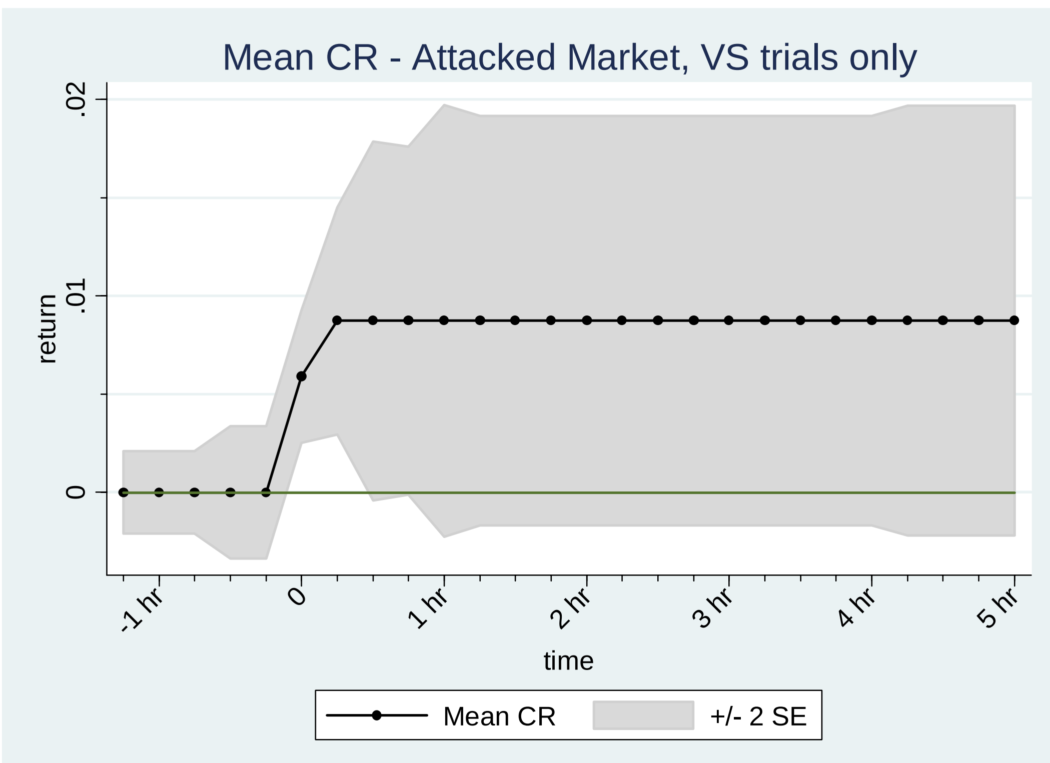
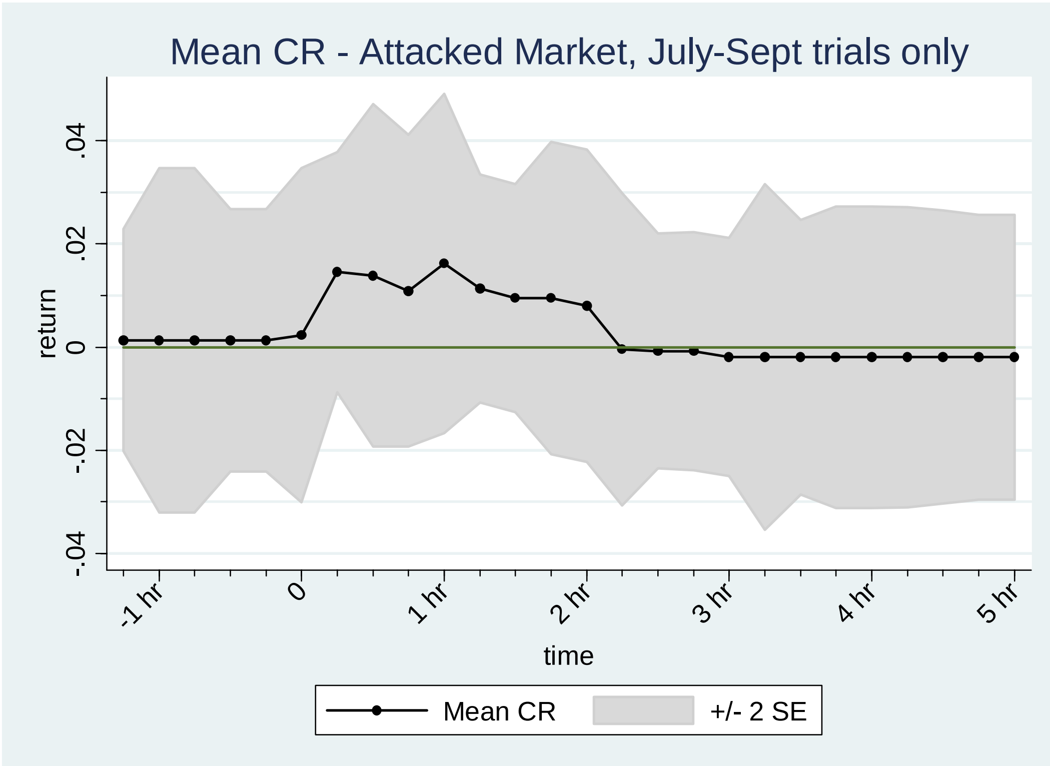


