Political uncertainty and the 2012 US presidential election:
A cointegration study of prediction markets, polls and a stand-out expert

by

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JEL Classifications: N20,D53, C58
Keywords: prediction markets, information aggregating markets, Intrade, Nate Silver, Iowa Presidential Election Market; international integration; futures markets

February 2015

The authors are grateful to removed, and other colleagues for useful comments, but remain solely responsible for the contents.

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Abstract

Political uncertainty is increasingly seen as important to financial markets. Particularly US presidential election uncertainty is linked to uncertainty regarding future US macroeconomic policy. But what is the best vehicle to measure political uncertainty? We examine both the cointegration and causal relationships between the Iowa and Intrade presidential futures markets (IOWA, INTRADE), along with the results of election polls (POLLS); as well as published election predictions of Nate Silver (SILVER), who was arguably the most followed political forecaster during the 2012 presidential election season. We document strong evidence that SILVER and the two prediction markets were all highly cointegrated; while POLLS was not. Consistent with the assertion made by others that INTRADE prices were manipulated in 2012 for non-pecuniary reasons, we also evidence that IOWA and SILVER both Granger-caused INTRADE. Our findings are also consistent with previous findings that election markets outperform polls as prediction vehicles. Overall, while confirming that INTRADE, IOWA and SILVER are cointegrated, we note that the three series consistently differed in the degree of optimism in an Obama victor. These results pose important questions for researchers interested in estimating political uncertainty, and assessing the efficacy of prediction markets and their international integration.

1. Introduction

Elections futures markets have an important place in finance literature because of their role in assessing election uncertainty. And consequently they have an important place in assessing the financial impact of election uncertainty. Leigh and Wolfers (2006) compare the efficacy of three diverse approaches to forecasting elections: econometric models that project outcomes on the basis of the state of the economy; public opinion polls; and election betting (prediction markets) and conclude that betting markets, as a form of prediction markets are reliable. Berg et al (2008) compare U.S. presidential election polls over pre-election periods with election futures traded on the Iowa Electronic Market and found that the election futures were invariably much closer to the winning candidate's actual margin of victory than the polls were. Further, recent research suggests that presidential predication markets can have important effects on the financial system. For instance, Goodell and Vahamaa (2013) find that presidential prediction markets affect the VIX; while Goodell and Bodey (2012) find presidential prediction markets affect the price earnings ratios of the S&P500. Therefore the study of prediction markets is important to understanding their potential utility for financial forecasting.

In parallel, we study two alternative mechanisms that attempt to assimilate news and sentiment into forecasts about the eventual election outcome. First, we examine the daily forecasts of Nate Silver (SILVER) over the same pre-election period. SILVER attracted a lot of attention during the 2012 election season because he was known for having correctly predicted the winner in 49 out of 50 states in the 2008 election. Our second alternative measure is the various election polls taken during the pre-election period. For statistical analysis of how this poll information relates to the three time series described above, we use the average (POLLS) of election polls compiled and published by Real Clear Politics, who are a widely known poll aggregator. An important concern in our study is the comparative efficiency with which these sources reflect new information. We offer new explanations as to why differences exist between these different series, which are ostensibly trying to achieve the same outcome, i.e. to identify the eventual winner.

Oliven and Rietz (2004) consider whether the Iowa Electronic Markets are skewed by a non-representative sample of mistake-prone and biased traders. They conclude that market-making traders are more rational than price-taking traders, allowing prediction markets to function efficiently. This is an important consideration with regard to US presidential election markets given the partisan nature of elections. Given that research strongly points toward voters supporting candidates based on sociotropic inclinations rather than economic self-interest (Caplan (2007)), do pecuniary interests of participants in presidential-election prediction markets outweigh possible sociotropic behavior?

A related question is whether election prediction markets can be manipulated for non-pecuniary reasons. Berg and Reitz (2006) present evidence of political campaigns' attempts to manipulate prediction market prices. Berg et al (2008) note that "given the success and increasing use of prediction markets", political campaigns might "want to influence prediction markets in the hope of influencing the future vote". Past research supports the idea that decisions about which candidate to vote for, or whether to vote at all, may be influenced by the perceived likelihood of the election outcome (Nadeau, Cloutier and Guay (1993); Skalaban (1988)).

The notion that prediction markets can be manipulated has close overlap with other forms of online manipulation. For instance, Dellarocas (2006) studies firms' planting of contrived positive information on consumer review sites. Dellarocas (2006) finds that the greater the number of consumers posting honest reviews the less cost effective it is for firms to post fraudulent reviews. This seems closely analogous to prediction markets of less depth being more easily manipulated by a small number of non-pecuniary motivated investors. It is also reasonable to consider that if firms find it cost effective to plant positive reviews on consumer-review websites, then president candidates or their authorized or unauthorized surrogates could have an interest in manipulating the prices of online presidential prediction markets. And of course, price manipulation of online prediction markets would distort the forecastability of these markets.

