

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

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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 the internet (2000-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 investigate the impact of actual and alleged speculative attacks—large trades, uninformed by fundamentals, intended to change prices—in political stock markets. First 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. We next 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. 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, 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. Our results potentially have implications for trader behavior in broader financial markets.

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I. Introduction

Prediction markets involve contracts which have 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. Such forecasts can be socially valuable if the market involves a topic of great importance.

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; Snowberg, Wolfers and Zitzewitz, 2007). 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, Best Buy, Corning, Electronic Arts, General Electric, Goldman Sachs, Google, Hewlett-Packard, Intel, Lilly, Microsoft, Siemens, and Yahoo! have set up internal prediction markets. Public prediction markets on current events, economic outcomes, and even the weather have become increasingly common as the internet has opened access to a growing number of on-line sites such as TradeSports-Intrade, Betfair, and News Futures. In political prediction markets alone, one-hundred thousand participants conducted over three million trades in 2006. The hope is such markets can aid forecasting and improve decision-making in economic policy, corporate project selection, and other areas.

Skeptics have advanced several theoretical challenges to the efficiency and predictive power of these markets. For example Manski (2006) 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. Responses include Wolfers and Zitzewitz (2005), Gjerstad (2005), and Ottaviani and Sørensen (2005).

A more damaging challenge to the forecasting ability of prediction markets is the possibility that investors could distort prices away from fundamentals for the strategic purpose of influencing the expectations and actions of others. Such manipulation is an inherent danger for prediction markets for several reasons. First, the potential reward

from a successful manipulation can far exceed the financial resources needed to implement it. Consider the case of political markets. The reported odds might influence the election if voters are unwilling to support a candidate who is faring poorly. Such changes in price require relatively small stakes (even big political markets attract volume in the tens of millions of dollars) but can shape a very large outcome (the federal budget involves trillions of dollars). As their visibly rises, prediction markets will likely become increasingly tempting targets for manipulators. A second issue is that insiders are not prohibited from trading in these markets. On-line services such as *TradeSports* or the Hollywood Stock Exchange do not explicitly ban insider traders and the Commodities Futures Trading Commission (CFTC) regulations permit such trading in future markets. So traders cannot be sure a seemingly inexplicable price change is the result of a manipulator or rather is the result of some new private information.

Theory aside, the potential for manipulation is often levied as a criticism of prediction markets. Stiglitz (2003) criticized the proposed Policy Analysis Market, a heavily publicized futures market on Middle East economic and military events, because it “could be subject to manipulation.” Such behavior is also an issue for internal corporate markets, with the organizer of Google’s market noting that he “repeatedly encountered concern about the potential for market manipulation from average employees as well as senior leadership” (Cowgill, 2006). At least one trader at Google later admitted to attempting to manipulate prices. .

Manipulation attempts are readily observed in the field. As a motivating example, consider movements in the price of shares for George W. Bush in the 2004 US Presidential election at *TradeSports*.¹ Figure 16 displays the price and volume during September and October. 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.

¹This was a large and influential market, attracting 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. *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.

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.”² 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.³ The press release asserted “Bush contract has become the battle ground of wills between a cadre of large, well financed rogue traders seemingly bent on driving down the Bush re-election contract and a growing list of financial traders who think they can predict the outcome of this election.”

In addition to the October 15 episode, the price of the “Bush Winner” contract also experienced a 13-point drop during a fourteen minute period around 12 pm EDT on Monday, September 13. Figure 17 shows the manipulation events in greater focus (Time in the figures is reported in GMT which is four hours later than EDT).

This paper investigates the open empirical question of whether manipulation causes important distortions in U.S. political prediction markets. We analyze speculative attacks, both alleged and actual, in three political stock markets: the 2000 Iowa Electronic Market (IEM) for President; the historical Wall Street betting markets for national, state, and city races; 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 Securities and Exchange Commission (SEC) cases regarding stock market manipulation 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

²Donald 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.

³“Bids and Offers,” *Wall Street Journal*, 22 Oct. 2004, p. C4; and “Let’s Make This Vote Interesting, Shall We?” *Time*. 25 Oct. 2004.

from both contemporary and historical prediction markets. We believe this breadth of approach substantially enhances the robustness of our findings.

Our analysis of these cases is framed in terms of a signal extraction problem. Market participants must determine whether a sudden price move, unaccompanied by fresh public news, is due to the trades of an uninformed manipulator or of an insider with private information. In practice both kinds of price innovations can be observed in political prediction markets. While we have already mentioned several examples of attempted manipulation, we can (ex post) identify likely instances of insider trading.⁴ The key point is that participants should respond differently to these two sources of price changes. If participants conclude it is due to an insider, prices should stabilize at their new level or even continue to move along on their new trajectory. Alternatively, a manipulation attempt should be viewed as a trading opportunity where prices deviate from their fundamentals, in which case prices should be shifted back to their initial level.

In each of the cases we study, the subsequent price moves are consistent with participants identifying the presence of uninformed manipulators. We find that the speculative attacks initially move prices, but these changes are quickly undone. The first 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

⁴One instance involves the TradeSports contract based on the tenure of Secretary of Defense Rumsfeld. Prices spiked up several days before he resigned, despite the repeated denials of President Bush and what a later *Washington Post* article showed was an absence of public release of information. The price change did occur around the time the resignation letter was submitted to the president. A second example occurred with TradeSport's contract on whether John Edwards would be the 2004 Democratic Vice Presidential candidate. There was a sharp price increase in this market ten hours prior to the public announcement of his selection. However, the price move occurred right when an aviation mechanic reported on an obscure aviation bulletin board that the Edwards name was being painted on the Democratic party campaign plane.

in a few hours. In the case of single market attacks, prices in the non-attacked market did not markedly move following our trades.

We next consider manipulation in the large historical political markets operating in New York City between 1880 and 1944. These markets involved millions of dollars in wagers on presidential, gubernatorial, and mayoral races and had a remarkable ability to predict the winner. Political operatives often made large investments in these markets, and the record is filled with accusations that certain trades were executed to make a candidate appear stronger than he really was. Interested parties associated with both Democrats (Tammany Hall) and Republicans (Wall Street) had war-chests which they employed for large attacks in these markets, with the goal of influencing undecided voters and turnout. While these speculative attacks are associated with a price change, prices return to near their pre-attack level within days.

The final cases we analyze are the two attacks in the 2004 *TradeSports* political stock market described above. 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.

Our results are innovative since it is difficult to study financial market manipulations using observational evidence. Most markets involve anonymous trading, so it is usually not possible to determine how many or which traders are the source of particular price movements. Similarly, it is usually not possible to describe a trader's information set, and so it is hard to determine whether he is a manipulator or an insider. All of this uncertainty makes it unclear which time periods or sets of trades should be studied. Our applications overcome these difficulties. In the field experiment, we know which trades to study and that they are fully uninformed. The historical markets are non-anonymous and we have detailed narratives on the names and motivations of the traders.

Our results also potentially shed light on broader financial markets. We investigate how traders respond to price spikes which are not accompanied by public news. Such price moves could stem from private information or noise. Engineering such episodes in stock or bond markets is not fiscally feasible (and illegal if it is deemed an attempted manipulation). To the extent that political stock markets are a suitable

microcosm for these more traditional financial markets, the results here suggest that traders can correctly identify non-informative price moves and therefore that successful manipulations will be difficult to execute.

II. Manipulation

a. Definitions and Literature

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 (we discuss the alternate definitions below).⁵ For the purpose of this study, *fundamentals* are any information that influences the underlying value of the contract. A *speculative attack* is defined as 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)⁶ 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

⁵These 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>).

⁶Consider 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.

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.

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.⁷ 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.⁸ 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

⁷Some 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.

⁸ 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.

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.⁹

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.

b. Models Allowing Successful Manipulation

A range of market microstructure models allow trade-based manipulation attempts to have long-term effects on prices under rational expectations. The common feature is information asymmetry, with some traders unsure whether there is an insider with private information.

Allen and Gale (1992) show that an uninformed manipulator may be able to profit by making a large purchase or sale which he then rapidly unwinds. In a pooling equilibrium an informed insider will make the same set of trades, and so the remaining traders will sustain the price move if their prior is that manipulators are uncommon. 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

⁹ 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.

empirical papers have documented the existence of trade-based manipulation in traditional financial markets.¹⁰

A second class of models involves all traders having private information. In this case 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).¹¹ 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). In this environment it may also be 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 are additional models in which manipulation may be possible. If there are multiple equilibria, 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 manipulation is possible when traders are not fully rational and exhibit behavioral biases (Mei, et al, 2004)

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

c. Comments on the Cases We Analyze

Before turning to the analysis, there are two comments about the cases we consider. First, our cases all involve episodic manipulation in which the trades (and in some cases supporting limit orders) are executed rather quickly. We do not consider the

¹⁰The 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).

¹¹While 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.

case of a deep-pocketed investor who continues to buttress prices for an extended period of time (weeks rather than days). While the latter case would of interest to study in future research, such sustained manipulation is more akin to a shift in the demand since it will involve significant increase in resources on one side of the market. We limit our attention to traders with some financial constraints.

A second note is 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.¹² Nonetheless, we test this possibility using postings in the *TradeSports* 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 B 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.

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 election futures using real money. In contrast to either the historical markets or

¹²First, 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 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).

TradeSports, 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. The market typically forecasts better than polls and passes many efficiency tests (Berg, Nelson, and Rietz, 2003).

IEM participants purchase contracts whose expiry payoffs are contingent on a future election outcome. Shares may be bought or sold at anytime via an anonymous and continually running double auction. A participant can either trade at the current best bid or ask, or can enter a limit order (an offer to buy or sell some number of shares at a particular price). Only limited information about the order book is observable, with only the best bid and ask price listed and no details on quantities. The only historical data available are daily summaries and the last traded price of each contract.

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). All contracts have expiration payoffs linked to three-party vote shares: each WTA share pays one dollar if the candidate receives the most votes and zero otherwise, while the VS payoff equals the candidate's vote share (prior to expiry, prices are constrained to the unit interval). For example in the 2000 presidential election the DEM candidate (Al Gore) received 49.9% of the three-party vote, the most of any candidate. Thus one share of DEM VS paid \$0.499 and one share of DEM WTA paid \$1. All other WTA contracts expired worthless. Note that (in contrast to both the historical markets and *TradeSports* presidential futures markets) the WTA is not based on the Electoral College winner.

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 1 charts the gyrations of the IEM WTA contract on the night of 7 November 2000 and morning of 8 November. According to the IEM contract definitions, Gore won the 2000 WTA. 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.

b. Experiment

In the four months preceding the 2000 election, we 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.¹³ 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.¹⁴ 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 privately informed insiders (and so prices did not revert).¹⁵ The next sub-section justifies our experimental design.

Figure 2 summarizes the size of our investments and the resulting change in prices (the next sub-section interprets these magnitudes). There were 11 planned trading episodes, roughly 10 days apart, starting 110 days before the election. The experimental design involved four types of trades: investing in the WTA contract alone; in the VS contract alone; in both the WTA and VS contracts; and selling all of our holdings. The

¹³The procedures are codified in official trade strategy document, which is available at <http://people.ku.edu/~cigar>. There was also an outside board which received this document prior to the execution of any trades.

¹⁴There was no attempt to manipulate the REF contract which had virtually no chance of getting a plurality (the leading third party in the 2000 election was the Green party, and the REF WTA contract was at \$0.005 a month before our trades began). In the analysis below, we normalize DEM and REP VS prices to be two-party shares, $\text{price}_{\text{DEM},t}/(\text{price}_{\text{DEM},t}+\text{price}_{\text{REP},t})$ and $\text{price}_{\text{REP},t}/(\text{price}_{\text{DEM},t}+\text{price}_{\text{REP},t})$.

¹⁵The 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

investments were made as follows. If the trade involved only 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. (This typically required multiple orders. At each order, we would instead buy the entire slate and sell 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. (Some of these did not trade, since the orders were set to expire two days after they were entered.) If the trade involved only VS contracts, the procedure was identical but for one-half the amount. When the trades involved both the WTA and VS, we used the amounts listed above and first completed the WTA orders (we planned to stop VS trades before the \$80 limit if prices in the two markets satisfied the equilibrium condition, but this constraint was never binding). Finally, we planned to sell all of our holdings in our second to last order (this was on 10/28 and involved \$566 in total).¹⁶ The initial trades and subsequent limit orders were typically executed in a 15-30 minute trading window.

The experiment was designed to exploit the existence of the two IEM presidential markets. As we described above, some investments were in one market only (VS or WTA) and others were in the two simultaneously. The reason for this is the two markets are linked to the same underlying fundamental, a candidate's final vote share. Under efficient markets, the VS price is the best estimate of a candidate's final vote total given the current available information while the WTA price is the best estimate as to the probability he will get a plurality of votes. There is an equilibrium relationship between the VS and WTA markets. Suppose that each day an iid news shock arrives which alters beliefs about the final vote totals. Under some functional form assumptions laid out in Appendix A, prices for a given candidate satisfy,

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

where “*” indicates an inverse normal transformation (used to transform prices, which lie on the unit interval, to the entire real line) and is σ_{vt} is a measure of uncertainty in final vote shares t periods before the election. Intuitively, the WTA price is higher when the

¹⁶Our trades deviated from the schedule twice. On 10/23 our limit orders could not be executed because of insufficient cash funds and the absence of shares to short in our portfolio. On 7/20, a trading mistake led to a reduced initial trade.

candidate is expected to receive more votes and (if this candidate is the favorite) when there is less uncertainty.¹⁷ An indirect piece of evidence in support of this equilibrium is that daily volume in the two markets has a correlation of 0.60. We use equation (1) in the analysis, investigating whether our trades upset the equilibrium relationship between the markets.

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. Under the first and second hypothesis, successful manipulations are possible. In the second case, investors incorrectly attribute our attacks to an insider and believe that there has been a change in fundamentals.¹⁸ Under the third hypothesis, our trades are correctly considered uninformative in which case it is difficult to successfully manipulate these markets. Table 1 summarizes the price dynamics following our trades under each of the three hypotheses.

c. Justifying the Experimental Design

It is important that our traders are uncertain whether the price changes we engineer are the result of a privately informed insider or rather are due to a manipulator. In this section we argue that our trades are comparable to actual cases of prediction market insiders and manipulators. Many of these cases are relatively high profile, and so should be familiar to well-informed prediction market traders.

Our trades created a sudden price move, unaccompanied by any public news, which we then sustain with supporting limit orders. Appendix C contains several examples of insiders and manipulators creating similar price changes in prediction

¹⁷An interpretation (2) using the untransformed prices is possible with a first-order Taylor approximation around one-half,

$$x^* \approx (x-0.5)/\varphi(0)$$

where $\varphi(0) \approx 0.399$ is the normal density evaluated at zero. So long as the election is close (both price^{VS}_t and price^{WTA}_t are in the neighborhood of 0.5), this can be applied to (2),

$$(2') \quad \text{price}^{\text{WTA}}_t \approx 0.5 + \sigma_{vt}^{-1} \times (\text{price}^{\text{VS}}_t - 0.5)$$

The WTA price is anchored at one-half, and is increasing in his expected vote margin (price^{VS}_t-0.5) Discounted by how much uncertainty remains (σ_{vt}).

¹⁸It 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.

markets. First, we discuss cases in which insiders create rapid price changes.¹⁹ Intuitively the insiders have time-sensitive information, and they must trade quickly to take advantage of it before others learn about it. For example, in one case traders knew that John Edwards was the Democrat's 2004 Vice-Presidential nominee several hours before it was announced. While this information allowed for profitable trades, it would clearly be valueless a short time later after the choice was made public. Consistent with this argument, prediction market prices respond rapidly to public information shocks.²⁰ Second, we show that manipulation attempts also involve price jumps. Manipulators want the other traders to believe there is an insider present, and so will implement price changes that mimic what an insider would do. This is precisely the strategy discussed in the theoretical models of market manipulation discussed earlier.

These cases aside, the main concern with our experiment is that traders might dismiss the possibility of an inside trader because of the limited financial stakes involved. We therefore tailored certain aspects of our trades to make insider trading appear more plausible. Our trades were always at night, starting at either 8 pm or 11:15pm CDT/CST. We selected this late evening schedule to make the possibility of insider trading appear more plausible. 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 non-public 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 an insider has fewer investing options during this time, since all of the traditional U.S financial markets are closed. Given the likely time-sensitive nature of any private information, the most profitable trading opportunity was likely the IEM. An insider trade

¹⁹There is also evidence that insiders engage in similar trading patterns in more traditional financial markets. Such evidence stem from SEC investigations of stock market insiders who trade based on material non-public information. Stock brokers who have advance warning of favorable news stories on certain stocks made rapid trades before the information became public (Fishe and Robe, 2004), and over a third of insiders who traded on advance knowledge of Anheuser-Busch's takeover of Campbell Taggart only made a single transaction (Cornell and Sirri, 1992).

²⁰The rapid response to news is evident in historical markets (Rhode and Strumpf, 2004), in contemporary markets (Snowberg et al, 2007), and in experimental prediction markets (Plott and Sunder, 1982). Specific examples illustrate this as well. During the 2004 Democratic primary the two main negative news stories involving John Kerry were his poor showing in the Wisconsin primary and an announcement that he had an affair with a former intern. In both cases, prices in the TradeSports Democratic nomination market responded rapidly: within a half-hour of the first public announcement of the Wisconsin primary outcome, Kerry's price fell from 89 to 72 and following the intern story Kerry's price fell from 92 to 72 (the latter story could not be corroborated and Kerry's stock returned to the mid-80's within three hours)

in the IEM is less plausible during the day, since a trader could instead invest in other thicker markets (many of the examples of insider trading discussed in the Appendix occurred at night).

We also set the size of our trades to be large enough to be noticed, but not so large that the resulting price movement would appear implausible. The trades in the 2004 TradeSports market discussed in the introduction were immediately recognized as a manipulation rather than an inside trade, because the price change was so anomalous. To avoid this, we never moved prices by more than what was observed on other days. Half of the days in which we did not trade had intra-day price ranges comparable to the average price change we engineered. But only a tenth had price ranges as large as the biggest which we caused. This suggests our largest trades were comparable in magnitude to the biggest observed stories during this election, such as the revelation a week before the election that Bush was charged with DUI in the 1970s. It is precisely the response to information like this which we are seeking to emulate.

Finally, the IEM's use of anonymous trading also helped lend credence to the possibility of insider trading. 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 others (but not him) know. The supporting limit orders which we place following our initial trades furthers this illusion, since it is consistent with the inside information propagating to additional traders.

d. Preliminary analysis

Table 2 provides some sense of the magnitude of each of the investments (Figure 2 graphs the trade volume, both the initial trades and the traded limit orders, as well as the price changes). Our trades were large relative to total trade volume. The third to fifth columns of Table 2 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 VS contracts involved 3.0 percent of the current market cap (listed in column 6) while the maximum for WTA contract was 2.7 percent. Note that the relative size of our fixed-sum trades declined over time, since the market cap grew. Each trading episode was also

large relative to daily trading volume. A typical episode trade represented about twice the average daily volume in the VS market ($=\$136/\66) and a third of the daily volume in the WTA market ($=\$271/\869).²¹

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 2. 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 3 illustrates the time path of prices following the 10/28 trades (notice that in the WTA traders undue the price change from our trades, but not those of the price drop preceding our trades). Figure 4 plots the last traded price each day along with markers of our trades. Prices tend to move in the direction of our 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 2). It is therefore important to show that our trades are not, by chance, reflecting changes in fundamentals. To do this we utilize prices from other prediction markets operating during the 2000 Presidential election. The first of these control markets is the Foresight Exchange (FX), an online futures market running continuously since 1996 and located at <http://ideosphere.com>. The FX has markets on a wide range of topics (current events, unresolved scientific questions, and finance), it has been used by companies such as Siemens, and it has an impressive forecasting record (Pennock, et al, 2001). Like the IEM, the FX is a double auction and the number of active traders is in the hundreds.²² Through a special agreement, we have access to trade-level data for the two FX markets

²¹The daily volume is based on the last 120 days before the election, the period during which our trades took place.