Figure 10: IEM 2000, by Time/Market Cap

(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)

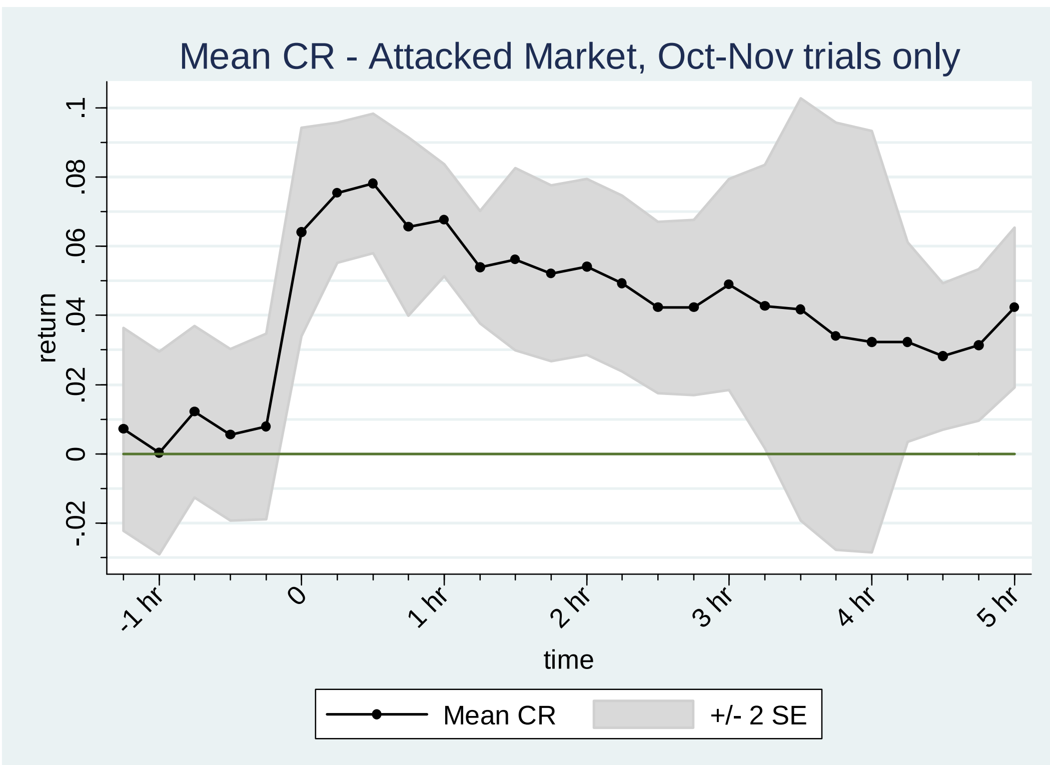
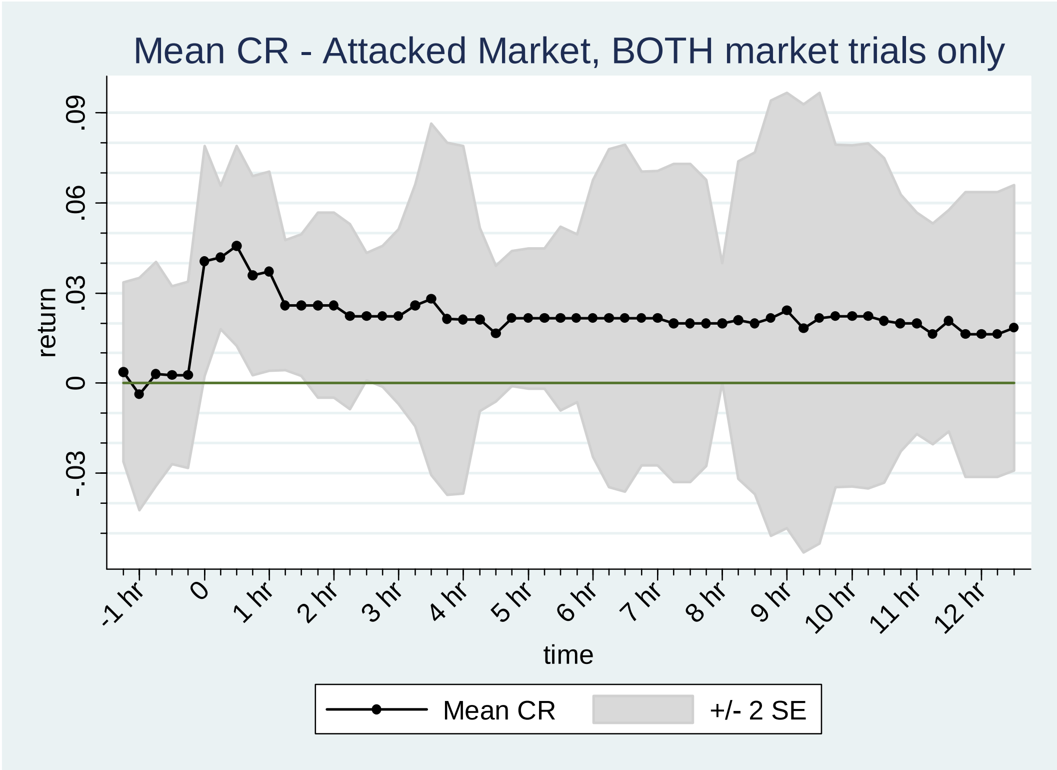