INTRADE and IOWA do not have the same vulnerability in relation to the potential for being manipulated. Berg et al (2008) note that IOWA possessed institutional features that make such manipulation difficult to implement. IOWA uses a unit portfolio issuance approach whereby the two opposing contracts, whose payoffs sum to one, are issued together to traders who then trade the components separately. This ensures that there is always a contract for each candidate. So a would-be market manipulator would not only have to drive up the price on his preferred candidate but would also have to drive down the price of his opponent. Furthermore, the maximum investment in IOWA was $500; whereas INTRADE allowed for a $2000 deposit limit in the first month and $5000 thereafter. The investment limit of IOWA suggests that differences between INTRADE and IOWA would be difficult to arbitrage. It also suggests that a small number of wealthy investment interests would be more likely to attempt a manipulation of INTRADE's implied probabilities than to attempt a manipulation of IOWA's probabilities. Indeed, there was media speculation that some investments in the INTRADE "Barack Obama to be re-elected president 2012" betting market were done with the express intention of influencing voters' decisions. In addition, INTRADE's implied probabilities regarding the possibility of an Obama victory were almost always strikingly lower than the probabilities implied by IOWA. Finally, Rothstein and Sethi (2013) document evidence that about one-third of the money invested in Romney tickets on INTRADE during the last two weeks of the 2012 US presidential election were conducted by one trader who subsequently incurred millions of dollars in losses.

In this paper, in order to assess the “efficiency” of IOWA, INTRADE, SILVER and POLLS, we examine the potential cointegration and causal associations between these prediction sources. We note that we are using the word “efficiency” broadly as, unlike commodity futures markets where there is a spot price, there is no way to determine which presidential prediction is best. However, we feel that since previous literature (e.g., Goodell and Vahamaa (2013); Goodell and Bodey (2012)) finds that presidential election predictions and election uncertainty are important partial determinants of US market uncertainty, it is important to investigate the degree of agreement amongst prediction vehicles.

As Granger (1988) posits, any cointegration necessarily implies some Granger causality. Therefore, we test for the cointegraton and Granger-causality amongst IOWA, INTRADE, SILVER and POLLS. We consider that if the other series Granger-causes INTRADE that this is consistent with INTRADE being manipulated for non-pecuniary reasons. This would especially be likely if INTRADE consistently reacts to the other predictions for an Obama victory with a lower Obama-victory prediction. This would be the result of investors bidding up the Romney ticket or shorting the Obama ticket. We examine both the cointegration and causal relationships between the IOWA, INTRADE, SILVER and POLLS. We document strong evidence that the first three series are highly cointegrated, while POLLS in not cointegrated with any of the other series. Like Leigh and Wolfers (2006) and Berg et al (2008), we found election polls to be erratic and not very informative. We document strong evidence that IOWA Granger-caused INTRADE; and some evidence that SILVER also Granger-caused INTRADE. Overall, our findings provide independent support for the notion of Rothstein and Sethi (2013) that INTRADE prices were manipulated in 2012 for non-pecuniary reasons, and crucially that this appears to have gone on for much longer than Rothstein and Sethi (2013) were able to show in their study.

Our results highlight important questions. Why was SILVER so much bolder in its forecasts than prediction markets?. To what degree did Silver himself have confidence in prediction markets? To what degree did prediction-market prices reflect the published predictions of Silver? We note that the SILVER forecasts, with respect to confidence in an Obama victory, strengthened and weakened over time in a similar manner to the prediction markets. Was IOWA or SILVER was the best election predictor? If SILVER was so widely regarded as a prognosticator, why was the SILVER-IOWA difference not exploited by investors such that the IOWA price increased? Alternatively, if prediction markets are acknowledged as optimal information aggregators, why did SILVER not update downward to close with IOWA? Was the IOWA prediction market a better estimator than SILVER? Or alternatively, for structural or non-pecuniary reasons, did IOWA not update sufficiently?

Our results should be of great interest to researchers interested in the efficacy of prediction markets as aggregators of information and the concomitant reactions of relevant agents. Additionally, our results will be of interest to researchers seeking to evaluate differing estimators of US election uncertainty, especially with regard to its accompanying consequences for financial markets.

2. Background

2.1 Prediction markets as aggregators of information

As noted by Bennouri, Gimpel and Robert (2011), predictions markets are increasingly seen as important vehicles for information aggregation (see also Plott (2000); Wolfers and Zitzewitz (2004); Wolfers and Zitzewitz (2009); Berg, Neumann and Rietz (2009)). Prediction markets are used in a wide variety of areas including weather prediction (weather derivatives on the Chicago Mercantile Exchange), sports (www.tradesports.com) and entertainment (i.e., the Hollywood Stock Exchange, www.hsx.com). As noted by Bennouri et al. (2011), prediction markets as information gathering mechanisms serve a closely similar function to information gathering prior to initial public offerings (Aussenegg, Pichler and Stomper (2006); Berg et al. (2009); Derrien and Kecskes (2007); Loffler, Panther and Theissen (2005); Sherman and Titman (2002)); as well as the market for treasury securities (Nyborg and Sundaresan (1996)). Recently, Goodell and Bodey (2012) and Goodell and Vahamaa (2013) have looked at the effect of the Iowa Presidential Election prediction market on price-earnings ratios and market volatility respectively.[1]

The value of prediction markets to forecast future outcomes continues to be of great importance. And so research into the nature of how agents update their forecasts and behavior based on the information aggregation of prediction markets continues to be of considerable interest. As noted by Bennouri et al. (2011), predictions markets are increasingly seen as important vehicles for information aggregation. Plott (2000) offers a view of what this partially implies: “it means that markets can find the solution to a complex set of equations that are part of the knowledge of no one.” Second, it means that while finding this solution, it can collect information that is dispersed across the economy, aggregate it like a statistician, and publish it in the form of prices.” This notion of Plott (2000) speaks to the possibility of information aggregating markets not just impacting agents but that agents can impact information aggregating markets.