²²Other similarities include the trading platform (both markets accept limit orders but only show traders the best bid/ask in queue) and the demographics of traders. There are two differences with the IEM: the FX contracts were based on the Electoral College winner rather than popular votes, and the FX uses play money rather than real stakes. These differences are not likely to be important since the election night prices suggest the IEM traders believed they were trading based on the Electoral College, and the real-money stakes at the IEM are quite limited.

covering the 2000 presidential election. These data include price, quantity, and trader-id's for each transaction and cover the entire period these markets were open (04/97-12/00).

We also consider as controls prices from two internet sports bookmakers, Intertops (<http://intertops.com>, located in Antigua) and Centrebet (<http://www.centrebet.com>, located in Australia). These prices differ from the other sources in that they are set by the bookmaker, with customers able to take either side of the bet at the listed odds.²³ There are other differences from the IEM which makes these useful control markets:

- The monetary stakes were far higher, with no limits on bet size. over one million dollars was bet at Intertops while \$0.3m was wagered at Centrebet in just the last three weeks before the election
- The markets are isolated from the IEM (Centrebet prohibited U.S. bettors in 2000), so persistent differences in the prices are possible. In particular, it is unlikely that bettors will arbitrage price differences with the IEM
- Specifically with Centrebet, 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.

Through a special arrangement we received posted odds from these two books: for Centrebet the exact time and level of each price change over 10/23/00-11/7/00 (the entire period during which they offered odds) and for Intertops the prices which were offered each day over 7/1/00-11/7/00.

Table 3 compares prices in the IEM WTA and the three control markets (we do not include the IEM VS since there is no analogous control market). The top two panels show the tight connection between the IEM and the FX (see also Figure 5).²⁴ The left part

²³Bookmakers set and continuously revise odds on events, with the goal of attaining equal bet volume on all sides of the event. This suggests that prices will be comparable with those from the double auction market used at the IEM. As with FX, these markets were based on the Electoral Collage rather than popular vote winner.

²⁴The sample covers the three months preceding the election where we made trades (7/00-11/00). For each IEM observation, we match the most recent transaction price in the FX. In the regressions, we weight observations by the inverse number of other observations in a fifteen minute window to ensure each time period receives equal weight (we get similar results if instead we use the last price in each fifteen minute window). We follow a similar procedure for the other two control markets discussed below (the one

of Panel A shows that the mean DEM and GOP price are virtually identical in the two markets, and using a two-tailed t-test we cannot reject the null of identical means. However, this link is broken in the hour following our trades: when we bought Democrats or sold Republican shares, the IEM DEM price rose / IEM GOP price rose relative to the FX, and this difference is statistically significant. The opposite occurs when we made trades in the opposite direction. Panel B provides regression evidence. In the left panel we pool DEM and GOP contracts. The first estimate shows that we cannot reject the null that prices in the two markets are identical (the slope is one and the intercept is zero). The next estimate adds a term which is one in the hour after we traded in favor of this contract, negative one in the hour after we trade against this contract, and zero otherwise. The estimates indicate that our trades had a statistically significant effect on IEM prices: a pro-DEM / anti-GOP trade raises the DEM shares 3.3¢ in the hour after a trade and depresses GOP share by a similar amount. The third column includes an interaction between FX prices and the trade variable described above. This term has neither an economic or statistically significant effect, further suggesting that our trades are unrelated to changes in fundamentals.²⁵ The right panel repeats the estimates using just the DEM WTA contract and finds similar results.

Panel C considers the two internet sports books, Centrebet and Intertops. These estimates reinforce those for the FX. The Centrebet market was open for the three weeks prior to the election and overlaps with our last three trades. We again find that the prices are close to the IEM market, though the estimates are far less precise than with the FX (this in part reflects the relatively slow frequency with which internet books change their prices, as well as the shorter sample period). Relative to the Centrebet, the IEM prices are significantly higher in a market right we made purchases or sold in the complementary market. The Intertops prices also matched with IEM prices, though we cannot use these data to evaluate the impact of our trades since they are at a daily frequency.

*****TO ADD:**

difference is with the Intertops market; since this is daily data, we restrict the IEM data to the last traded price each day).

²⁵ As further evidence, we examined price spikes in the FX data. There were N=90 large changes in FX prices (10 points or more relative to the previous fifteen minute price) during the times when the IEM WTA was open. None of these changes coincided with our trades, though about two-thirds of them correspond to similar price spikes in the IEM.

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

There is one last point before turning to the main analysis. We need an estimate of the price dispersion term σ_{vt} from equation (1). Using a functional form assumption described in Appendix A, we have $\sigma_{vt} = \text{sqrt}(s_2^2 + s_1^2 \times (T-t))$ where $T-t$ =number days until election, and $s_i \geq 0$.²⁶ The estimates using daily data are listed in Table 4 (the equation is estimated using NLLS, and bootstrapped standard errors are listed since the error term is heteroscedastic and autocorrelated). Consistent with the equilibrium model, the constant is economically and statistically small. The terms in σ_{vt} are consistent across parties and also across elections. In all cases, most of the dominant term is the time invariant term. The estimates imply that a day before election, the vote share standard deviation is about 0.04. while one hundred days before the election it is about 0.05.²⁷

e. Results

We have eleven episodes of trades, which include fifteen attacks (four of the episodes involved both the VS and WTA markets). We employ a standard methodology, described below, to evaluate the economic and statistical significance of the resulting price changes. We aggregate the data from our eleven trades into fifteen-minute periods. 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,

$$(2) \quad R_t \equiv (\text{price}_t - \text{price}_{t-1}) / \text{price}_t$$

²⁶We also considered a non-parametric approach where we estimated a separate implied volatility measure for each day, $\sigma_{vt} = \text{price}_t^{\text{WTA}^*} / \text{price}_t^{\text{VS}^*}$. This approach proved infeasible since for several days $\sigma_{vt} < 0$, e.g. $\text{price}_t^{\text{WTA}^*} > 0.5$ and $\text{price}_t^{\text{VS}^*} < 0.5$.

²⁷Using a linear Taylor approximation $\text{StdDev}(p^{\text{VS}}) \approx \phi(0)\text{StdDev}(p^{\text{VS}^*})$ and $\phi(0)=0.4$.

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, and so allow us to combine data from the different markets (WTA, VS) and contracts (DEM, GOP). The cumulative return at time t of an investment made at time t_{min} is,

$$(3) \quad CR_t \equiv \sum_{s \geq t_{min}} R_s$$

We will start the calculation an hour prior to the start of each trade ($t_{min}=-4$).

Our main objective is to see whether the average CR_t over some set of trading episodes differs from zero. To determine statistical significance, we use,

$$(4) \quad \text{Var}(CR_t | \Omega_{t_{min}}) = \text{Var}(\sum_{s \geq t_{min}} R_s)$$

where $\Omega_{t_{min}}$ is the information set at t_{min} . This dispersion will typically grow as the horizon t is increased. To generate confidence intervals from (4) we need a measure of $\text{Var}(\sum_{s \geq t_{min}} R_s)$, or intuitively to establish the counter-factual of what prices would be in the absence of our trades. We use the FX market which the last sub-section shows has prices which are tightly linked to those in the IEM (a previous version of the paper used IEM prices a day prior to our trades, and the results are similar).²⁸ We first calculate the CR from the FX market over each of our trading periods. Our measure is based on the variance of these CR's after accounting for the smaller dispersion in the VS market. We use,

$$(5) \quad \text{Var}(\sum_{s \geq t_{min}} R_s) = \text{Var}(I(WTA) + \sigma_{vt}(1-I(WTA)) \sum_{s \geq t_{min}} R^{FX}_t)$$

where $I(WTA)$ is an indicator that this trade involves a WTA market and $\sigma_{vt} < 1$ accounts for the reduced dispersion in the VS market.²⁹ Since we only have a fitted value of σ_{vt}^2 ,

²⁸One potential problem, not ruled out in the earlier regression, is that the volatility of ROR's are different in the two markets (this is important since our goal is use volatility in the FX market to form confidence intervals for the IEM). But when we look at times away from our trades (at least three hours before and one day after), the observed volatilities are quite similar: $\text{StdDev}(R^{IEM})=0.0084$, $\text{StdDev}(R^{FX})=0.0076$.

²⁹Both the FX and WTA are winner-take-all markets. The VS market has a smoother payoff and so a smaller variation. To show this substitute the linear Taylor approximation $p_t^* \approx (p_t - 0.5)/\phi(0)$ into the rate of return formula.

$$R_t \approx (p_t^* - p_{t-1}^*) / (p_{t-1}^* + (2\phi(0))^{-1})$$

The equilibrium relationship between the IEM markets is, $p_{WTA,t}^* = p_{VS,t}^* / \sigma_{vt}$. For the high frequency data we consider $\sigma_{vt-1} \approx \sigma_{vt}$. Substituting these equations into the formula yields,

$$R_{VS,t} / R_{WTA,t} \approx (p_{VS,t-1}^* + \sigma_{vt} / (2\phi(0))) / ((p_{VS,t-1}^* + 1 / (2\phi(0)))$$

we bootstrap this equation using the equilibrium equation estimated in Table 4. Using equations (4) and (5), we can 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 (roughly a ninety-five confidence band).

We begin the analysis by considering all of our market attacks. Figure 6 shows the average CR for the full set of eleven trading episodes, which include fifteen attacks. The figure plots CR values and their associated confidence intervals for the first four and a half hours after the trades. There is little trend in the return for the hour 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 and a half hours (and the effect is no longer statistically different from zero). The CR returns to zero within twelve hours (figure omitted). The relatively rapid unwinding of the attacks is impressive given that they occur during low volume periods, as discussed earlier.

We next consider various subsets of attacks. Figure 7 shows the average CR for the seven episodes in which only one market is attacked (four WTA-only and three VS-only attacks). In the WTA trades the returns spike up even more sharply following the attack, with a six 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 four 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 ten hours, reflecting the relatively low activity in this market (see the market caps listed in Table 2), at which point prices return to their initial level. We do

This can be further simplified using the condition $p_{VS,t}^* \approx 0$ which is needed for the linear approximation to be valid,

$$R_{VS,t} \approx \sigma_{vt} R_{WTA,t}$$

and so,

$$\text{Var}(R_{VS,t}) \approx \sigma_{vt}^2 \text{Var}(R_{WTA,t})$$

Note that $\sigma_{vt}^2 \ll 1$ based on the estimates described in the last subsection.

not read too much into this slow reversion, given the small levels involved and the lack of statistical significance.

Figure 8 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 seven percent increase in the CR in the first half hour. Prices continually revert for the next four and half hours until they are no longer statistically different from zero (the average CR returns to zero after twenty-four hours).

Figure 9 shows two sets of trading episodes in which the CR reverts to zero more slowly. When both markets are attacked, the positive CR effect levels off at about one and a half 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 bottom panels shows that the CR slowly reverts when the trial involves a purchase of Democrats and/or a sale of Republicans (the CR returns to zero after a day). The explanation for this case is less obvious and may reflect some partisan sentiment.³⁰ Still it is worth stressing that our trades were eventually fully undone.

Figure 10 presents results for the control market in single market attacks (the control market is the market—VS or WTA—in which we did not trade). While the VS and WTA are linked by the equilibrium condition in (1), prices in the non-attacked control market should not move if market beliefs are unchanged. The top panel 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 less than one percent). Moreover, the CR becomes negative (and still small) within forty-five minutes at which point we have already seen the returns are still positive in the attack market.

³⁰It is important to note 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).

The bottom panel 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. We first calculate the normal price based by inverting equation (1), for WTA price $\text{price}_{t-1}^{\text{Normal}} = \Phi(\sigma_{vt}^{-1} \times \text{price}_{t-1}^{\text{VS}*})$ and for VS price $\text{price}_{t-1}^{\text{Normal}} = \Phi(\sigma_{vt} \times \text{price}_{t-1}^{\text{WTA}*})$ where $\Phi(\cdot)$ is the standard normal distribution. These can be used to calculate the normal rate of return at time t,

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

In analogy to equation (3), the cumulative abnormal return at time t of an investment made at time t_{\min} is,

$$(7) \quad \text{CAR}_t \equiv \sum_{s \geq t_{\min}} (R_s - R_s^{\text{Normal}})$$

The standard errors can be calculated from a formula analogous to equation (5), which again must be bootstrapped since it involves the fitted parameter σ_{vt} . The bottom panel shows that the CAR for the control market becomes negative right after the attacks and then starts to revert to zero (it fully reverts within ten hours). This pattern is the roughly a mirror image of the CR for the attacked market in Figure 6.³¹ 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 trading episodes 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

³¹The comparison is even clearer when the attack market CR is graphed for single market attacks.

traders. In total, these results suggest that the long-term market dynamics were not influenced by uninformative trading.

IV. The New York Betting Market, 1880-1944

a. Context

We now explore the impact of manipulation in the large markets for election betting centered in New York City between 1880 and 1944 (Rhode and Strumpf, 2004; 2006). Participants wagered on national races as well as on state and local elections. In the era before scientific polls, the leading newspapers intensively reported movements of the betting odds, providing nearly daily quotes from early October until Election Day. These historical markets are of special interest because partisans, including Democratic and Republican operatives, actively and publicly traded. Accusations of manipulation and staged bets were rife.

In contrast to our investigation of the IEM, we are outsiders rather than insiders. We can not observe the actions and motives of the potential manipulators, only timing and price movements associated with public charges of speculative attacks. Nonetheless, examining these historical episodes promises to shed substantial light on similar accusations in modern-day prediction markets.

The structure of the historical betting markets evolved over time.³² Although it was on the borderline of legality, election betting was openly 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 and the Curb Market and the several uptown hotels. The standard practice was for a “betting commissioner” to hold the stakes (or signed agreements) of both parties, charging a five percent commission on the winnings. During the market’s heyday in the late 1890s and early 1900s, the names and four-figure stakes of bettors filled the pages of New York’s

³²Moving 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.

daily newspapers. Unlike today's markets, betting in Old New York was not anonymous. The stories may have served to advertise the political affiliation of the bettors as well as to confirm the existence of the wagers.³³ Tammany Hall, the New York City Democratic machine, purportedly had a special war chest to finance its wagering.³⁴

Compared with modern prediction markets, the betting volume in the historical New York market was huge. Figure 11 assembles estimates from selected newspapers of the sums wagered in the New York market from 1884 to 1928, converted to year 2000 purchasing power.³⁵ The betting volume varied depending the race,, 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.³⁶ The average bet volume for the 25 elections appearing in the figure was roughly \$22 million (in 2000 purchasing power). As a point of contrast, trading volumes on the IEM for the 1988-2000 elections never exceeded \$0.15 million in any one contest (see Berg, et al, 2003).

The Wall Street betting market was noted for its 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'."³⁷ Rhode and Strumpf (2004) shows 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

³³ 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.

³⁴ SOURCE. But Tammany famously did not keep written records of its activities.

³⁵ 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 that the betting volumes in 1932 and 1936 were higher than in 1928.

³⁶ The ratios were on the order of 100:39:37. *New York Times*, 3 Nov. 1924 p. 2 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.. 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.

³⁷ *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.

there is a decisive winner, the markets correctly forecast the next president as early as four months prior to the election. 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.”³⁸ The odds were “generally considered the best forecasters of Presidential elections,” as well as “good indicators of probable results in gubernatorial and Mayoralty results.”³⁹ Rhode and Strumpf (2006) provides further details on the predictive capacity of these markets in all three types of elections.⁴⁰

Contrary to these assessments were the frequent assertions that active partisan involvement, especially by Tammany Hall, systematically distorted the betting odds. As one example, in closing days of 1926 race for the NY Governor, supporters of Republican Ogden Mills charged that Tammany Hall was using election wagers as “indirect propaganda” for Al Smith.⁴¹ At other times, charges circulated that Republican brokers on Wall Street financed 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.’”⁴²

While there are a variety of reasons for the partisans’ entry into the political betting markets, the primary goal was to sway public opinion, alter the momentum of the race, and affect voter turnout. 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.

³⁸ *Wall Street Journal*, 27 July 1920, p. 11.

³⁹ *Wall Street Journal*, 17 Aug. 1925, p. 5. See also 27 July 1920, p. 11; 29 Sept. 1924, p. 13.

⁴⁰ We show that the markets were not fully efficient and suffered from long-shot bias, a typical shortcoming of prediction markets.

⁴¹ *New York Times*, 17 Oct. 1926, p. XX10.

⁴² *Washington Post* 5 Nov. 1916 p. 1.

b. Our Data on Manipulations

To analyze the impact of manipulation, 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 includes 4302 daily odds price quotes for 142 candidates in 52 contests: 16 Presidential elections (1880-1944); 22 Gubernatorial elections (1888 -1936), and 14 Mayoral races (1884-1937).⁴³

We investigate whether episodes associated public charges of manipulations induced long-lasting prices movements unwarranted by the fundamentals. Given the available information, 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. Unlike our investigation of the IEM, we are outside observers. To identify the relevant events, we have surveyed the leading New York daily newspapers and classified the “manipulation” stories into two categories: (a) charges of intentional manipulation with investors betting to drive odds prices away from the levels justified by fundamentals; (b) charges of wash bets --those made between confederates at non-market odds for publicity purposes-- and of bluffs-- offers to make bets at non-market odds which are withdrawn when the offer is accepted. 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 12 gives an example of the manipulation charges as well as the names, dates, and amount of larger bets.⁴⁴

⁴³ 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.

⁴⁴ 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

We first provide a general description of these trades and then return to the question whether these were in fact manipulation attempts.

Table X provides summary statistics regarding the timing and market conditions prevailing when charges of manipulation and bluffs occurred. It provides a breakdown between democratic and republican events and examines all races and presidential contests only. We identify 46 charges of manipulation/wash sale/bluffing events: 19 charges of full-blown manipulation, 11 raising the Democrat's odds price and 8 the Republican's. 11 involved presidential races with the remainder on state and local races. Note that Republican events occur almost exclusively in the presidential contests, implying the analysis can be combined. In general, the accusations of manipulation occur in the direction of the favorite. As examples, when Democratic manipulation in the presidential race is charged, the Democratic candidate has, on average, an odds price of 0.58; when a Republican manipulation is charged, the price on the democrat is only 0.22. This effect remains true if we examine odds several days before the charged events (to avoid potential contamination). The Democratic odds prices three days before the democratic and republican manipulation in the presidential market are 0.54 and 0.30, respectively. Republican bluffs also tend to occur when the democrat is the underdog, although the effect is not as pronounced. Only Democratic bluffs – the so-called Tammany trick— deviate from this pattern. These occur in presidential races when the Democratic candidate is given, on average, about a one-third chance of winning.