Figure 11: IEM 2000, Slow Reverting trials

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



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

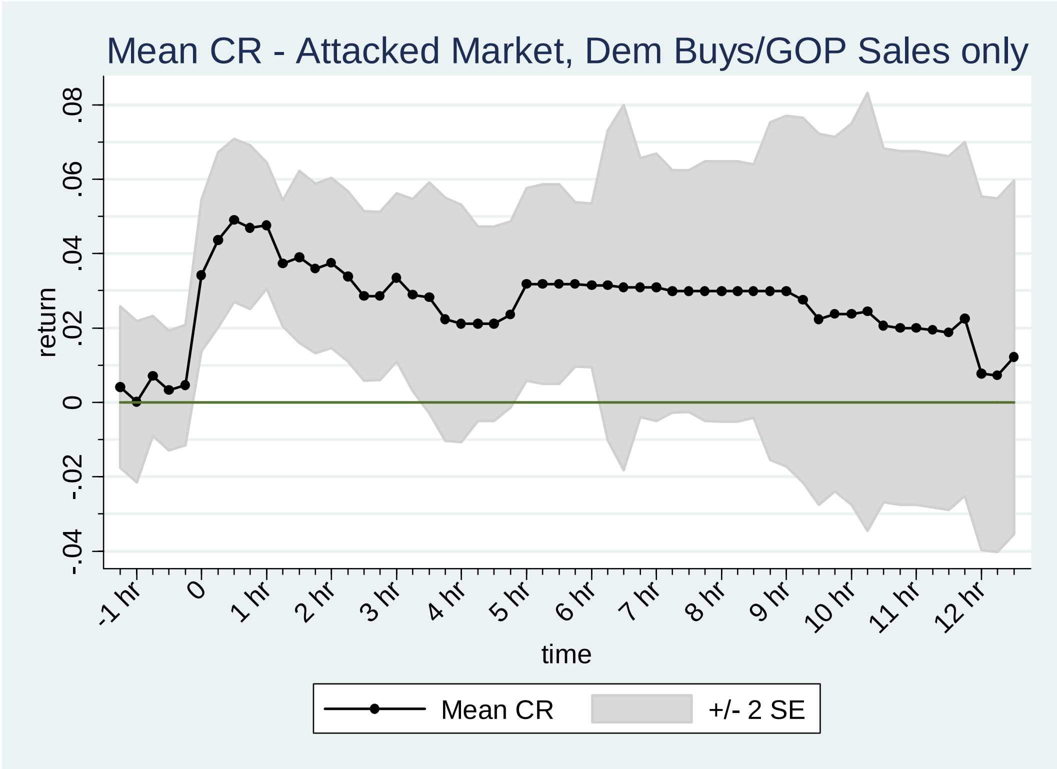
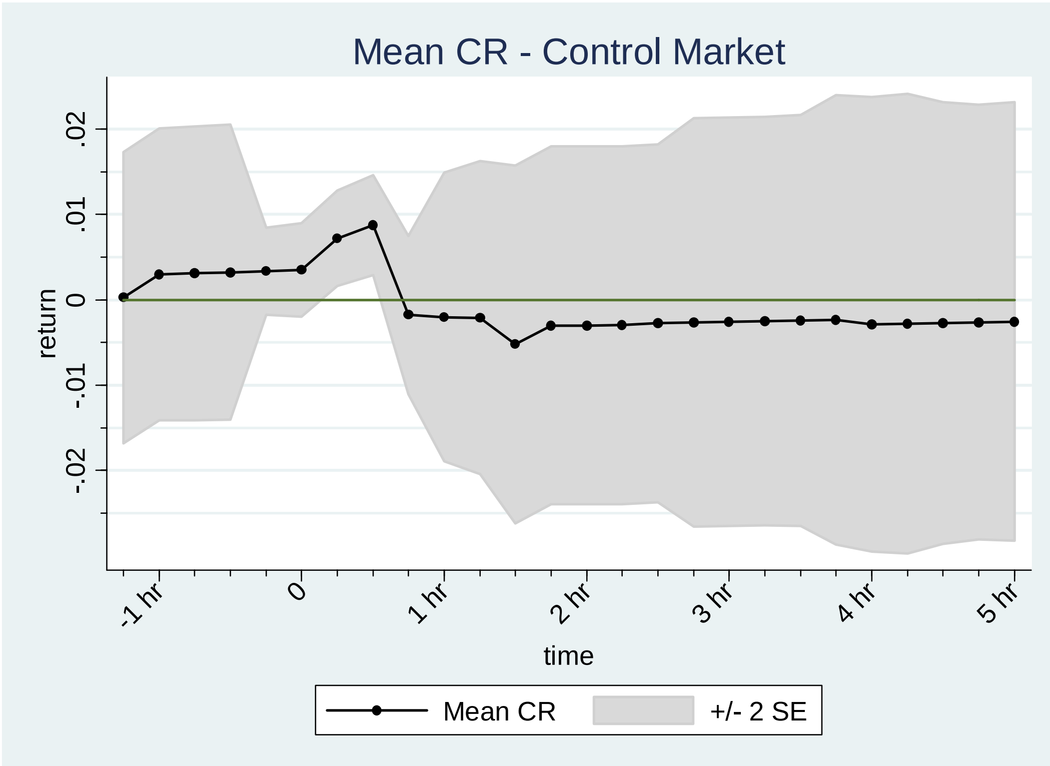


Figure 12: IEM 2000, Control Markets

(a) Mean CR (N=7)



(b) Mean CAR (N=7)