Recently a document composed and signed by a number of the most distinguished scholars in economics has advocated for the US government to allow more leeway in the creation of prediction markets, arguing their value for society: The authors posit that prediction markets can significantly improve decision making in both private and public sectors and would create greater transparency and accountability. (Arrow, Forsythe, Gorham, Hahn, Hanson, Kahneman, Ledyard, Levmore, Litan, Milgrom, Nelson, Neumann, Ottaviani, Plott, Schelling, Shiller, Smith, Snowberg, Sunder, Sunstein, Tetlock, Tetlock, Varian, Wolfers and Zitzewitz (2007)).

2.2 Election futures as estimates of probability

Elections futures markets have an important place in finance literature because of their role in assessing election uncertainty. And consequently they have an important place in assessing the financial impact of election uncertainty. Leigh and Wolfers (2006) compare the efficacy of three diverse

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[1] In 2001, Defense Advanced Research Projects Agency (DARPA) of the US government, began to fund research on prediction markets. This research program was eventually named FutureMAP. By December 2001 two firms had secured research grants. In 2003, when two US senators suggested prediction markets might allow individuals to bet on individual terrorist attacks, FutureMAP was cancelled.

approaches to forecasting elections: econometric models that project outcomes on the basis of the state of the economy; public opinion polls; and election betting (prediction markets). They conclude that betting markets, as a form of prediction markets are reliable. As noted above, Oliven and Rietz (2004) consider whether the Iowa Electronic Markets are skewed by a non-representative sample of mistake-prone and biased traders. They conclude, a la Black (1986), that market-making traders are more rational than price-taking traders, allowing prediction markets to function efficiently. This is an important consideration with regard to US presidential election markets given the partisan nature of elections. Wolfers and Zitzewitz (2004) examine whether prediction markets as information aggregators are able to efficiently forecast. They conclude that market-generated forecasts are typically fairly accurate, and that they outperform most moderately sophisticated benchmarks. Clearly the study of prediction markets is integral to understanding their usefulness for forecasting.

Recently some papers (e.g., Goodell and Bodey (2012); and Goodell and Vahamaa (2013)) have used data from the Iowa Election "winner-take-all" Market (IEM) to infer probabilities of presidential candidates winning the election. As noted by Berg, Nelson and Rietz (2008), Arbitrage Pricing Theory implies that

$$P_t = \frac{E(P_T)}{(1+k)^h} \qquad 1)$$

where P_t is the price today, P_T is the price on election day (T election date), k is the sum of the risk-free rate and other risk factors and h is the time to election. Under the assumption that k = 0, this leads to

$$P_t = E(P_T). \qquad 2)$$

Berg et al. (2008) suggest it is reasonable to assume the risk-free rate and other risk factors are zero, as the outcome to the overall sum of payoffs in the IEM winner-take-all market does not depend on the election. The probabilities are inferred by the assumption (ignoring third-party candidates) that purchasing both a Republican and a Democratic ticket would entail a certainty of payoff equal to the cost of the futures.[2] The market prices of the IEM presidential contracts reflect probabilities because the payoff to the Republican ticket is $1 if the Republican candidate wins and $0 otherwise. Similarly, the payoff to the Democratic candidate is $1 if the Democratic candidate wins and $0 otherwise. Therefore, if the Republican ticket costs 60 cents, the Democratic ticket must cost 40 cents. This is because buying both tickets would ensure a payoff of $1. This relation is directly analogous to the relation between the probabilities of a Republican and Democratic victory.

Whether US presidential election prediction markets are suitable to form election probabilities is important in the context of much recent literature that has investigated the association of the shorter-term effects of the U.S. presidential elections and election uncertainty on stock markets (e.g., Nippani and Medlin (2002), Nippani and Arize (2005), Li and Born (2006), He et al. (2009), Goodell and Vahamaa (2013), and Goodell and Bodey (2012)).

Li and Born (2006) use polling data on the U.S. presidential elections from 1964 through 2000 to examine the effects of election induced uncertainty on stock returns and volatility. Their findings suggest that stock prices and market uncertainty increase before elections when neither of the candidates has a dominant lead in the presidential preference polls. Nippani and Medlin (2002), Nippani and Arize (2005), and He, Lin, Wu and Dufrene (2009) focus on the curious case of the 2000 presidential election with delayed results. These studies demonstrate that the U.S. and international stock markets were negatively affected by the uncertainty caused by the delay in election results. Most recently, Goodell and Bodey (2012) investigate price-earnings ratios of the S&P 500 firms around U.S. presidential elections and document that stock market valuations are negatively associated with the lessening of election uncertainty.

Li and Born (2006) document that volatility increases before U.S. presidential elections when the outcome of the election is uncertain. Gemmill (1992) and Bialkowski, Gottschalk and Wisniewski (2008) also examine the impact of political elections on market uncertainty. Gemmill (1992) focuses on the

[2] See http://www.biz.uiowa.edu/iem/index.cfm for further details about the Iowa Electronic Markets.

British parliamentary election of 1987, and finds that opinion polling was connected to both the level of the FTSE 100 index as well as market volatility. In particular, Gemmill (1992) documents that the implied volatility of the FTSE 100 index increased substantially in the last two weeks before the election at the same time as opinion polls were predicting a Conservative victory with increasing probability. Bialkowski et al. (2008) use data on 27 OECD countries to investigate the effects of national parliamentary and presidential elections on stock market volatility. Their empirical findings indicate that national elections are associated with periods of increased volatility. Consistent with Gemmill (1992), they also report that implied volatilities move upwards in the last week before elections. Goodell and Bodey (2012) find market price-earnings ratios surprisingly falling as election uncertainty decreases. Goodell and Vahamaa (2013) find that market volatility increases with the election prospects of the eventual winner.