The manipulations and wash bets/bluffs occurred at widely-scattered times, from election day to over three months before. The median manipulation event, in both presidential and all races, was 4 days before the election, that is, on the Friday before the election. The median wash bet/bluffs occurred 7 days before Election Day. For all races, the manipulations were concentrated on Mondays (6 events) and Fridays (5) with 8 on all other days of the week. There were no identifiable differences between political parties regarding this aspect of timing.

occur on only about 2 percent of days with reported betting odds. One reason that charges were not made more frequently is that the election cycles represented repeated games and the making unsubstantiated charges of manipulation would adversely affect one's reputation and the creditability of one's future charges.

Table X: Timing and Direction of “Manipulation” Events

		Obs	Dem Odds Price		Min	Max	Days Before Election			
			Mean	Std. Dev.			Mean	Std. Dev.	Min	Max
All Races										
	Manipulation									
	Dem	11	0.569	0.209	0.279	0.862	9.7	11.7	0	33
	Rep	9	0.249	0.180	0.059	0.467	5.3	4.8	1	15
	Bluff									
	Dem	22	0.465	0.182	0.157	0.871	8.7	7.2	1	26
	Rep	5	0.430	0.259	0.132	0.715	30.6	40.9	4	103
Presidential Races Only										
	Manipulation									
	Dem	3	0.581	0.200	0.435	0.809	20.3	14.8	4	33
	Rep	8	0.222	0.172	0.059	0.443	5.9	4.9	1	15
	Bluff									
	Dem	7	0.331	0.166	0.157	0.518	7.3	4.7	3	16
	Rep	4	0.359	0.236	0.132	0.615	35.0	45.8	4	103

An important challenge is whether these accusations were in fact manipulation attempts. For example, they could just be sour grapes as partisans trying to rationalize unfavorable movements in prices or they could be attempts to encourage bettors to move the market in the other direction. There are several pieces of evidence suggesting this is not true. First, it is inconsistent with the prior direction of price moves. Under the alternate theory, price changes remain informative and reflect newly arrived information. Since most accusations were made near the election, these price changes should tend to be in the direction of the eventual winner. But in the table below no such pattern is evident.

Accusation	Election Outcome	
	DEM lose	DEM win
Dem manipulation	4	7
Rep manipulation	5	3
Dem bluff	13	9
Rep bluff	3	2

A second piece of evidence comes from attempting to forecast the manipulation accusations. If these accusations are made under certain market conditions, then it should be possible to predict when they occur. For each of the four kinds of manipulations, we fit a logit model where the dependent variable was whether a manipulation occurred and

the explanatory variables were the number of days until the election, the price that day, the rate of return from the previous day (reflecting price changes), and indicators for Mondays and Fridays. The parameters conform to the cross-tabs above, e.g. a negative parameter on number of days until the election and typically a positive. shows, there are a large number of false positives

*****TO ADD:**

Parameter estimates from logit***

We use these parameter to fit the likelihood any day will have a manipulation accusation. We use as our cutoff the mean forecasted value among the days with an actual accusation. As the table below show, there are a large number of false positives.

Accusation	Number of events	Number of other forecasted days
Dem manipulation	11	122
Rep manipulation	8	27
Dem bluff	22	258
Rep bluff	5	28

A third piece of evidence against is that many other large price increases were not labeled as manipulations. While it was easy to make these charges, they were rarely made. If levying an accusation was done to reverse previous large price changes, this is hard to understand. We used the rate-of-return calculations to determine if our events were simply very large price movements. The Democratic events were not generally associated with exceptional price movements. The Republican events were associated with significant price movements, but days with comparable changes were 17-19 times as frequent as these events. (Focusing on the period two weeks before the election, the average rate-of-return of the democrat stock on the first day of the 6 relevant Republican manipulations was -6.6 percent. In our sample, there were 70 days in this near election period when the democrat stock experienced negative rate-of-return movements of equal or greater magnitude and yet no manipulation charged appeared in the press.)

c. Analysis of Manipulation

We investigate the separate effects of the Republican and Democratic “attacks” on the “Democrat’s price.”⁴⁵ To control for differences across the races, we include election-specific dummy variables. Given that the events often occur close to the election, we 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.) A purported attack is dated to one day before the newspaper allegation is published, in line with the odds quoted 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 5 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,

$$(8) \quad \text{Demprice}_{it} = \sum_s \alpha_s I(t=s)I(\text{DemM}) + \sum_s \beta_s I(t=s)I(\text{RepM}) + \sum_s \gamma_s I(t=s)I(\text{DemWB}) + \sum_s \delta_s I(t=s)I(\text{RepWB}) + v_i + \varepsilon_{it}$$

We estimate the impact of a Democratic manipulation s days away from the action (α_s), the impact of a Republican manipulation (β_s), the impact of a Democratic wash/ bluff (γ_s), and the impact of a Republican wash/bluff (δ_s), all while controlling for election fixed effects (v_i). We consider these impacts roughly a week before and after each event ($-7 \leq s \leq 5$). As a consequence, we will focus on the impact of manipulation events. These impacts may be more easily visualized by examining Figures 13-15, which shows the movements in the “Democrat” odds prices as well as the error bounds.

⁴⁵ 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).

Figure 13 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 14 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 15 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, lasting 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.

V. *TradeSports* 2004 Presidential Market

We now return to exploring the alleged manipulation of the *TradeSports* president market in 2004. Through a special agreement, *TradeSports* provided access to real-time trade data on the quantity and price (though not identity of the traders) of every transaction for this market from its opening in June 2003 to the election day. Figure 16 displayed 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 13-point drop during a fourteen minute period around 12 pm EDT on Monday, September 13. Figure 17 puts the manipulation events in greater focus (Time in the figures is reported in GMT or four hours later than EDT). These price spikes are difficult to reconcile since large price changes in *TradeSports* can usually be associated with the arrival of news.⁴⁶ And while *TradeSports* prices typically closely track those at Betfair (another large online political stock market), the markets were not in sync during these episodes.

****ADD:**

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

Table 6 summarizes the key results from our analysis of the two alleged attacks. 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 6, were

⁴⁶The IEM section gives two examples in which public information results in rapid price changes. Private information can also lead to price spikes. 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.

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 during 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. The last row of Table 6 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.⁴⁷ Figure 18 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

⁴⁷One difference is that we use the following formula to calculate the rate of return,

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

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

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 18 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 ($t=14$).⁴⁸

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

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. If manipulation were possible, prices would neither aggregate information nor would they serve as a useful forecasting tool. 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 Iowa Electronic Market in 2000, the historical Wall Street betting markets, and the 2004 *TradeSports* market for President. In almost every speculative attack prices

⁴⁸ 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 an attack. Using all trades over the last three months prior to the election, we cannot reject $H_0: \alpha_2, \beta_2 = 0$ for either of the attacks. This suggests that neither set of trades had a permanent effect on the rates of return.

experienced measurable initial changes. However, these movements were quickly reversed 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 differs from 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 numerous 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).

Yet it is not possible to claim that manipulative attacks such as those at *Tradesports* in 2004 were failures, at least, if the goal was to attract media attention. The second attack (15 Oct 2004) 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.

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

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

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

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

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

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

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

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. Using (A3) this implies $\text{price}_t^* = \text{VoteShare}_t^* / \sigma_{vt}$.

Vote Share Market

Equation (A2) gives the law of motion for vote shares. Under efficient markets a market for vote shares should be priced based on the best current estimate of the final vote totals, $\text{price}_t^{\text{VS}} = E(\text{VoteShare}_T | \Omega_t)$. Using equation (A2) and applying the inverse normal transform this means $\text{price}_t^{\text{VS}*} = \text{VoteShare}_t^*$. Combined with the last result of the previous section, this can be used to determine the relationship between efficient prices in a winner take all and vote share market,

$$(A4) \quad \text{price}_t^* = \text{price}_t^{S_t^*} / \sigma_{v_t}.$$

A Functional Form for σ_{v_t}

Since we will utilize the equilibrium condition (A4) it is necessary to impose some structure on σ_{v_t} . We presume that each day prior to the election is expected to bring a comparably sized news shock, but that there is still some residual uncertainty remaining on election day. Formally this means $\sigma_{s_t} = s_1 \forall t \neq 0$ and $\sigma_{s_T} = s_2$ or

$$(A5) \quad \sigma_{v_t} = (s_1^2(T-t) + s_2^2)^{0.5}$$

where 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).

Section B. 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.⁴⁹ 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 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

⁴⁹To 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").

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.⁵⁰

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 B.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 obtain 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 B.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 B.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 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.

⁵⁰Consistent 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.

Table B.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
$\Delta Price_{last\ hour}$	-0.499 (0.09)	-0.613 (0.09)	-0.244 (0.21)	-0.484 (0.07)	-0.589 (0.08)	-0.237 (0.21)	-0.208 (0.05)	-0.292 (0.06)	-0.097 (0.06)
$\Delta Volume_{last\ hour}$	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.001)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.001)	-0.0003 (0.0002)	-0.0004 (0.0003)	-0.0001 (0.0002)
NewsStory	1.124 (1.02)	1.917 (1.02)	---	1.095 (1.00)	1.914 (1.00)	-13.884 (0.24)	0.170 (1.01)	1.073 (1.01)	-39.030 (0.22)
constant	-5.233 (0.08)	-6.045 (0.12)	-6.187 (0.13)	-5.191 (0.08)	-6.019 (0.12)	-6.157 (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 = $\Delta Price$, $\Delta Volume$)

	OLS $\Delta Price$			OLS $\Delta Volume$		
$I(Message)_{last\ hour}$	0.104 (0.13)	---	---	11.476 (23.88)	---	---
$I(Buy\ Message)_{last\ hour}$	---	0.012 (0.126)	---	---	-15.145 (44.55)	---
$I(Sell\ Message)_{last\ hour}$	---	---	0.312 (0.33)	---	---	26.160 (31.20)
NewsStory	-0.049 (0.16)	-0.047 (0.16)	-0.047 (0.16)	136.747 (73.77)	137.139 (73.78)	136.944 (73.76)
$NewsStory_{last\ hour}$	-0.635 (0.11)	-0.636 (0.11)	-0.636 (0.11)	-173.816 (60.16)	-174.029 (60.16)	-173.880 (60.16)
Constant	0.004 (0.003)	0.005 (0.003)	0.004 (0.003)	0.084 (1.15)	0.192 (1.15)	0.095 (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.

Section C. Insiders and Manipulators in Real-World Prediction Markets

This Appendix shows that insiders and manipulators in real world prediction markets both engineer rapid price changes similar to those we create in the 2000 IEM.

As with more traditional financial markets, it is difficult to know when manipulators or investors with private information are participating in the market (this is consistent with the framework in Section II, since other traders also face the same detection problem). But there are two instances in which we can be reasonably confident that insiders are present: when evidence becomes available ex post and when there is commentary from market analysts. We consider examples from both these sources below.

We begin with insiders. The cases we study are summarized in **Figure C.1**. The first panel shows Intrade's 2006 market on whether Defense Secretary Donald Rumsfeld would resign. Rumsfeld publicly announced his resignation on 8 November, the day after several high profile Senate elections. The Intrade contract, however, spiked up the weekend before and stabilized about 15 points higher; there were no comparable price jumps during the contract's history. A later news story revealed this was around the time the resignation letter was written, though it was closely guarded and only a few people saw the letter prior to the official resignation announcement (*Washington Post*, "Rumsfeld Resigned as Defense Secretary on Day Before Elections," 16 August 2007). The price move was likely due to trades by one of these insiders, or their confederates.

The second panel shows TradeSports' 2004 market on whether John Edwards would be selected as the Democratic Vice-President. Prices in this market spiked up 40 points over five hours prior to the official announcement of his nomination. Not only was there no public announcement during this period, the *New York Post* incorrectly reported on their cover and their online site at this time that Richard Gephardt was selected. However, a mechanic reported on an aviation enthusiast website, usaviation.com, that Edwards name had been painted on the Democrat's presidential campaign plane. It seems likely that this was the source of the price rise, since it was posted right around when prices began to change.

A third example of inside trading was TradeSports' market on whether Harvard President Lawrence Summers would resign. Prices increased 20 points and then stabilized at 10 points higher six hours prior to the first public announcement of his resignation (the story appeared on the *Wall Street Journal's* webpage and the timing was confirmed with blogger Richard Bradley). However, reports leaked from the Harvard Crimson circulated on various internal Harvard listservs during the time when prices increased (cambridgecommon.blogspot.com, 20 February 2006).

The last example of inside trading is Intrade's market on who would be nominated in Fall 2005 to the Supreme Court of the United States. Following the withdrawal of Harriet Miers on 27 October, there was significant uncertainty as to who President George Bush would select. Indeed, there were several reports that three candidates were being considered on Monday 31 October, the day when Samuel Alito was officially selected (*Washington Post*, "President to Name Nominee for Court," 31 October 2005). The graph shows that Alito's price spiked three days earlier, in two sets of 20 point jumps before stabilizing 30 points higher. Several blogs noted these price moves the day they occurred and concluded they were the work of an insider since there was no public news about the nomination that day (*Daily Kos*, 28 October 2005; *Business Law Blog*, 29 October 2005).

Figure C.2 presents market activity from known cases of manipulation. While these cases are all based on third party reports, in each case we discussed the price moves with a trader or market manager with first hand knowledge of the manipulation. The first example is from the TradeSports market on the 2004 Presidential Election winner. This case is discussed extensively in the Introduction. The second example involves Google's internal market, and this case is discussed in the Conclusion.

The final example of manipulation is from the 1996 Republican nomination market at the IEM. In February 1996, Pat Buchanan's website asked members of "Buchanan Brigade" to help the candidate through trading at IEM (personal correspondence from Buchanan site administrator Linda Muller, 13 December 2007). At the end of that month and a week after Buchanan's surprise win in the New Hampshire primary, a single trader lifted the price of Buchanan shares by a fifth within a single day. The price change was completely undone late that day.

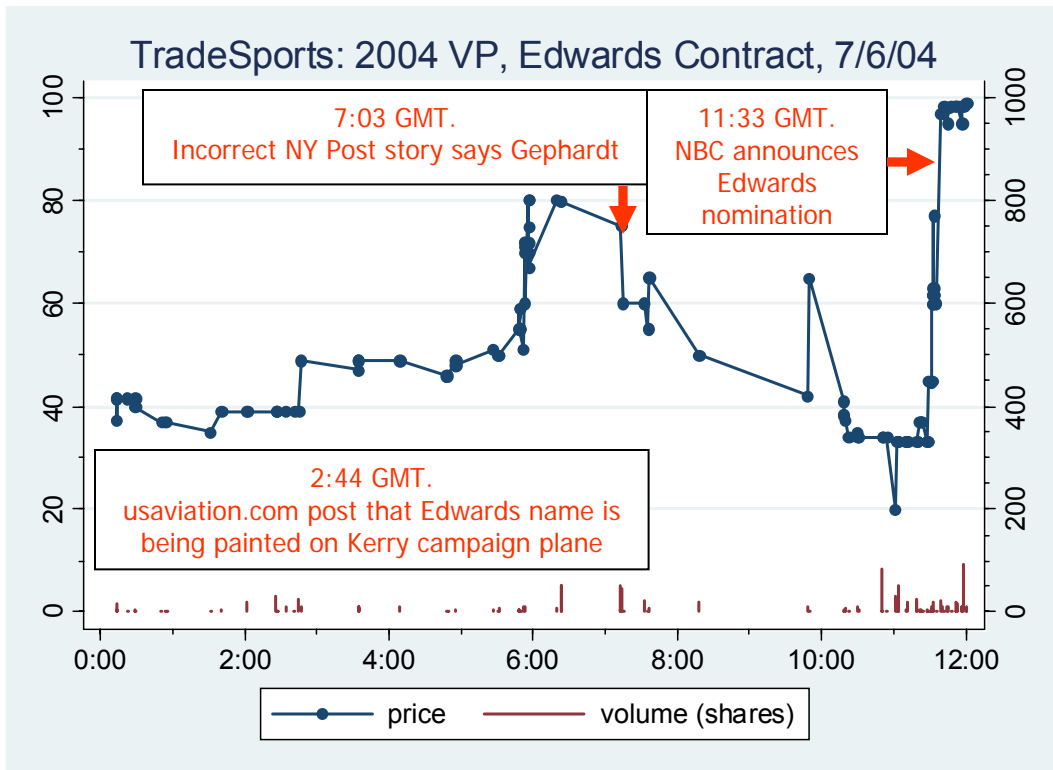
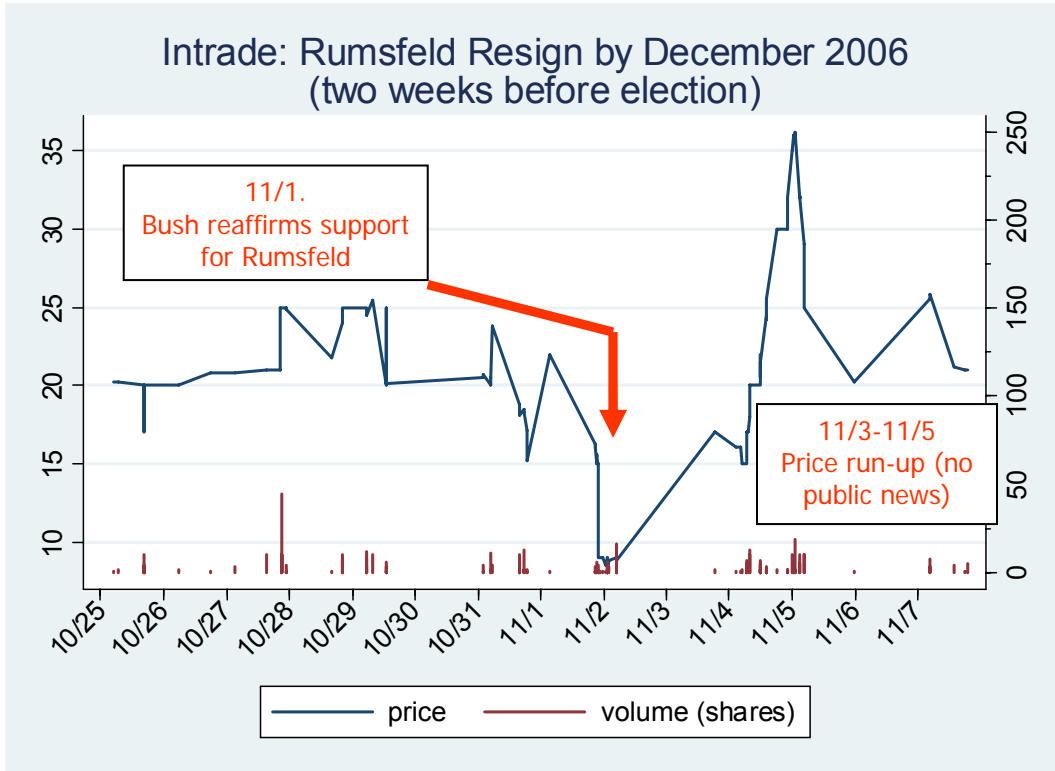
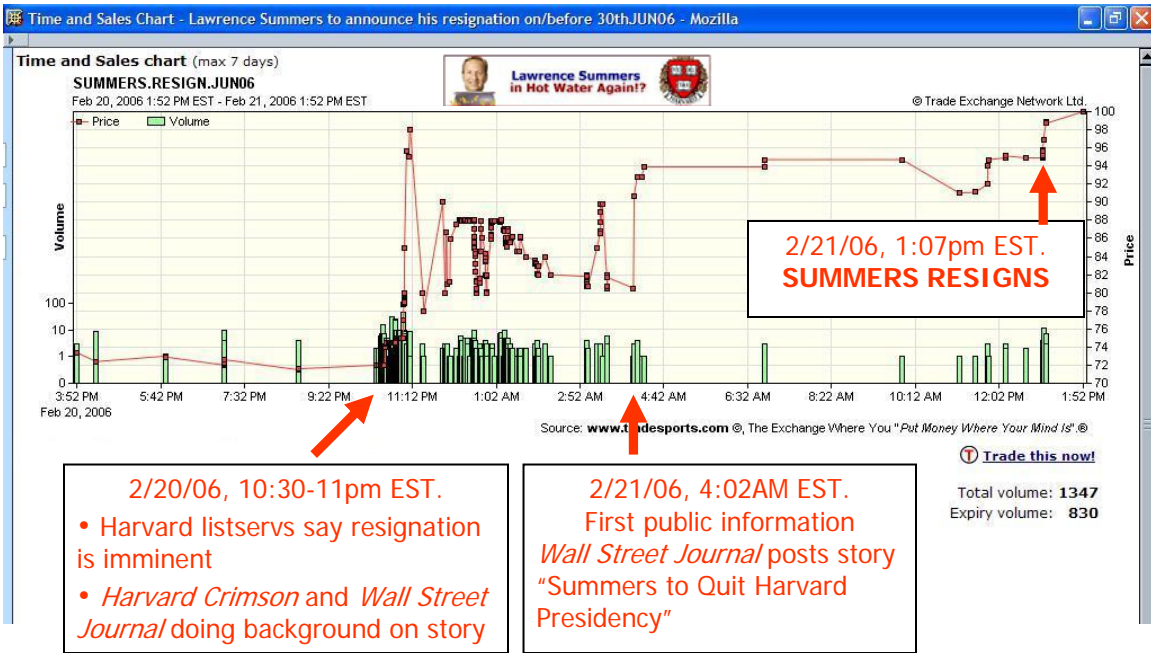