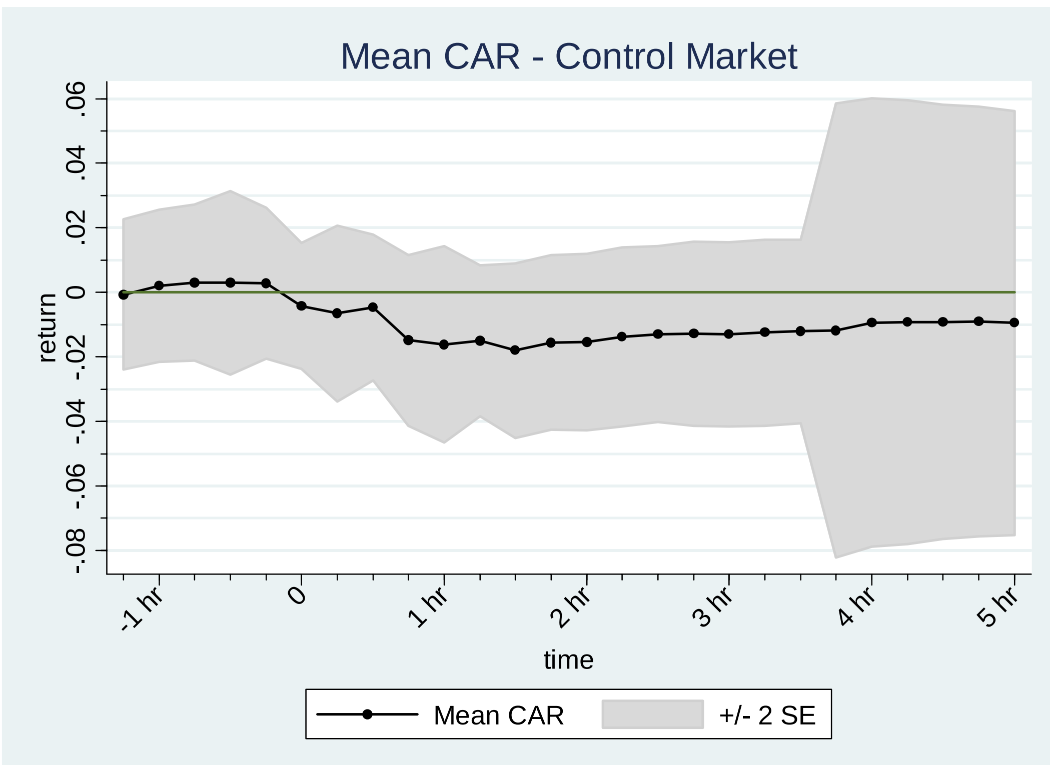


Figure 13: TradeSports 2004 US Presidential Market (Sept-Oct 2004 only)