2.3 Nate Silver predictions

We include the predictions of Nate Silver because they are both particularly relevant as agent updates—from the perspective of Nate Silver predictions being potentially influenced by election prediction markets. Additionally, the daily probability estimates of Nate Silver closely resemble the daily probability estimates of election prediction markets inferred from their closing prices. In this latter case it is worth investigating whether prediction markets are influenced by Nate Silver's predictions.

As an example of an agent, Silver is particularly appropriate as he is 1) widely known, being reported daily in *New York Times*; 2) publicly purports to be influenced by an assessment of all polling and prediction market data; has a strong past record of success. As a proxy for a prediction market, while not a market place, Silver's predictions are aggregators of information that have a widely publicized "price" (the daily probability assessment). Indeed by being prominent daily in the *New York Times*, it is arguable that Nate Silver's predictions were much more in the public eye than the prices of prediction markets. And so if a prediction market was to be manipulated to raise the price of a favored candidate it would be reasonable for this behavior to be influenced by the daily Nate Silver prediction.

In March 2008, Nate Silver established his blog *FiveThirtyEight.com,* in which he developed a system for tracking polls and forecasting the outcome of the 2008 general election. Silver's final 2008 presidential election forecast accurately predicted the winner of 49 of the 50 states as well as the District of Columbia. He also correctly predicted the winners of every open election for the US Senate. With regard to the 2012 US presidential election, the final update of Silver's model at gave President Barack Obama a 90.9% chance of winning a majority of the 538 electoral votes. Silver correctly predicted the winner of every one of the 50 states and the District of Columbia. In contrast, individual pollsters were less successful. For example, *Rasmussen Reports* was widely noted for its inaccuracy.

2.4 Contribution

As noted by Bennouri et al. (2011), predictions markets are increasingly seen as important vehicles for information aggregation. We mention above the enormous variety of contexts and potentialities of prediction markets as information aggregating markets. Bennouri et al. (2011) also note that there has been little prior literature investigating directly the effect of prediction markets on agents. Exceptions would be Goodell and Bodey (2012); and Goodell and Vahamaa (2013) who study the impact of prediction markets on the valuations and volatility of the S&P500. In this case market participants in the S&P equity are the agents.

But is it also worth considering whether agents impact predictions markets. As noted above, Plott (2000) suggests that markets can find the solution to a complex set of equations that are part of the knowledge of no one and that they effectively aggregate all information (including the predictions of well publicized individuals such as Nate Silver) in prices. This notion of Plott (2000) speaks to the possibility of information aggregating markets not just impacting agents but that agents can impact information aggregating markets. Clearly if Bennouri et al. (2011) are correct, that there has been little previous research investigating the effect of prediction markets, then there has been even much less research considering whether agents impact prediction markets.

This paper helps to fill a gap in the literature: there has been very little investigation of the efficiency of presidential election markets. Additionally, this paper presents new information relevant to how agents affect prediction markets along with how prediction markets affect agents. Further, more specifically, there has been little prior literature on the cointegration of election futures markets. Additionally this paper contributes to the literature by testing the causal relationships between election futures markets and polling. If prediction markets are to be again used in the future to infer election uncertainty, the cointegration of election markets is extremely important. This paper should be of considerable interest to researchers.

3. Methodology

This study uses different techniques to analyze the relationship between the SILVER, INTRADE, IOWA and POLLS prediction series. Below we set out the bivariate analysis we conduct, where we analyze two of the prediction markets at a time. However we also use multivariate analysis where all three prediction markets are studied together[3]. Our data is the daily price of an Obama ticket on the Iowa or Intrade markets, or in the case of Nate Silver, the daily published probability of an Obama victory. Our elections polls data is from the Real Clear Politics website (www.realclearpolitics.com), where our POLLS variable is the daily average of election polls that they computed and published. Our period is from May 31 2012 to November 5 2012.

3.1 Cointegration tests

The first method adopted is the Engle-Granger cointegration approach (Engle and Granger (1987)) which is based on analysing the stationarity of error term series obtained from the equation derived with level values of time series that are not stationary on the level but become stationary when their difference is taken.[4] If the error term series is stationary, this means that there is a cointegration relationship between the mentioned two time series. In the first step, we estimate the following equation

$$y_t = \alpha_0 + \beta_1 x_t + \varepsilon_t \qquad 3)$$

[3] The methodology for the multivariate analysis is omitted for brevity but along the same lines as the bivariate analysis.

[4] Cointegration tests have been previously used to assess forecasting potentials in a wide variety of contexts (e.g. Baillie and Selover (1987) (forecasting exchange rates); Clements and Galvao (2004) (US interest rates); Enders and Falk (1998) (purchasing power parity prices);and Kulendran and King (1997) (tourist flows)

Where y_t and x_t are two different series. The estimated residuals $\hat{\varepsilon}_t$ from the above equation are considered to be temporary deviations from the long-run equilibrium, then they were investigated by using the following ADF unit root test[5]:

$$\Delta\hat{\varepsilon}_t = \alpha_1\hat{\varepsilon}_{t-1} + \sum_{j=1}^{p}\alpha_j\Delta\hat{\varepsilon}_{t-j} + \upsilon_t \qquad 4)$$

Where α are the estimated parameters and υ_t is the error term. The cointegration test is conducted by a hypothesis test on the coefficient of α_1. If the t-statistic of the coefficient exceeds a critical value, the residuals from equation 3) are stationary, and thus the series y_t and x_t are cointegrated (i.e. they move together in the long-run). This test is caused for each bivariate combination of the series, as well as a multivariate combination of all three series.