Figure C.1: Examples of Insider Trading in Prediction Markets



Intrade 2005 SCOTUS Nominee Market

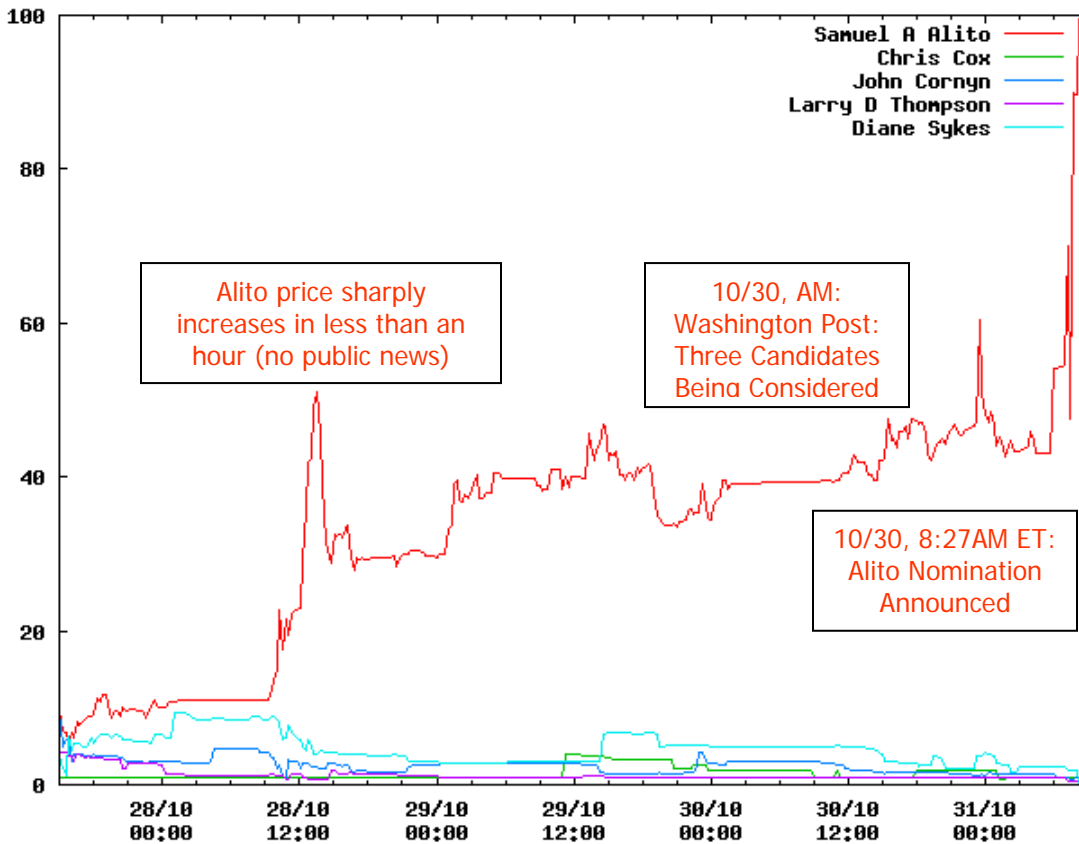
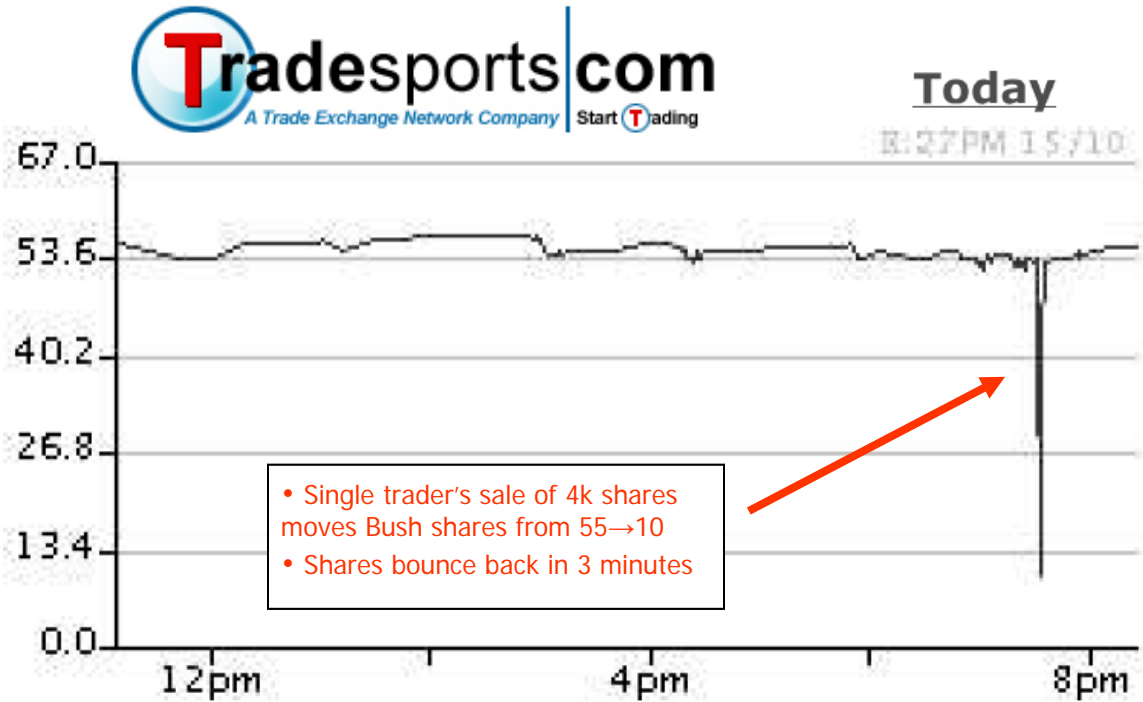


Figure C.1: Examples of Insider Trading in Prediction Markets (cont)

TradeSports 2004 Bush Election: 15 October 2004

George W Bush is re-elected as United States President.



Google Internal Market



Figure C.2: Examples of Attempted Manipulation in Prediction Markets

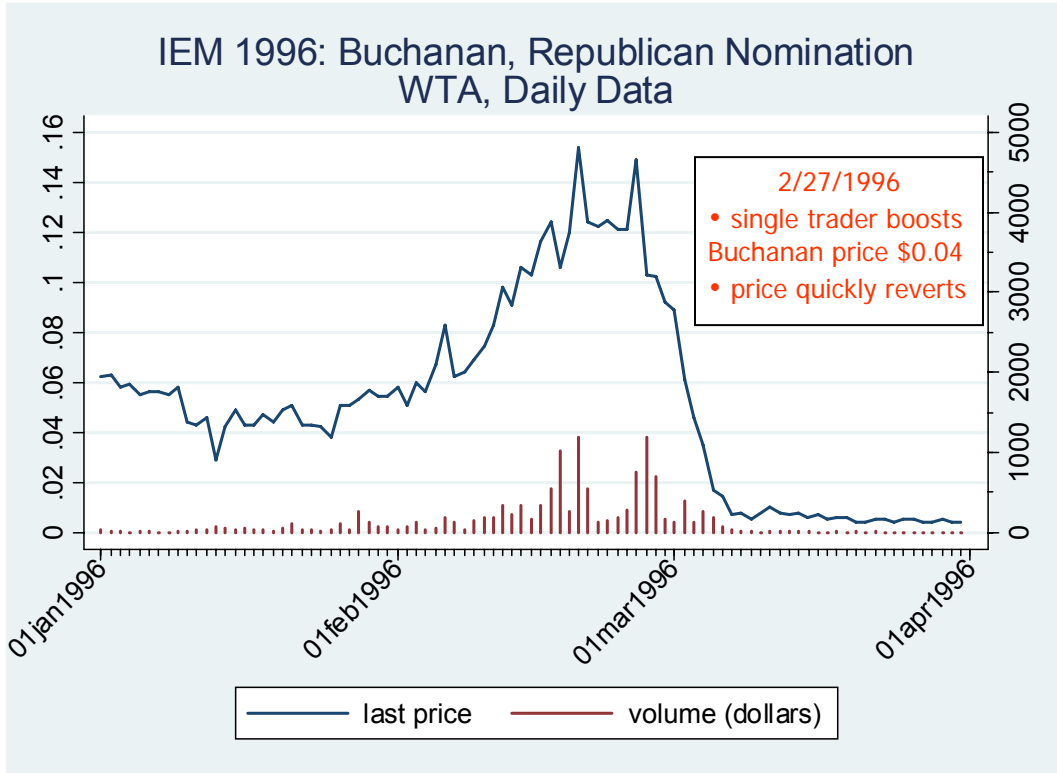


Figure C.2: Examples of Attempted Manipulation in Prediction Markets (cont)

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Table 1: 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 2: Timing and Features of Investments in 2000 Presidential IEM

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

Notes:

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

Table 3: IEM WTA Prices versus Control Markets

A. FX Market: Summary Statistics (Mean and Standard Deviation)

	Overall		1 Hr Following pro-DEM/anti-GOP Manipulation in IEM		1 Hr Following anti-DEM/pro-GOP Manipulation in IEM	
	IEM (WTA)	FX	IEM (WTA)	FX	IEM (WTA)	FX
DEM	0.456 (0.11)	0.457 (0.10)	0.465* (0.12)	0.446* (0.11)	0.373** (0.12)	0.445** (0.10)
GOP	0.545 (0.12)	0.544 (0.10)	0.539** (0.13)	0.567** (0.11)	0.582** (0.11)	0.530** (0.07)
N	1563		127		89	

* indicates mean IEM and FX prices for party are statistically different at 5%-level (paired t-test)

** indicates mean IEM and FX prices for party are statistically different at 1%-level (paired t-test)

Each observation is an IEM price matched to the most recent FX price. The data are at intervals of roughly ten minutes. “pro-DEM/anti-GOP Manipulation” indicates that we bought DEM shares and/or sold GOP shares in the IEM; “anti-DEM/pro-GOP Manipulation” indicates that we sold DEM shares and/or bought GOP shares in the IEM.

B. FX Regressions (dependent variable = IEM WTA price)

	DEM+GOP IEM Price			DEM only IEM Price		
	FX price	0.992 (0.01)	0.999 (0.01)	0.999 (0.01)	0.976 (0.012)	0.977 (0.012)
I(Manip Period)*BuyDem	---	0.033 (0.002)	0.037 (0.01)	---	0.034 (0.003)	0.052 (0.014)
I(Manip Period)*BuyDem *FX price	---	---	-0.008 (0.02)	---	---	-0.041 (0.03)
Constant	0.003 (0.01)	0.000 (0.01)	0.000 (0.01)	0.010 (0.01)	0.008 (0.01)	0.008 (0.01)
R ²	0.76	0.77	0.77	0.77	0.78	0.78
N	3134			1563		
Dep. Var. mean	0.501			0.456		
Dep. Var. std. dev.	0.12			0.11		

I(Manip period) is an indicator for the hour after an IEM manipulation. BuyDem= 1 if pro-DEM/anti-GOP manipulation, 0 if no manipulation, -1 if anti-DEM/pro-GOP manipulation.

Robust standard errors in parentheses. Each observation is an IEM price matched to the most recent FX price. The data are at intervals of roughly ten minutes (to ensure each time period receives equal weight, each observation is weighted by the inverse number of observations in a fifteen-minute window).

C. Additional Regressions: Internet Sports books (dependent variable = IEM WTA price)

	Centrebet				Intertops	
	DEM+GOP		DEM only		DEM	GOP
FX price	1.220 (0.18)	1.264 (0.13)	0.797 (0.14)	0.718 (0.15)	1.097 (0.12)	1.085 (0.11)
I(Manip Period)*BuyDem	---	0.059 (0.04)	---	0.118 (0.05)	---	---
I(Manip Period)*BuyDem *FX price	---	-0.014 (0.07)	---	-0.118 (0.22)	---	---
Constant	-0.071 (0.05)	-0.008 (0.06)	0.084 (0.06)	0.054 (0.06)	-0.031 (0.06)	0.058 (0.05)
R ²	0.84	0.87	0.49	0.54	0.55	0.58
N	1140		570		130	130
Dep. Var. mean	0.505		0.332		0.461	0.539
Dep. Var. std. dev.	0.18		0.06		0.06	0.06

I(Manip period) is an indicator for the hour after an IEM manipulation. BuyDem= 1 if pro-DEM/anti-GOP manipulation, 0 if no manipulation, -1 if anti-DEM/pro-GOP manipulation.

Robust standard errors in parentheses.

Centrebet: each observation is an IEM price matched to the most recent Centrebet price; the observation period is 10/23/00 (when CentreBet began posting odds) until 11/7/00. The data are at intervals of roughly ten minutes (to ensure each time period receives equal weight, each observation is weighted by the inverse number of observations in a fifteen-minute window)

Intertops: daily data 7/1/2000 until 11/7/00; no manipulation indicators are used because the data is not high frequency.

Table 4: Equilibrium Relationship between IEM VS and WTA

Relationship from Appendix A

$$p^*_{WTA,t} = p^*_{VS,t}/\sigma_{vt}$$

$$\sigma_{vt} = \text{sqrt}(s_2^2 + s_1^2 \times (T-t))$$

where * indicates an inverse normal transform, (T-t)=number days until election, and $s_i \geq 0$

Estimate

$$p^*_{WTA,t} = \alpha + p^*_{VS,t}/\text{sqrt}(\beta_2^2 + \beta_1^2 \times (T-t)) + \epsilon_t$$

where $(\alpha, \beta_1, \beta_2)$ are parameters to estimate, and so fitted $\sigma_{vt} = \text{sqrt}(\beta_2^2 + \beta_1^2 \times (T-t))$

A. 2000 IEM election

	DEMS	GOP	DEM+GOP
α	-0.016 (0.011)	0.021 (0.013)	0.004 (0.008)
β_2	0.108 (0.018)	0.107 (0.020)	0.104 (0.013)
β_1	0.022 (0.005)	0.023 (0.005)	0.024 (0.003)
R^2	0.70	0.66	0.67
N	109	109	218

The 11 days with trading activity are excluded (estimates are comparable when these days are included)

B. 1996 IEM election

	DEMS	GOP	DEM+GOP
α	-0.087 (0.066)	-0.004 (0.052)	-0.010 (0.013)
β_2	0.095 (0.008)	0.102 (0.008)	0.101 (0.004)
β_1	0.015 (0.001)	0.016 (0.001)	0.016 (0.001)
R^2	0.74	0.78	0.95
N	120	120	240

Estimation Details

- $\pm\beta_i$ are both solutions since the β_i terms are squared. To ensure the positive root, we estimate $\exp(\gamma_i)$ in place of β_i^2 , so that $\beta_i = \text{sqrt}(\exp(\gamma_i))$.
- NLLS is the estimation technique.
- Bootstrap standard errors (based on 1000 repetitions) are used since v_t is heteroscedastic and autocorrelated
- The model is estimated using the last prices of each day for the 120 days preceding the election
- VS prices are converted to two party shares (assumes REF is evenly split between DEM and GOP)

Table 5: Impact of Manipulations and Wash Sales/Bluffs on Democratic Odds Price in Historical New York Markets

Dependent variable = Democrat odds price.