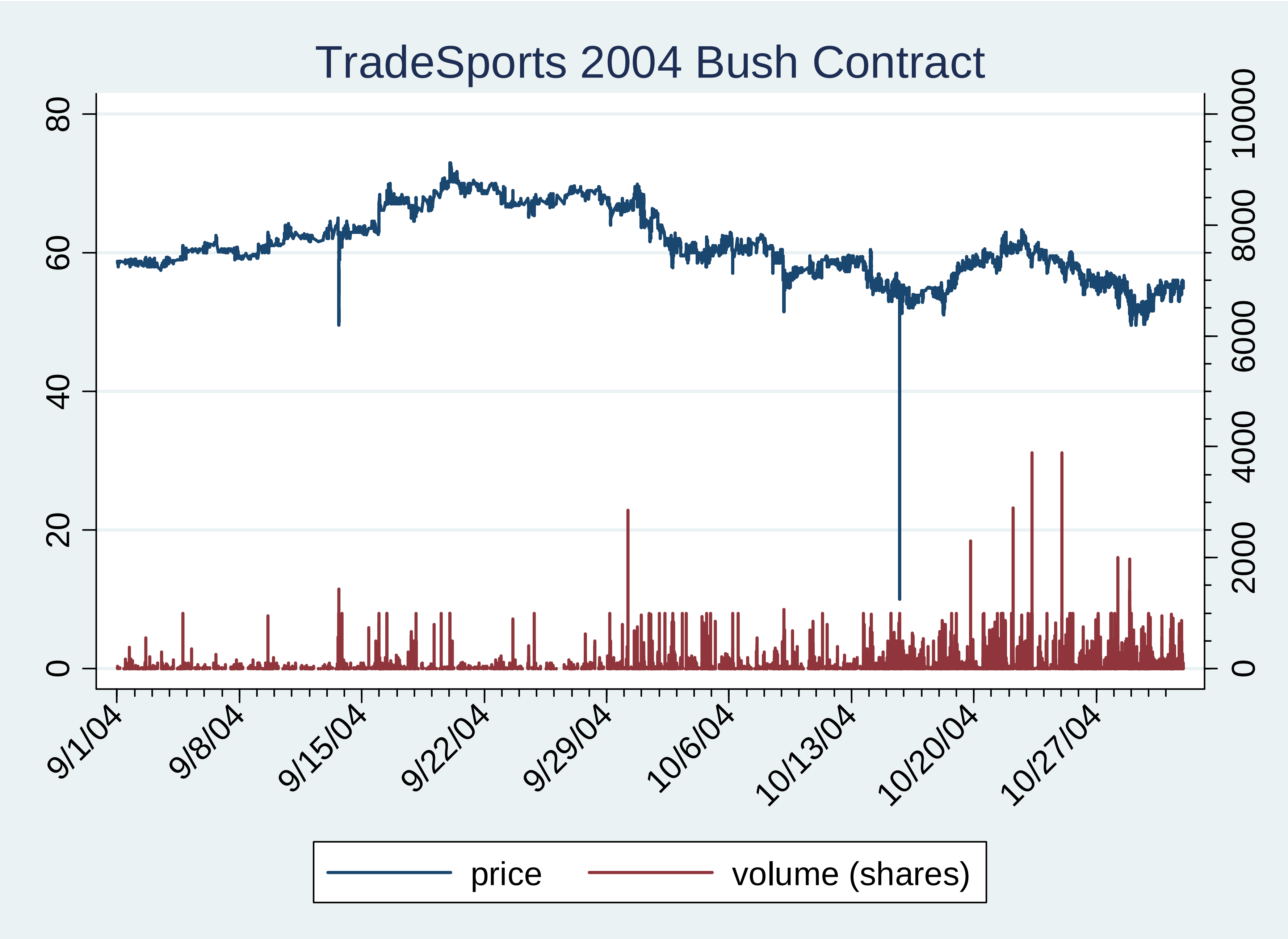