3.2 Linear Granger Causality Test

The Granger causality test is a popular way to test if there is any temporal statistical relationship with a predictive value between two time series (Granger (1969)). This test indicates any possible short-run predictive interrelationships among the series. When 'X Granger causes Y', it does not mean that Y is the effect or the result of X. Granger causality measures precedence and information content but does not by itself indicate causality in the common-sense use of the term. Thus 'causality' is defined in terms of predictability, hence variable X causes variable Y if present Y can be better predicted by using past values of X than by not doing so, with respect to a given information set that includes X and Y.

In order to test for Granger causality, we considered two series x_t and y_t, then we estimated the following equations;

$$\Delta x_t = \beta_0 + \sum_{i=1}^{n}\beta_{1i}\Delta x_{t-1} + \sum_{i=1}^{m}\beta_{2i}\Delta y_{t-1} + \varepsilon_{1t} \qquad 8)$$

[5] The Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are also conducted for robustness purposes, but the equations are omitted for brevity.

$$\Delta y_t = \delta_0 + \sum_{i=1}^{n} \delta_{1i} \Delta y_{t-1} + \sum_{i=1}^{m} \delta_{2i} \Delta x_{t-1} + \varepsilon_{1t} \qquad 9)$$

After estimating the Granger-causality we run an F-test for joint insignificance of the coefficients. Assuming the null hypothesis that x_t does not Granger cause y_t, a rejection of the null hypothesis shows a presence of Granger causality. The Granger causality tests are performed for each pair of prediction series.

3.3 Error Correction Mechanism

We further our analysis by using an Error Correction Mechanism (ECM). Engle and Granger (1987) state that if two variables are cointegrated, then each series can be represented by an (ECM) which includes both the last period's equilibrium error and the lagged values of the first difference of each variable. Let x_t and y_t represent the logs two series respectively then, the ECM can be written as the following:

$$\begin{aligned} \Delta y_t &= \alpha_y + \gamma_y \Delta y_{t-1} + \rho_y \Delta x_{t-1} + \beta_y \upsilon_{t-1} + \varepsilon_t^y \\ \Delta x_t &= \alpha_x + \gamma_x \Delta x_{t-1} + \rho_x \Delta y_{t-1} + \beta_x \upsilon_{t-1} + \varepsilon_t^x \end{aligned} \qquad 10)$$

Where Δy_t is the first difference of the y variable and Δx_t is the first difference of the x variable. α is the constant, γ is the coefficient attached the previous dependent variable, ρ is the coefficient attached to the independent variable and β is the coefficient of the previous lagged residual from equation 3). Both equations are run to determine the direction (if any) of the causation. The error correction mechanism is represented by the coefficient β, which measures how quickly current prices correct the last period deviation and restore to their long run equilibrium. For instance, if β_y is significant, it indicates that current x values will adjust to last period's deviation from equilibrium. ρ will show the lead/lag relationship of the data. We conduct bivariate ECM for each pair of prediction series, and we also run a multivariate ECM to include all three prediction series such that;

$$\Delta y_t = \alpha_y + \gamma_y \Delta y_{t-1} + \rho_y \Delta x_{t-1} + \theta_y \Delta z_{t-1} + \beta_y \upsilon_{t-1} + \varepsilon_t^y$$

$$\Delta x_t = \alpha_x + \gamma_x \Delta x_{t-1} + \rho_x \Delta x y_{t-1} + \theta_x \Delta z_{t-1} + \beta_x \upsilon_{t-1} + \varepsilon_t^x$$
$$\Delta z_t = \alpha_z + \gamma_z \Delta z_{t-1} + \rho_z \Delta x_{t-1} + \theta_z \Delta y_{t-1} + \beta_z \upsilon_{t-1} + \varepsilon_t^z \qquad 11)$$

3.4 Nonlinear Granger Causality Test

One important problem with the linear Granger causality test is that it may ignore the nonlinear relations between economic variables. Thus Baek and Brock (1992) propose a nonparametric method to test for the nonlinear causal relations between variables. Hiemstra and Jones (1994) use a modified Baek and Brock (1992) test to examine the relationship between stock price and volume and find bidirectional nonlinear causation, when the linear causation test just found unidirectional causality from stock returns to trading volume.

Let $\{x_t\}$ and $\{y_t\}$ be two strictly stationary and weakly dependent time series, denote the *m*-length lead vector of x_t by x_{tm} and the *lx*-length and *ly*-length lag vector of $\{x_t\}$ and $\{y_t\}$, respectively, by x_{t-lx}^{lx} and y_{t-lx}^{lx}. For $lx \geq 1$, $ly \geq 1$, $m \geq 1$ and $e > 0$, *y* does not strictly Granger cause *x* if;

$$\Pr\left(\| x_t^m - x_s^m \| < e \mid \| x_{t-lx}^{lx} - x_{s-lx}^{lx} \| < e, \| y_{t-ly}^{ly} - y_{s-ly}^{ly} \| < e\right)$$
$$= Pr(\| x_t^m - x_s^m \| < e \mid \| x_{t-lx}^{lx} - x_{s-lx}^{lx} \| < e) \qquad 12)$$

Where Pr(·) and ||·|| denote the probability and the maximum norm, respectively. The left side of equation 12) is the conditional probability that two arbitrary *m*-length lead vector of $\{x_t\}$ are within a distance *e* of each other, given that the corresponding *lx*-length and *ly*-length lag vector are within *e* of each other. Equation 12) states that if *y* does not strictly Granger cause *x*, then adding lagged values of *y* will not improve the prediction power of *x* from lagged *x* values. The strict Granger noncausality condition in equation 12) can be expressed as;

$$\frac{C1(m+lx, ly, e)}{C2(lx, ly, e)} = \frac{C3(m+lx, e)}{C4(lx, e)} \qquad 13)$$