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

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

Table 6: Analysis of TradeSports 2004 Presidential Election Speculative Attacks

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

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

Figure 1: IEM 2000 WTA Market: Day After Election (CST)

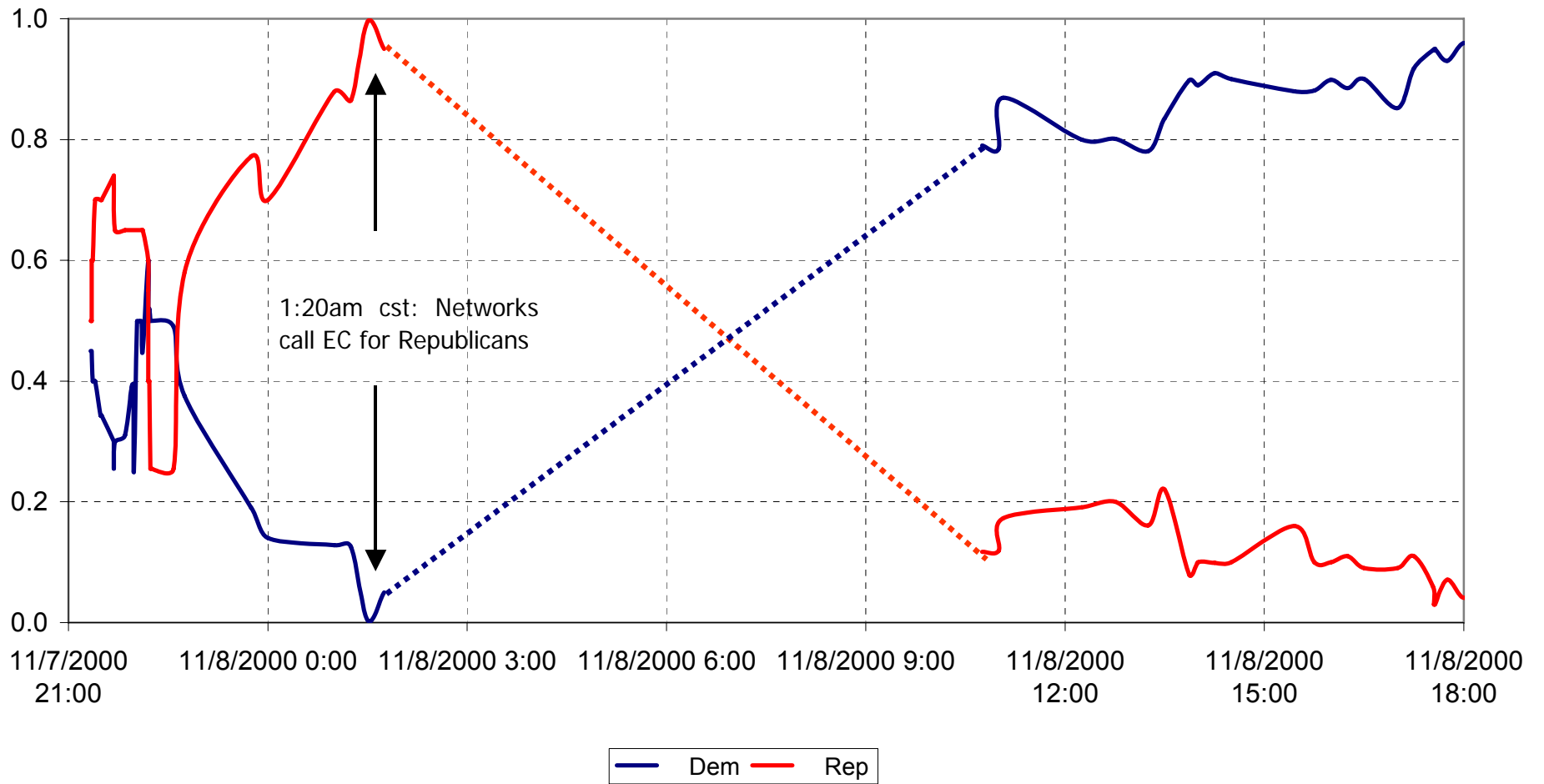


Figure 2: IEM 2000: Summary of Trades (Volume and Initial Price Change)

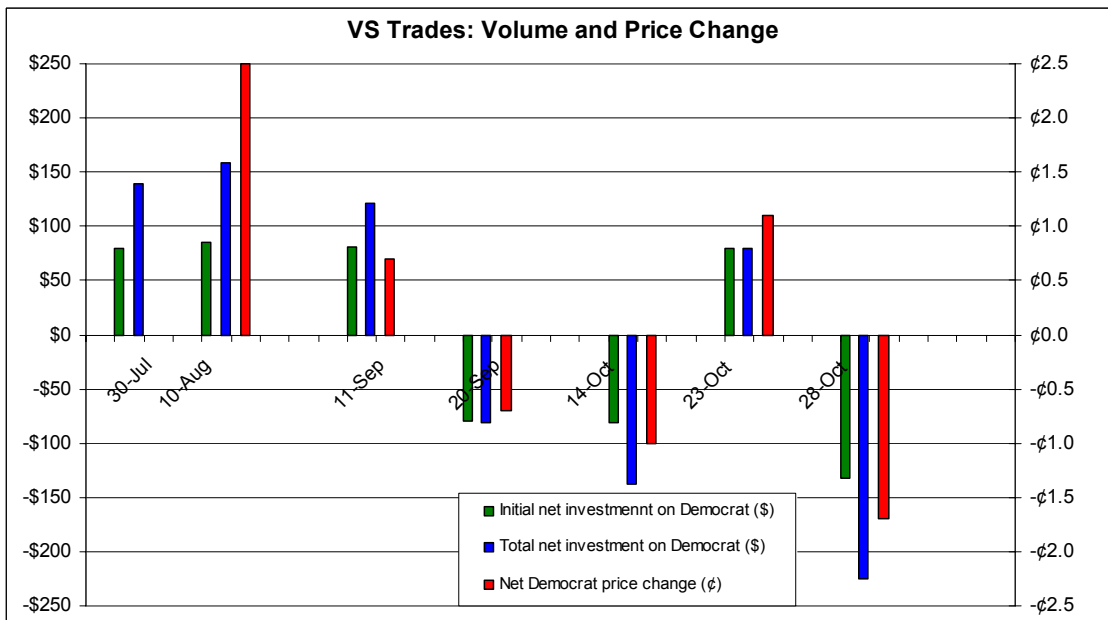
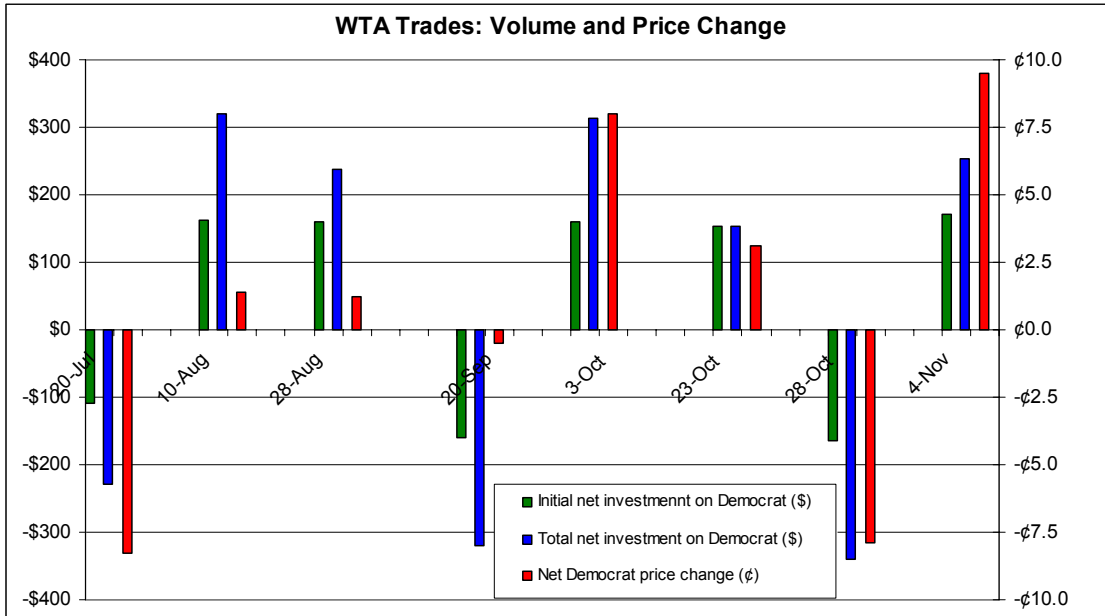


Figure 3: IEM 2000: 10/28/00 Trades (Sell Democrats in WTA+VS)

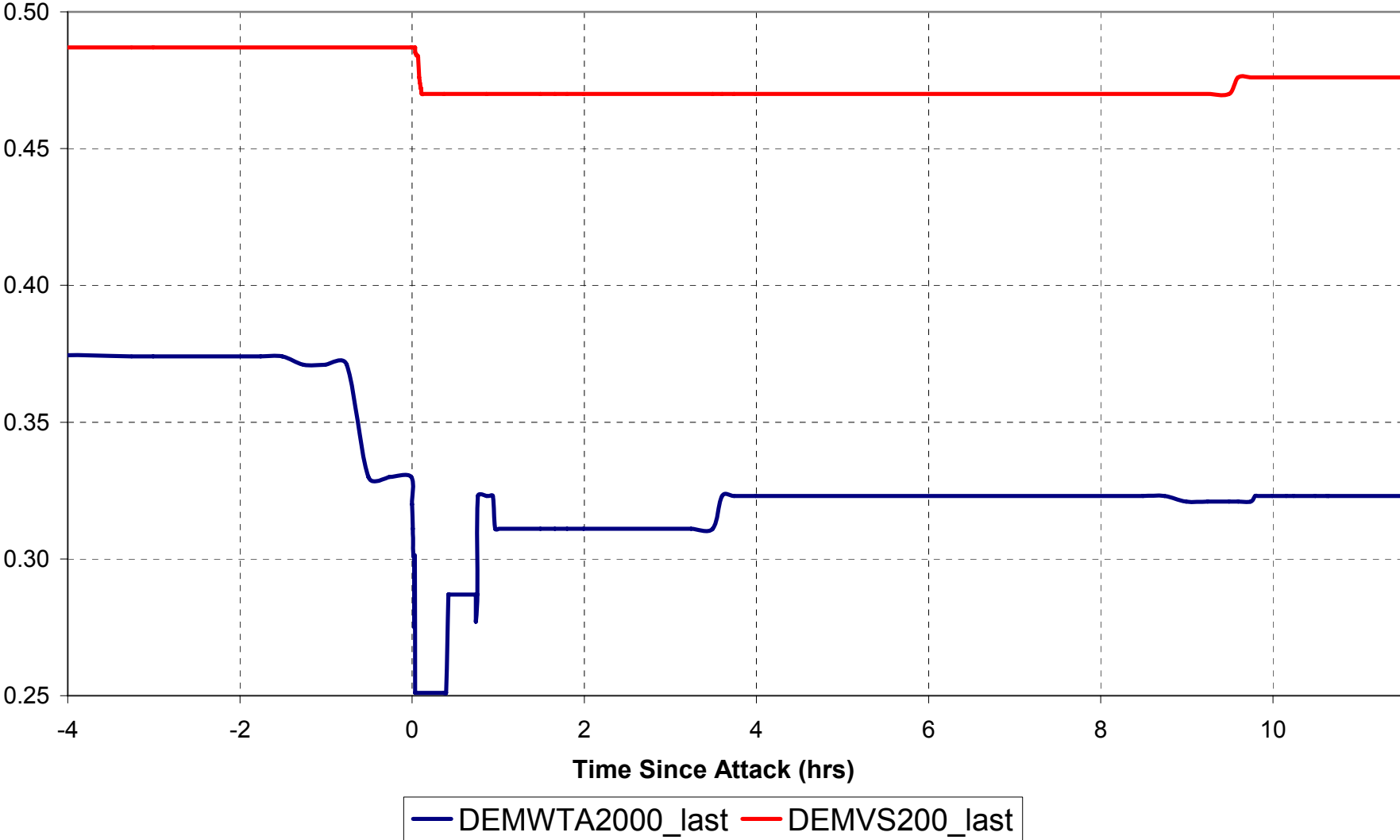


Figure 4: IEM 2000 and Manipulations

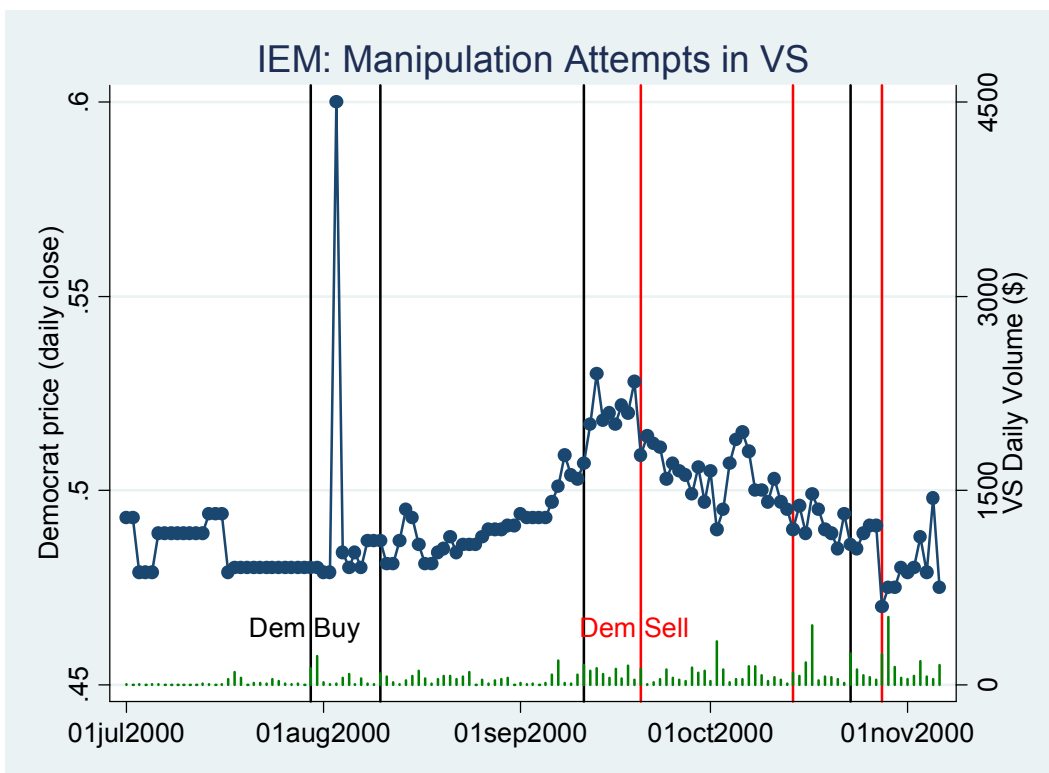
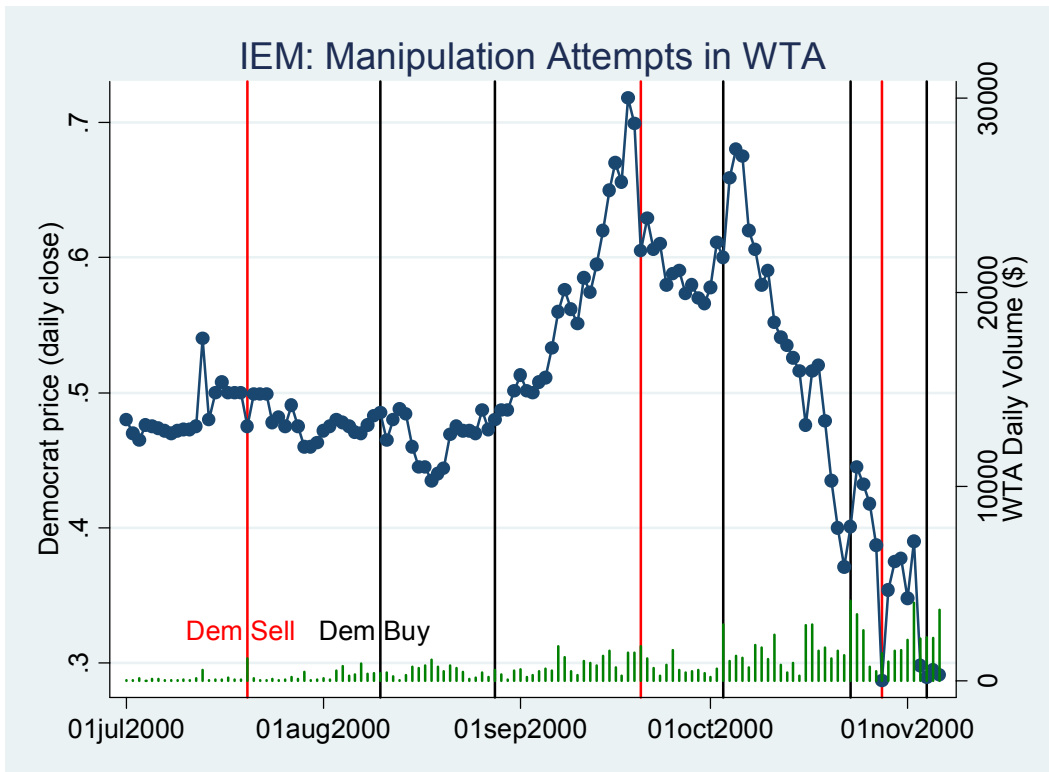


Figure 5: IEM 2000 and FX

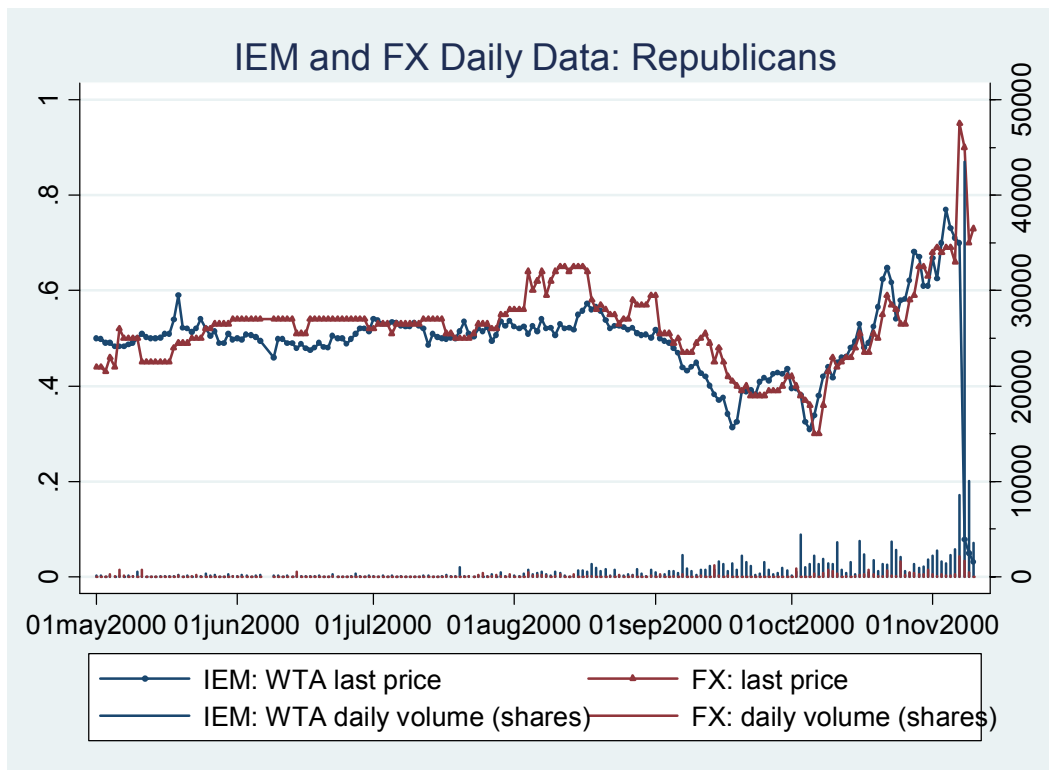
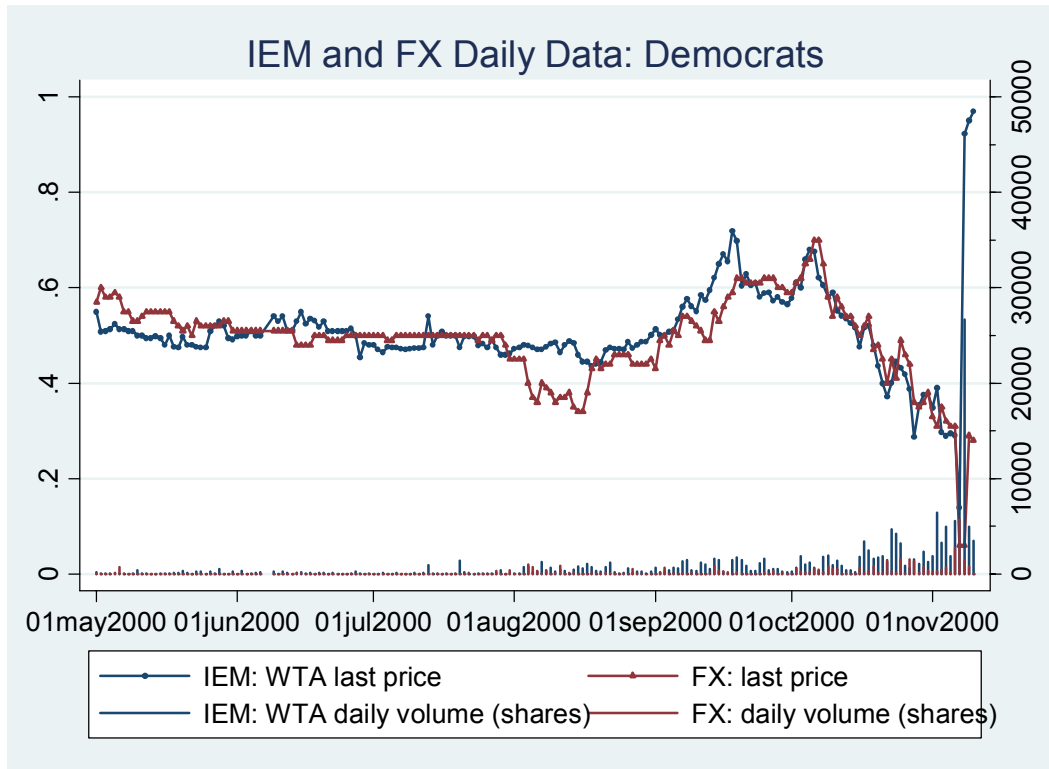


Figure 6: IEM 2000.