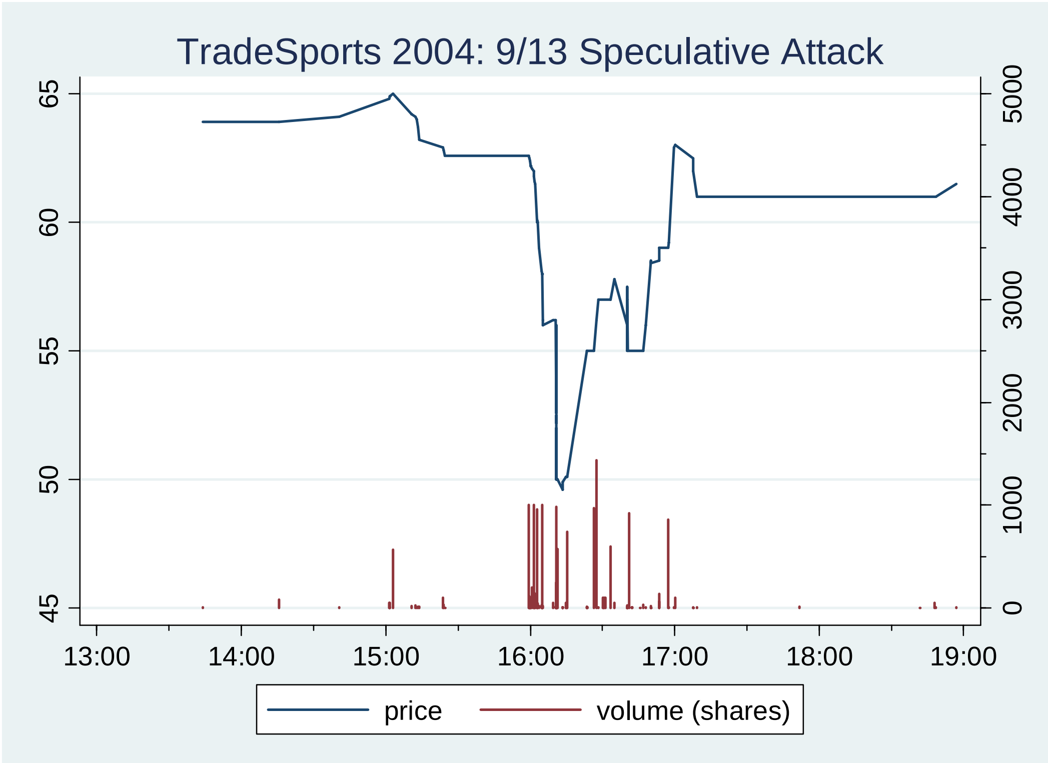