Where;

$$C1(m+lx,ly,e,n)=\frac{2}{n(n+1)}\sum_{t<s}\sum_{s}I\left(x_{t-lx}^{m+lx},x_{s-lx}^{m+lx},e\right)\times I(y_{t-ly}^{ly},y_{s-ly}^{ly},e), \qquad 14)$$

$$C2(lx,ly,e,n)=\frac{2}{n(n+1)}\sum_{t<s}\sum_{s}I\left(x_{t-lx}^{lx},x_{s-lx}^{lx},e\right)\times I(y_{t-ly}^{ly},y_{s-ly}^{ly},e),$$

$$C3(m+lx,e,n)=\frac{2}{n(n+1)}\sum_{t<s}\sum_{s}I\left(x_{t-lx}^{m+lx},x_{s-lx}^{m+lx},e\right),$$

$$C4(lx,,e,n)=\frac{2}{n(n+1)}\sum_{t<s}\sum_{s}I\left(x_{t-lx}^{lx},x_{s-lx}^{lx},e\right).$$

$$t,s=\max(lx,ly)+1,\ldots T-m+1,n=T+1-m-\max(lx,ly).$$

Where $I(Z_1, Z_2, e)$ denote a kernel that equals 1 when two confirmable vectors Z_1 and Z_2 are within the maximum-norm distance e of each other and 0 otherwise. Using the joint probability estimators in equation 14), the strict Granger noncausality conditions in equation 12) can be tested as follows. For $lx \geq ly \geq 1$, $m \geq 1$, and $e > 0$;

$$\sqrt{n}\left(\frac{C1(m+lx,ly,e,n)}{C2(lx,ly,e,n)}-\frac{C3(m+lx,e,n)}{C4(lx,e,n)}\right)\sim AN\left(0,\sigma^2(m,lx,ly,e)\right). \qquad 15)$$

Which is used as a test statistic to test for nonlinear Granger causality. By choosing $lx = ly = m = 1$, condition 2 can be expressed in terms of ratios of joint distribution of (X_t, Y_t, X_{t+1}) as follows;

$$\frac{f_{xt,yt,xt+1}(X_t,Y_t,X_{t+1})}{f_{xt,yt}(X_t,Y_t)}=\frac{f_{xt,xt+1}(X_t,X_{t+1})}{f_{xt}(X_t)} \qquad 16)$$

Where the null hypothesis of no Granger causality would be rejected if the discrepancy between the two sides of equation 16) is statistically insignificant.

However, Diks and Panchenko (2006) show that the Hiemstra and Jones (1994) test tends to incur spurious discovery of nonlinear Granger causality, and the probability to reject the Granger noncausality increases with sample size. Instead they provide an alternative nonparametric test for nonlinear Granger causality that circumvents the problem in the Hiemstra and Jones (1994) test through replacing the global statistic by the average of local conditional dependence measures. We follow their method to test for nonlinear Granger causality where Diks and Panchenko (2006)modified the null hypothesis as;

$$E\left[\left(\frac{f_{xt,yt,xt+1}(X_t,Y_t,X_{t+1})}{f_{xt,yt}(X_t,Y_t)} = \frac{f_{xt,xt+1}(X_t,X_{t+1})}{f_{xt}(X_t)}\right) \times g(X_t,Y_t,X_{t+1})\right] = 0 \qquad 17)$$

Where g(·) is a positive weight function defined as $f^2_{xt}(X_t)$. Using equation 16), the null hypothesis is expressed as;

$$E\left[f_{xt,yt,xt+1}(\cdot)f_{xt}(\cdot) - f_{xt}(\cdot)f_{xt,yt,xt+1}(\cdot)\right] = 0 \qquad 18)$$

Resulting in the following test statistic;

$$T_n(e) = \frac{n-1}{n(n-2)}\sum_{i}^{n} \hat{f}_{xt,yt,xt+1}\,(x_{it},y_{it},x_{it+1})\hat{f}_{xt}(x_{it}) - \hat{f}_{xt,yt}(x_{it},y_{it})\hat{f}_{xt,xt+1}(x_{it},x_{it+1}) \qquad 19)$$

The local density estimate of each *dz*-variate random vector is obtained as;

$$\hat{f}_z(z_i) = \frac{(2e)^{-dz}}{n-1}\sum_{j,j\neq i} I(z_i, z_j, e) \qquad for\ z_i = X_{it}, Y_{it,} X_{it+1} \tag{20}$$

According to Diks and Panchenko (2006) the $T_n(e)$ test statistic is asymptotically distributed as N(0,1) if for any C > 0 and $\beta \in (1/4, 1/3)$, the sequence of bandwidth values are determined by $\epsilon_n = C_n^{-\beta}$[6].

4. Empirical Results

4.1 Descriptive statistics

Table 1 reports the descriptive statistics for the four series. SILVER has the largest mean and POLL the smallest, while IOWA has the largest standard deviation and POLL the smallest. Further each series is right skewed, with a significant Jarque-Bera statistics indicating the non-normal nature of all series.

(Please insert Table 1 about here)

Table 2 reports the correlation and covariance statistics among the three series. The results suggest that there is strong and significant three-way correlation between the prediction markets and Silver. Further each covariance is also significant, with SILVER–IOWA having the strongest covariance. One very notable feature is that POLLS exhibits low correlation with all the other series.