Mean CR in the Attacked Market over the Full Set of Trades (11 episodes involving 15 markets)

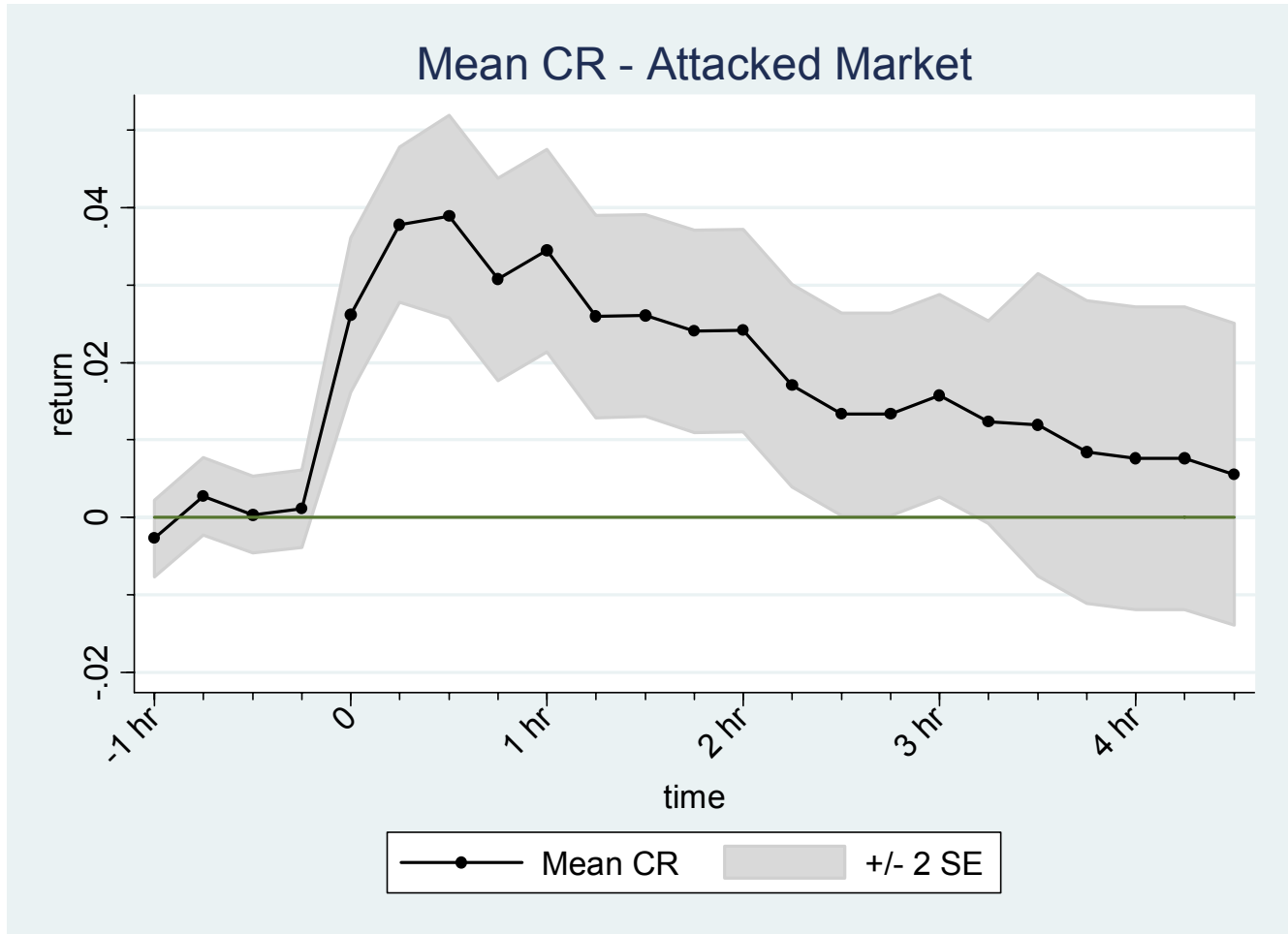
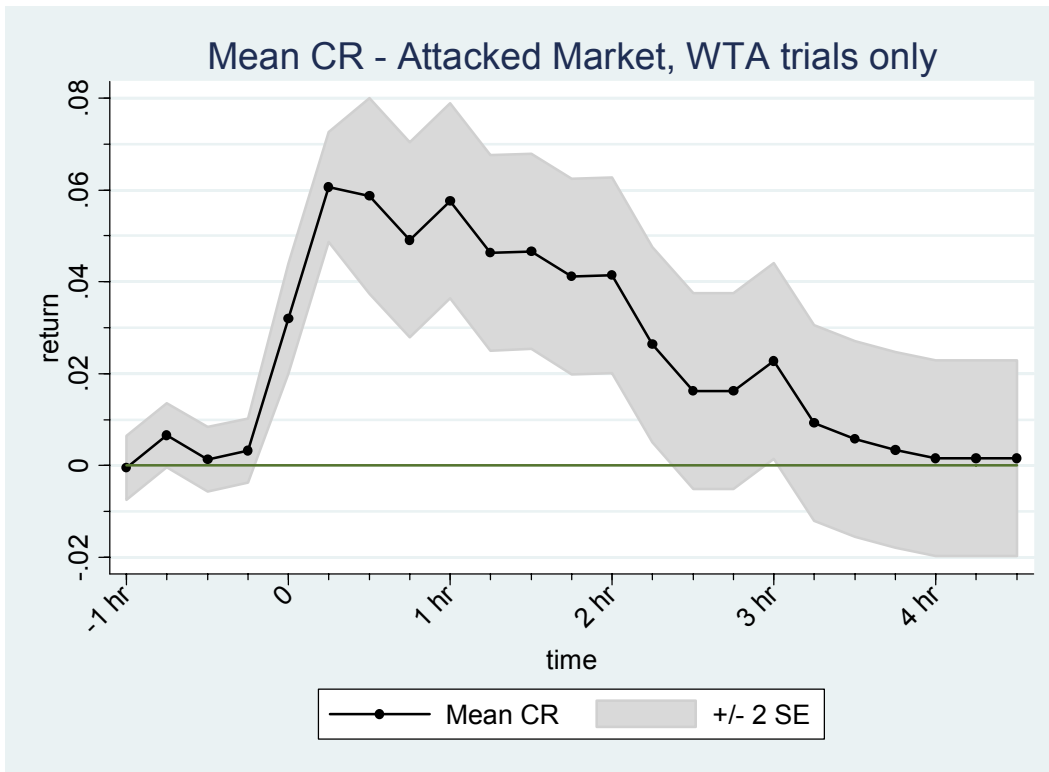


Figure 7: IEM 2000, by Market

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



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

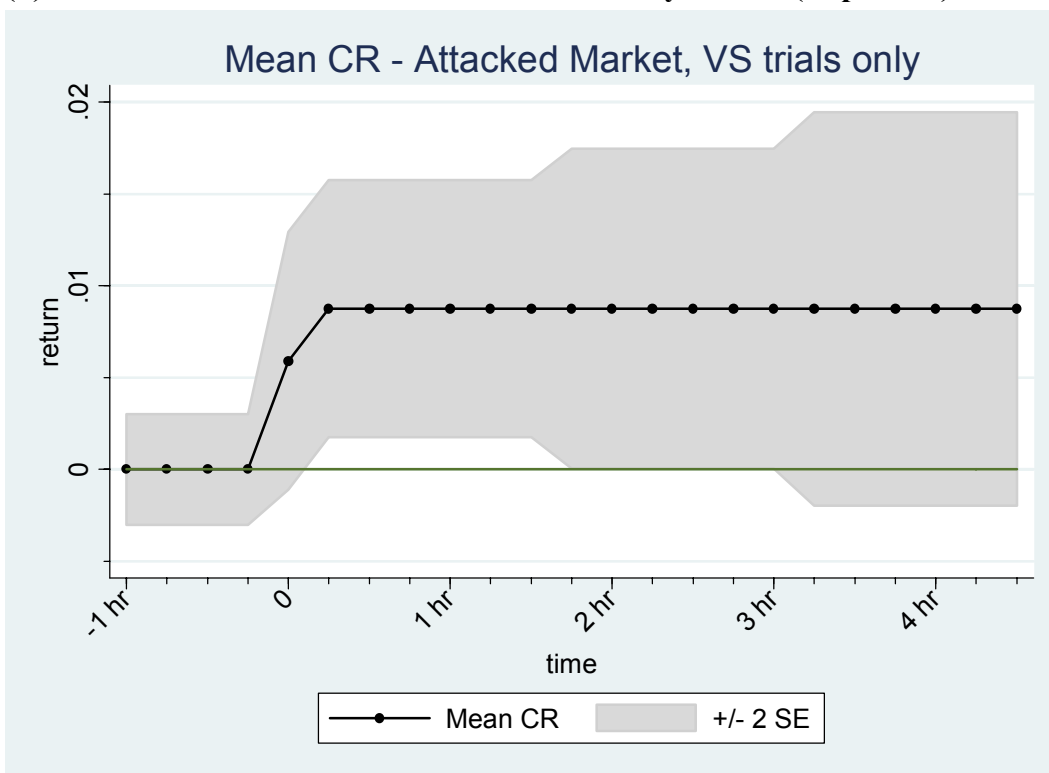
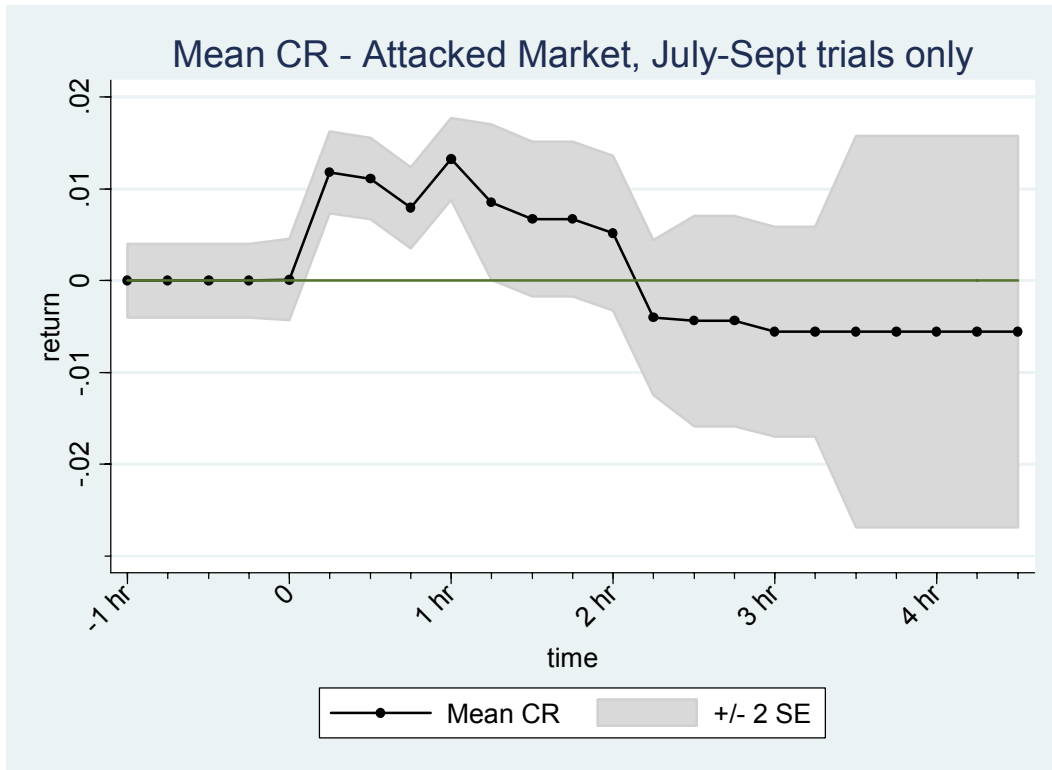


Figure 8: IEM 2000, by Time/Market Cap

(a) Mean CR in the Attacked Market for Early/Small Cap Trades (6 episodes involving 8 markets)



(b) Mean CR in the Attacked Market for Late/Large Cap Trades (5 episodes involving 7 markets)

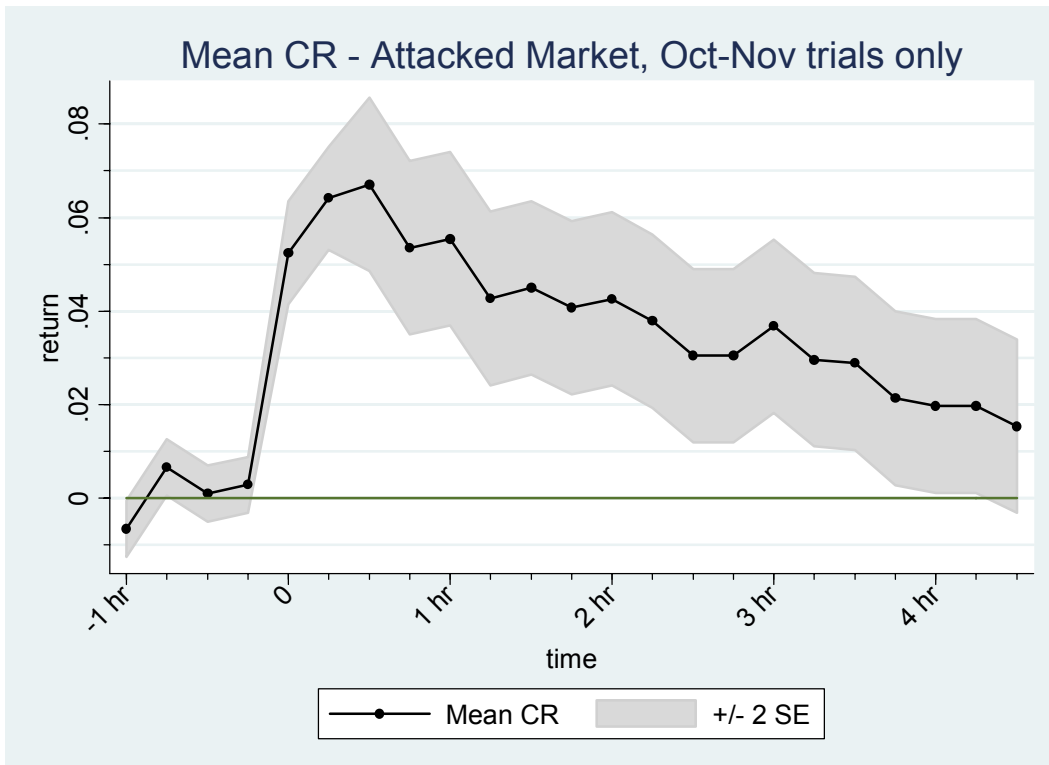
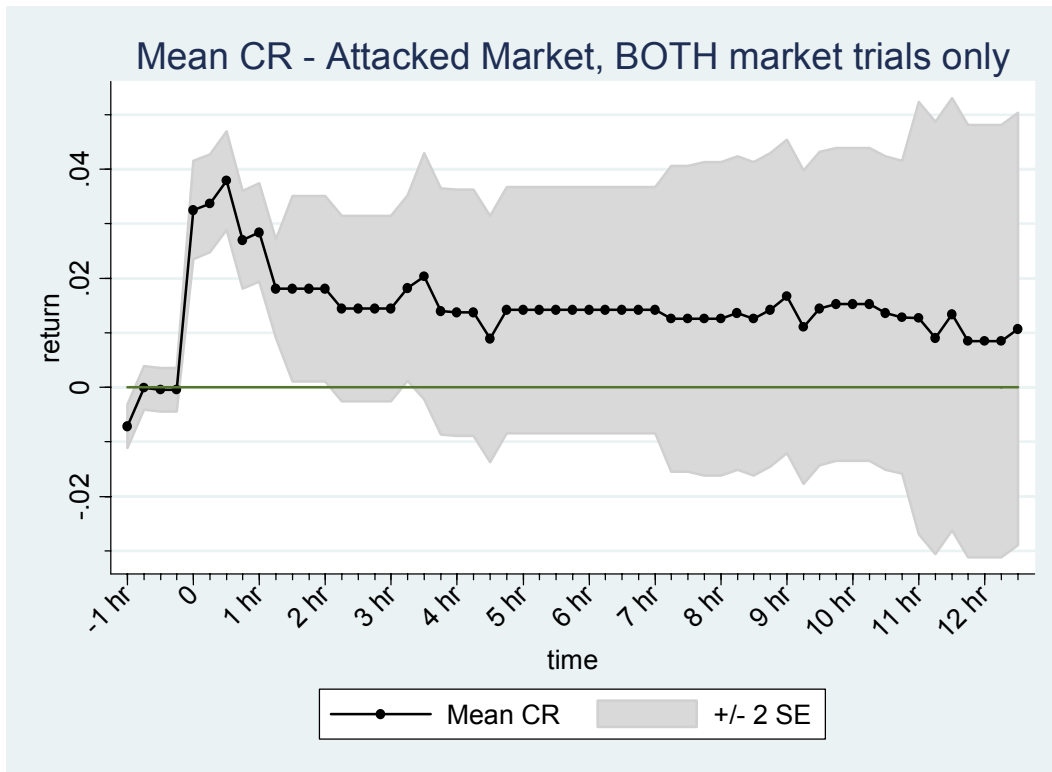


Figure 9: IEM 2000, Slow Reverting trials

(a) Mean CR in Two Market-Attacks (4 episodes involving 8 markets)



(b) Mean CR in Trials with Democrat Purchases/Republican Sales (7 episodes involving 9 markets)