Figure 14: Speculative Attacks in *TradeSports* 2004



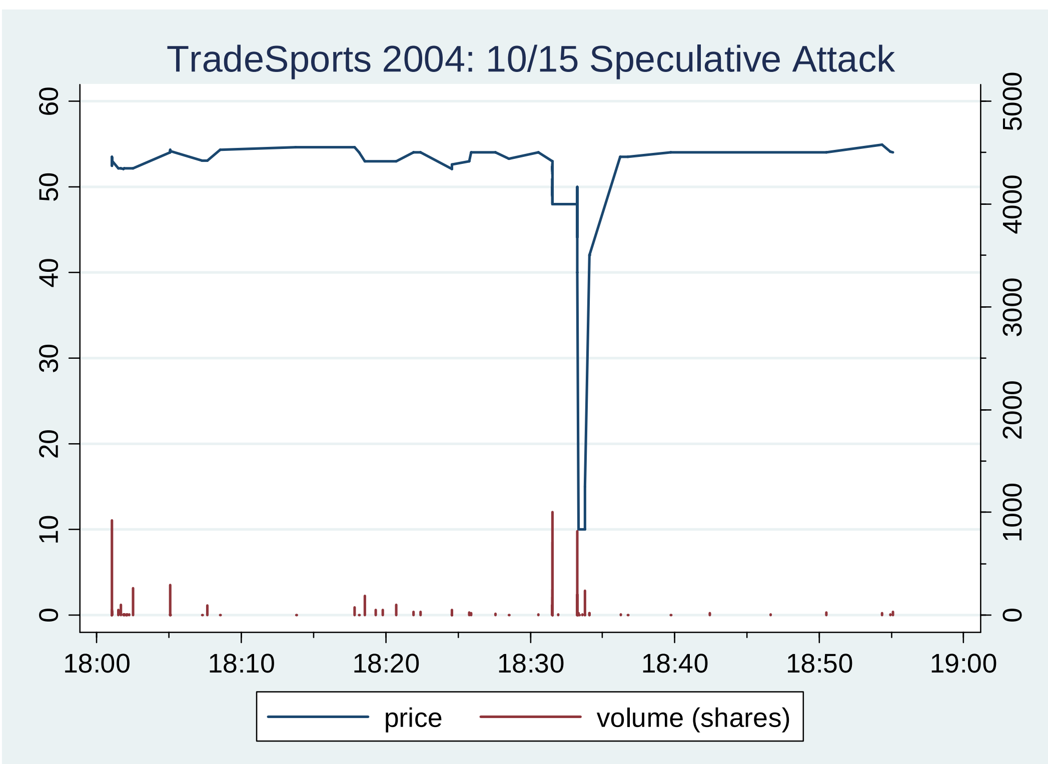


Figure 15: Cumulative Returns during Speculative Attacks in *Tradesports* 2004