(Please insert Table 2 about here)

Figure 1 plots the time series plots of the series showing that they general move together in the same direction with SILVER always the highest and INTRADE generally lower than IOWA. We show the various election polls that were administered over the period as individual points on this graph. From this we see that there is considerable variation among election polls, even among polls that are taken on

[6] See Diks and Panchenko (2006) for more details.

the same day. POLLS, which is the RCP-computed average of election polls meanders through the cloud of election poll results, bears remarkably little resemblance to the three series that fluctuate above it.

(Please insert Figure 1 about here)

A necessary condition to perform a cointegration test is that the order of integration of the variables has to be the same. In order to detect the order integration we employed three unit root tests, namely the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller (1979)) Phillips-Perron test (PP) (Phillips and Perron (1988)) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) (Kwiatkowski, Phillips, Schmidt and Shin (1992)). Table 3 shows that the null hypothesis of a unit root is not rejected for all series in log levels, where it is rejected when they are taken in their log first differences form. Thus the first difference of all series will be used in the subsequent analysis.

4.2 Results of Engle Granger cointegration test

If the series have a cointegration relationship, the residual error series of each of the equations estimated in the first step, should have stationarity. Table 4 reports the unit root test results for the Engle Granger two-step approach for cointegration for the three variations of the two-series approach. The ADF test and the PP test both reject the null hypothesis of the no unit root in the residuals for each bivariate variation, indicating stationarity and cointegration between SILVER, IOWA an INTRADE. Further, the KPSS fails to reject its null of unit roots in the residuals for each variation, again indicating cointegration between these three series. The multivariate results also show that there is strong cointegration since the residuals reject the null of no units for the ADF and PP test, and fails to reject the null of unit roots for the KPSS test. Thus the results from Table 4 suggest that there is a long-run relationship between these three series and hence cointegration[7]. The evidence suggests that POLLS is not cointegrated with the other three series.

(Please insert Table 3 about here)

(Please insert Table 4 about here)

4.3 Results of Linear Granger Causation

The first three series are first difference stationary and cointegration results show clear evidence of robust cointegration between them. We further our analysis by examining if there is any causation between the prediction markets. Table 5 reports the Granger causality results and shows Granger casuality from SILVER to IOWA. Further, SILVER and IOWA both Granger causes INTRADE suggesting that INTRADE is sluggish compared to SILVER and IOWA. When examining the POLLS data, there is no causality between POLLS and any of the other series indicating that POLLS is completely independent of SILVER, IOWA and INTRADE.

(Please insert Table 5 about here)

4.4 Results of Error Correction Model

Panel A of Table 6 reports the bivariate ECM results. The γ is the coefficient associated with the lagged dependent variable, ρ is the coefficient associated with the lagged independent variable while β is the coefficient associated with the error correction. The null hypothesis that in independent variable does not lead the dependent variable cannot be rejected since ρ is insignificant for all combinations except when IOWA leads Intrade. In this case, ρ is significant indicating that the Iowa price contains useful information in forecasting the next periods INTRADE, and that this is a unidirectional causality. β_I is significant for the IOWA–SILVER, INTRADE–SILVER and INTRADE–IOWA combinations, indicating that the dependent variable's next period price will also be positive. Panel B of Table 6 reports the multivariate ECM results. The null hypothesis that INTRADE and IOWA do not lead SILVER cannot be rejected since ρ_s and θ_s are insignificant, thus suggesting that INTRADE and Iowa provide little information in forecasting the next period's SILVER. The β_s is the error correction coefficient, which is

[7] We also conduct the Johansen test for cointegration and find broadly similar results.

negative which implies that if the current SILVER price is above its equilibrium level, it will decrease in value in the next period thus eliminating any disequilibrium.

Regarding the situation when the INTRADE is the dependent variable, SILVER has little power in forecasting next period's INTRADE. However, θ_I is significant indicating that the null hypothesis that Iowa does not lead INTRADE can be rejected suggesting that that the Iowa price contains useful information in forecasting next period INTRADE. This is a unidirectional causality since when Iowa in the dependent variable, the ρ_w is insignificant. β_w, however, is positive and significant at 1% indicating that if β_w is positive the Iowa price in the next period will also be positive. The autocorrelation coefficient θ_w is significant indicating that Iowa prices can be forecasted by their historical levels. Our results show that there is long run equilibrium between INTRADE and IOWA, though the speed of adjustment in faster for the Iowa prices, and that Iowa can be used to forecast INTRADE.

(Please insert Table 6 about here)

4.5 Results of Nonlinear Granger Causality

As a robustness test, we also investigate whether there are non-linear causal relationships between INTRADE, IOWA and SILVER. We wish to determine whether the linear Granger causality tests conducted above have captured all of the causation between SILVER and the two prediction markets. Table 7 reports the on nonlinear Granger causality tests applied to the estimated residuals $\{\varepsilon^y_t\ \varepsilon^x_t\ \varepsilon^z_t\}$ from equation (10). We find no evidence of any directional causality between IOWA, INTRADE and SILVER, with all nonlinear Granger causality test statistics failing to reject the null hypothesis of no causality at 5%. This contrasts with the results of the linear Granger causality test, which found significant evidence of causation from IOWA to INTRADE, and some evidence that SILVER also Granger-caused INTRADE. Thus we conclude that the linear Granger causality test has captured all of the causation between SILVER and the two prediction markets.