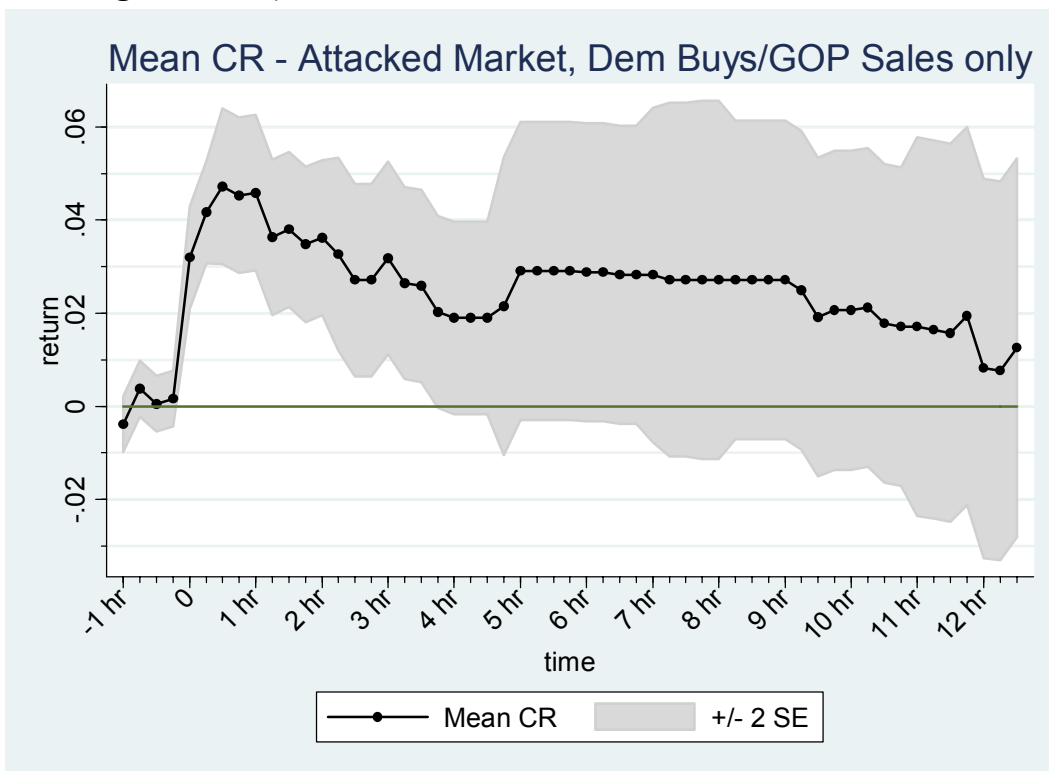
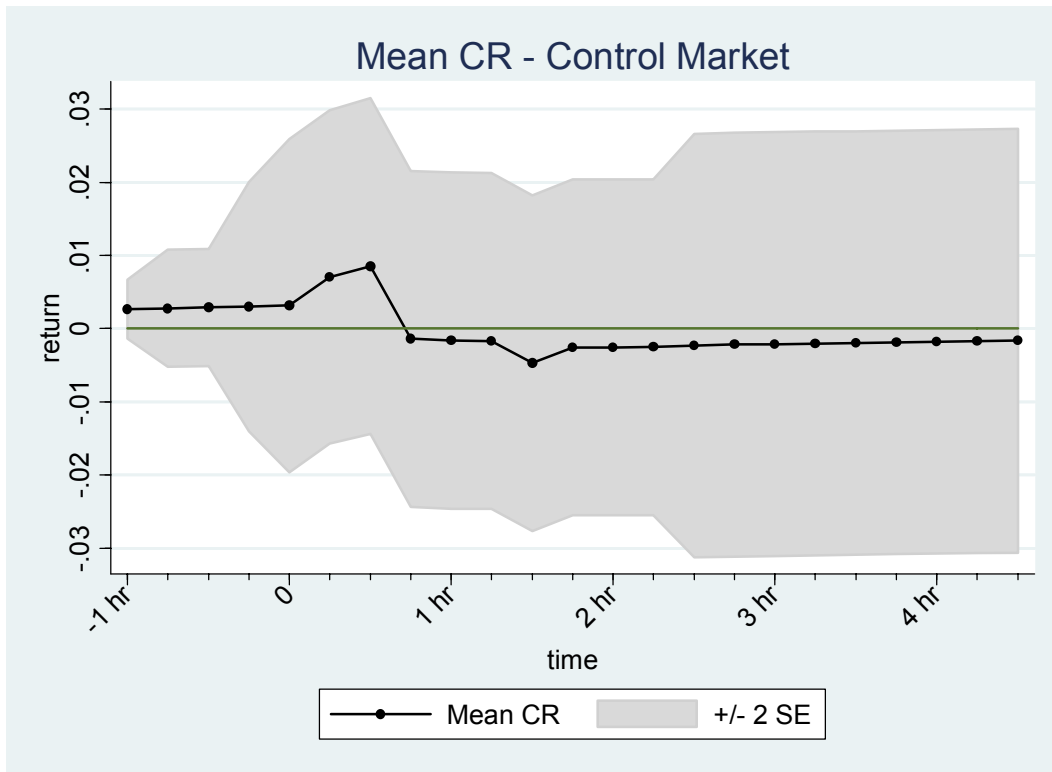


Figure 10: IEM 2000, Control Markets

(a) Mean CR (7 episodes)



(b) Mean CAR (7 episodes)

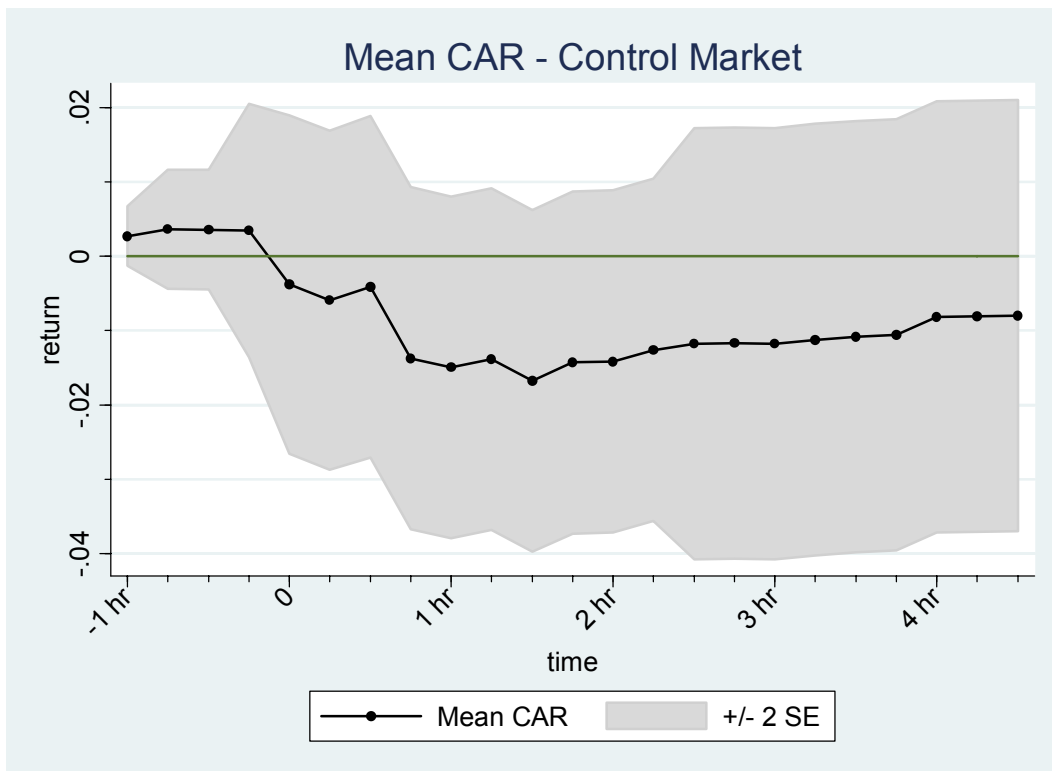
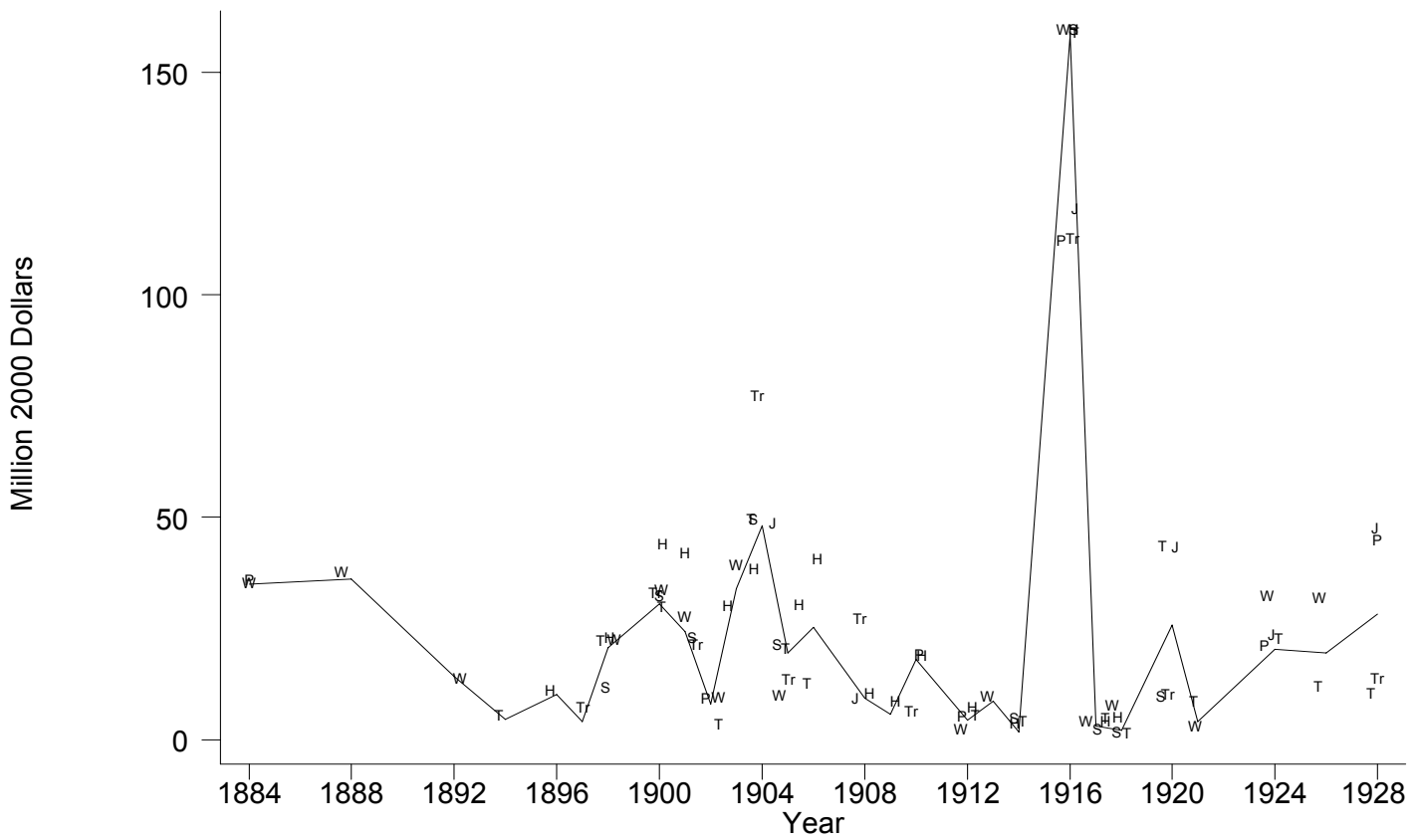


Figure 11: Estimated Volume in Historical New York Markets, 1884-1928



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

Figure 12: Newspaper Accounts of Historical New York Markets

A. Individual Bets (*New York 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 10 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 Mathews-Alexander Caldwell
Sept. 28	1,000	1,000	Leo Taylor-W. Grossman
Sept. 28	1,000	1,000	Walter & Fields-W. Grossman
Oct. 1	10,000	10,000	John Mahoney-George Whalock
Oct. 2	2,000	4,000	Robert Ross-George Whalock
Oct. 2	400	1,000	C. H. Tibbels-Tom O'Neill
Oct. 2	400	1,000	C. H. Tibbels-George Black
Oct. 2	400	1,000	T. A. Hamilton-Thomas L. Hamilton
Oct. 2	400	1,000	Walter Devo-Alexander Moore
Oct. 2	250	200	Donna Sullivan-John Whalen
Oct. 2	400	1,000	Maurice Untermyer-W. H. Fleming
Oct. 15	420	600	J. Judge-Alfred de Cordova
Oct. 14	1,000	2,500	James Wakely-Abraham Levy
Oct. 14	200	400	Joe Vande-Fredrick Walbaum
Oct. 15	200	400	Bell & Co.-J. M. Martin
Oct. 15	800	1,000	Bell & Co.-J. M. Martin
Oct. 15	10,000	10,000	Maurice Untermyer-W. H. Oliver, Jr.
Oct. 15	2,000	1,500	Frank P. Keeley-George
Oct. 15	4,000	2,500	Joe Vande-Gedried Wy
Oct. 15	1,000	2,500	E. B. Talbot-A. B. Barbe & Co.
Oct. 15	1,000	1,000	E. B. Talbot-J. S. Barbe & Co.
Oct. 15	900	200	E. B. Talbot-W. H. Mendham
Oct. 15	150	250	JAMES Wakely-P. Johnson
Oct. 15	1,000	2,500	J. Judge-J. Egan
Oct. 15	1,500	2,500	Abraham Levy-S. Butler
Oct. 15	2,500	2,500	E. B. Talbot-H. P. Toler
Oct. 15	1,000	1,500	Charles Kistner-M. Demoran
Oct. 15	1,000	2,500	Bell & Co.-Harry P. Toler
Oct. 15	1,000	1,000	Bell & Co.-Washington Bellman
Oct. 15	500	100	Bell & Co.-J. S. Barbe
Oct. 15	1,000	1,500	E. B. Talbot-W. H. Mendham
Oct. 15	500	500	Bell & Co.-Dick Brax
Oct. 15	500	500	E. B. Talbot-R. A. Peabody
Oct. 15	1,000	1,000	J. Poppelsinger-J. Donohue
Oct. 15	200	500	J. Judge-J. S. Barbe
Oct. 15	1,500	1,500	J. Judge-H. Davis
Oct. 15	2,500	1,500	E. B. Talbot-Norris & Tubittell
Oct. 15	500	1,500	Frank P. Keeley-A. B. Barbe & Co.
Oct. 15	1,000	1,000	Frank P. Keeley-F. H. Wardwell
Oct. 15	1,000	1,000	Lan Wager-Dan. B. O'Neil
Oct. 15	1,000	1,000	E. B. Talbot-E. B. Sheldon
Oct. 15	500	500	E. B. Talbot-P. N. Spruille
Oct. 15	500	500	Frank P. Keeley-George Walton
Oct. 15	500	500	Frank P. Keeley-W. H. Oliver
Oct. 15	500	500	E. B. Talbot-J. Reigalberg
Oct. 15	1,000	1,000	Henry C. Winters
Oct. 15	500	500	E. B. Talbot-H. Constant
Oct. 15	1,000	1,000	E. B. Talbot-Haven & Hunt
Oct. 15	1,000	1,000	E. B. Talbot-E. B. Curtis
Oct. 15	1,500	1,500	Lan Wager-Bell & Co.
Oct. 15	1,500	1,500	Frank P. Keeley-William Oliver
Oct. 15	2,500	2,500	L. S. Benedict-J. A. Neira & Co.
Oct. 15	1,500	1,500	E. B. Talbot-E. B. Handolph
Oct. 15	2,000	2,000	E. B. Talbot-H. H. Handolph
Oct. 15	4,000	4,000	E. B. Talbot-Theodore Fox
Oct. 15	1,000	1,000	E. B. Talbot-H. H. Handolph
Nov. 1	10,000	2,500	Bell & Co.-John O'Neil
Nov. 1	10,000	1,000	Bell & Co.-Republican Syndicate
Nov. 1	10,000	1,000	Bell & Co.-J. McDonald-Jacob P. Sika
Nov. 1	10,000	10,000	Bell & Co.-B. D. O'Neil

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 13: Manipulations in Presidential Races in Historical New York Markets

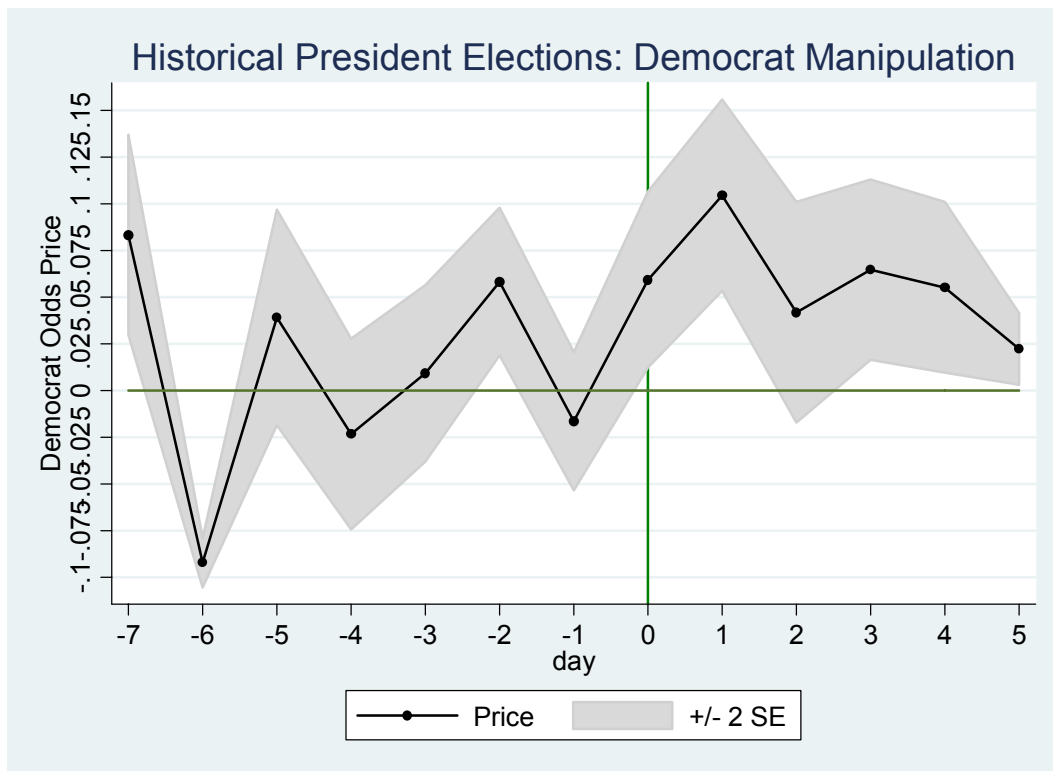
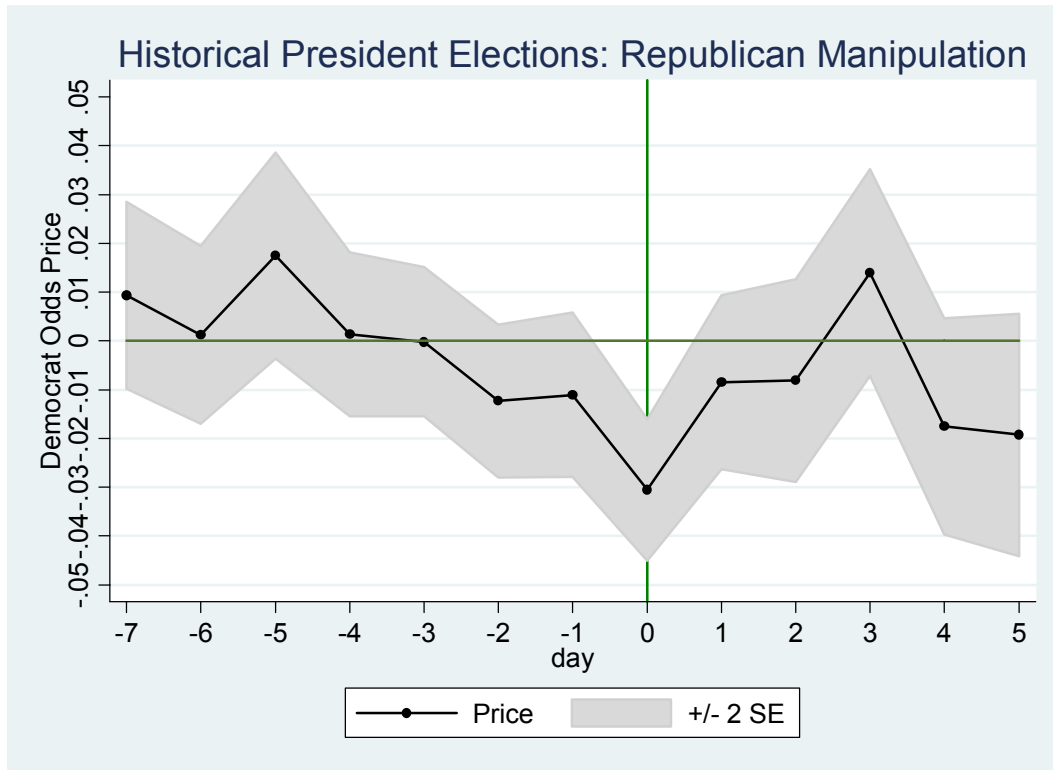


Figure 14: Manipulations in All Races in Historical New York Markets

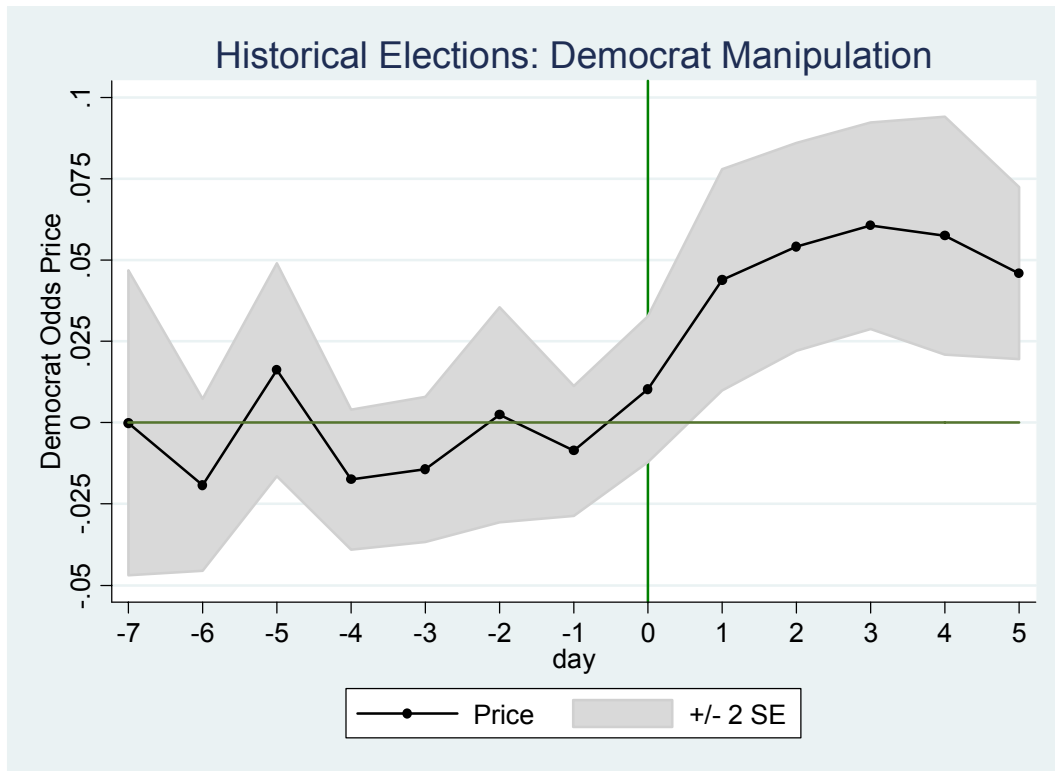
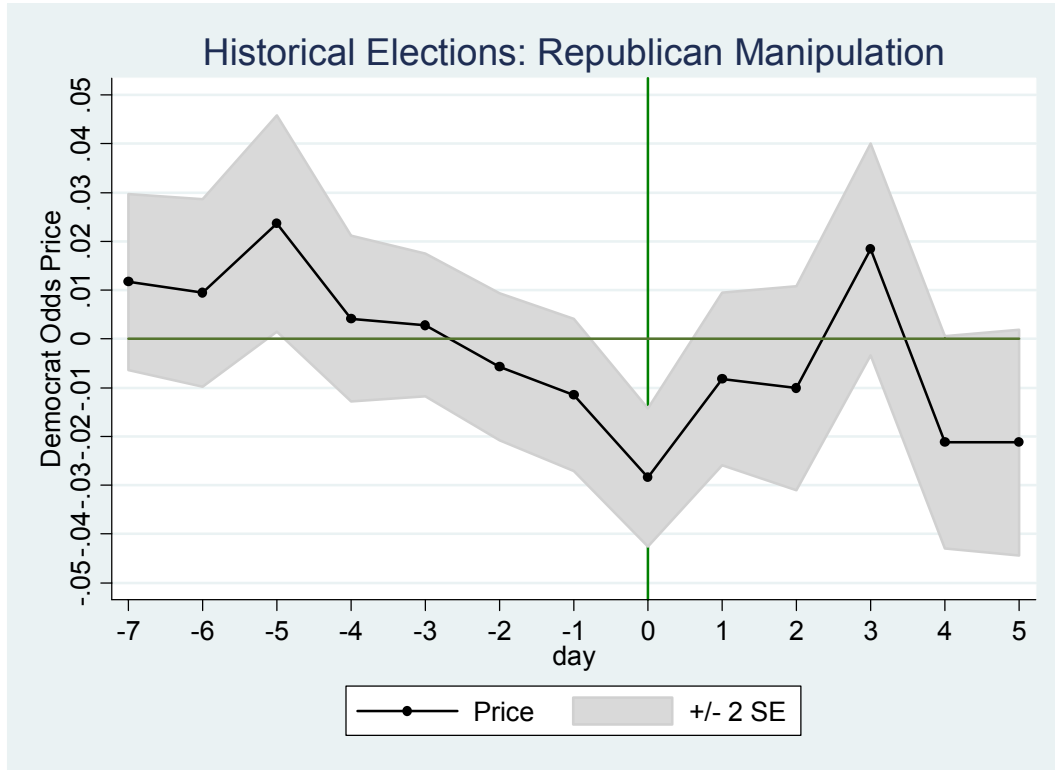


Figure 15: Results Combining Manipulations for Historical New York Markets

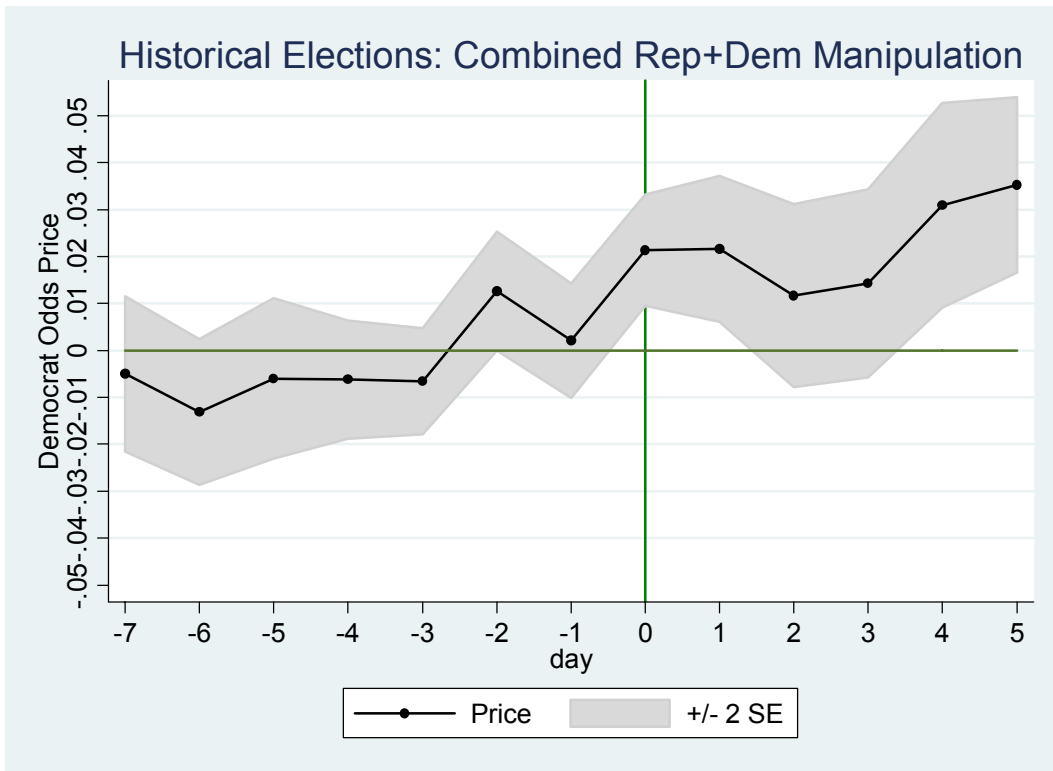
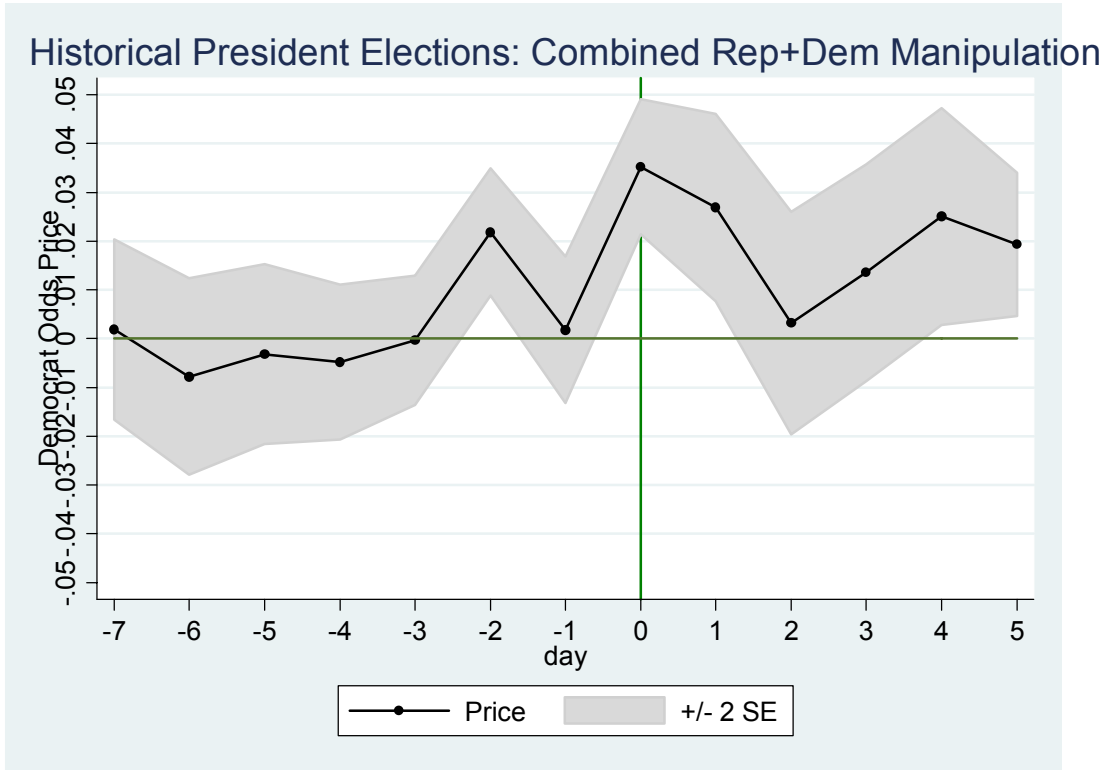


Figure 16: TradeSports 2004 US Presidential Market (Sept-Oct 2004 only)

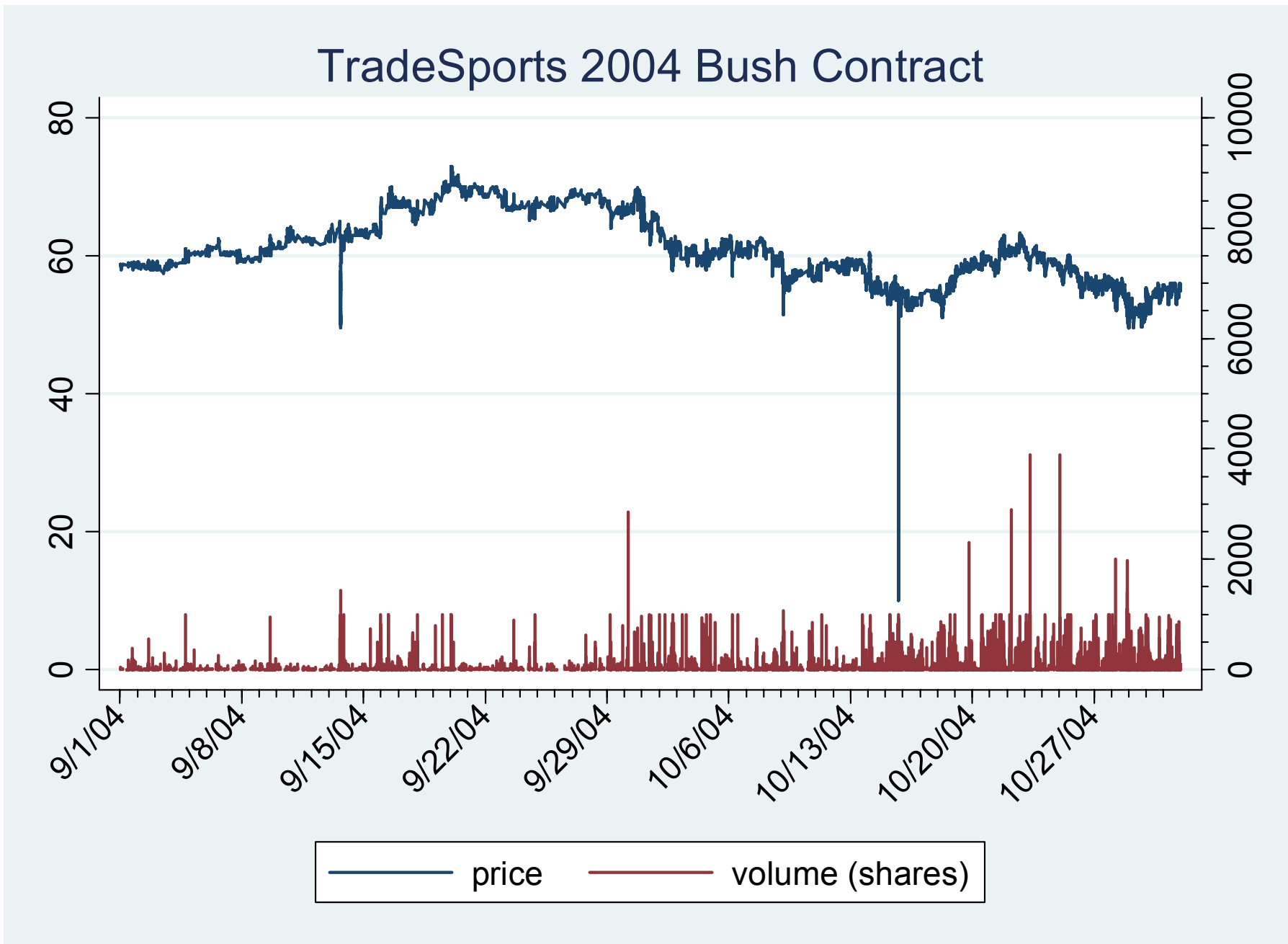


Figure 17: Speculative Attacks in *TradeSports* 2004

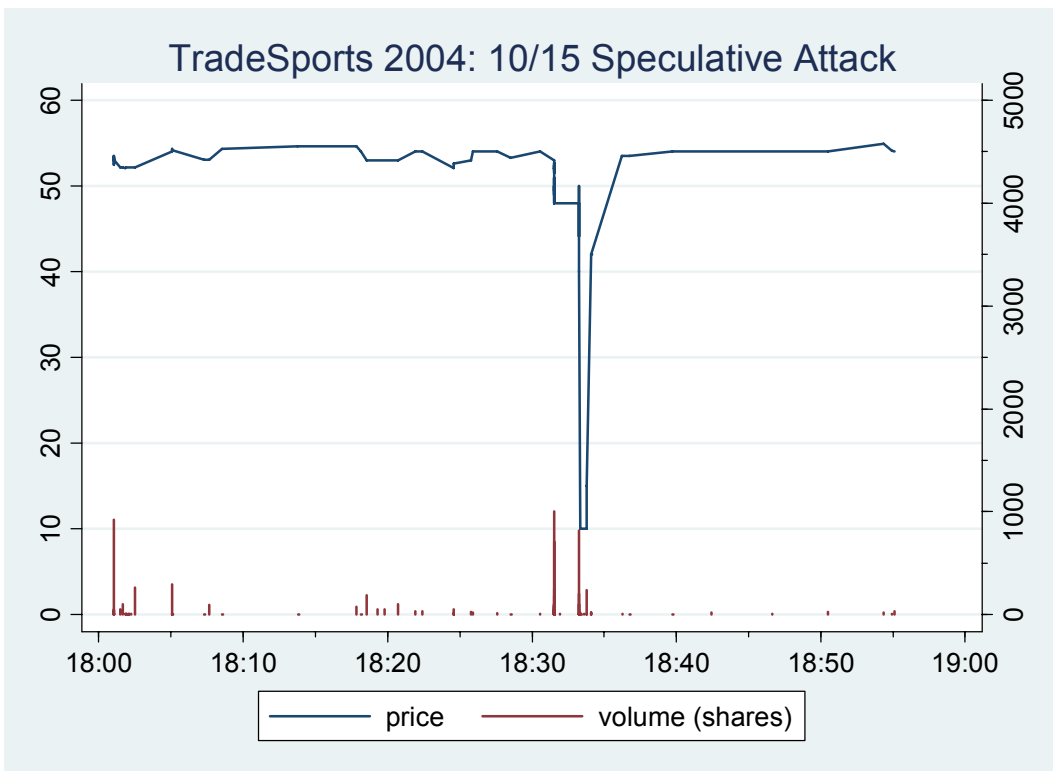


Figure18: Cumulative Returns during Speculative Attacks in *Tradesports* 2004