(Please insert Table 7 about here)

4.6 Robustness Check

Rothstein and Sethi (2013) report evidence that INTRADE was manipulated during the last two weeks of the presidential election in 2012. To test whether this 2 week period was the main driver of our results, we re-ran our analysis on the same data but excluded the final 2 weeks, i.e. we examined the relationship between the series between May 31 2012 and 22 October 2012. The results are collated together in Table 8 and Panel A shows there is strong evidence of cointegration between the markets through the Engle-Granger test. The Granger causality test results reported in Panel B suggest that the IOWA Granger causes INTRADE remains strong. However, the SILVER Granger causes INTRADE results is now weaker, at only 7% significance. Therefore, after excluding the final two weeks of the sample period, we find weaker evidence of SILVER Granger causing INTRADE. The univariate ECM results in Panel C are very similar to the original results, with evidence that IOWA contains useful information in forecasting the next period INTRADE. Panel D reports the multivariate ECM and suggests evidence INTRADE lags IOWA, similar to the univariate results.

5. Discussion

5.1 IOWA to INTRADE results

As shown in our results for the Engle and Granger (1987) cointegration tests and the Johansen cointegration tests, we robustly find the IOWA and INTRADE prediction markets to be cointegrated. Further, Granger causality testing finds that INTRADE is partially caused by IOWA. Our results point toward INTRADE lagging IOWA short-term. Therefore there is the potential for IOWA to predict INTRADE. These results are consistent with IOWA updating quicker than INTRADE or alternatively (or concomitantly) money interest reacting to IOWA and subsequently trying to lower INTRADE.

Rothstein and Sethi (2013) conclude that a huge amount of trades on INTRADE during the last two weeks of the 2012 US presidential election were conducted by one trader who ended up with multi-million dollar losses. They found that one-third of the money invested in INTRADE during this period came from this one single source. Rothstein and Sethi (2013) consider three possible reasons for their findings 1) that the investor judged the Romney ticket to be underpriced; 2) that the investor was hedging an idiosyncratic risk, or 3) the investor was trying to influence the price of INTRADE for non-pecuniary reasons—most likely to reinforce the appearance of a higher probability of a Romney victory. Our results are consistent with Rothstein and Sethi (2013). Our results of IOWA Granger causing INTRADE are particularly consistent with the third possibility and argue against possibility 1): if IOWA is reflecting a lower probability of a Romney victory (see Figure 1) this would tend to dissuade a speculative investment on the Romney ticket being underpriced, but would encourage reinforcing the Romney ticket on INTRADE for appearance reasons. A notable aspect of our results is that we still got the IOWA Granger causes INTRADE result when we excluded the final two-week Rothstein and Sethi (2013) period. Together with INTRADE's season-long sharply higher Romney win-probability, this suggests that INTRADE may have been manipulated for a much longer period than the final two weeks.

5.2 SILVER results

Granger (1988) discusses that the identification of cointegration necessarily implies the existence of a Granger causality. In our results we document evidence of cointegration of SILVER with IOWA and INTRADE. However we do not find evidence of Granger causality in either direction with regard to SILVER with IOWA. We do document evidence at the looser 10% level that SILVER Granger-causes INTRADE. These results, along with the theoretical writings of Granger (1988) are consistent with the relationship between SILVER and IOWA being not short-term but rather one of a long-run trend-line nature. We document some evidence of SILVER having a short-term causation on INTRADE.

Our results for SILVER Granger causing INTRADE are again consistent with Rothstein and Sethi (2013). As in the case above of IOWA Granger causing INTRADE, our results of SILVER Granger causing INTRADE are consistent with the possibility that investors (or the single large investor identified by Rothstein and Sethi (2013)) were trying to influence the price of INTRADE in order to reinforce the appearance of a higher probability of a Romney victory: if SILVER is presenting a lower probability of a Romney victory (see Figure 1) this tends to dissuade a speculative investment that the Romney ticket is underpriced, but adds impetus to any motivation to reinforce the Romney ticket on INTRADE for appearance reasons.

5.3 The Difference between Election Polls, Prediction Markets and SILVER

A stark feature of Figure 1 is that SILVER, the prediction markets and the election polls each seem to occupy their own distinct region of space on the graph. This might be partially due to each attempting to answer a different question: election prediction markets offer estimates of the probability of an Electoral College victory; Silver offered an estimate of the probability of Obama winning a majority of the popular vote; and election polls attempt to measure the current popular vote. As polls ask registered and likely voters who they intend to vote for, they are attempting to measure the popular vote. However, on four separate occasions (1824, 1876, 1888 and 2000), the US presidency was won by a candidate who lost the popular vote. It is the number of Electoral College votes, not the popular vote, which determine which candidate will be president. In 2012, while Obama only won 51.1% of the popular vote, his margin of victory in Electoral College votes was 61.7%. Of course there will by some pecuniary-driven smart money in the prediction markets which will recognize this difference. This may be why, as Berg et al (2008) shows, prediction markets give results much closer to eventual outcomes than election polls.

5.4 Remaining questions

Our results still leave open the question of why SILVER is so much bolder in his forecasts than prediction markets. To what degree did Silver himself have confidence in prediction markets? To what degree did prediction-market prices reflect the published predictions of Silver? We note that the SILVER forecasts, with respect to confidence in an Obama victory, strengthened and weakened over time in a similar manner to the prediction markets. The fact that the winner of the popular vote and the Electoral College winner are not necessarily equivalent seems insufficient to explain SILVER being so much more confident than IOWA or INTRADE.

The dynamic between IOWA and SILVER is contrasts sharply with the simple case of normal market functioning with respect to an expert offering a price prediction for two reasons: 1) A widely publicized expert offering advice on an investment can affect prices. On the other hand, electoral outcomes are certainly determined by partisan voting and not pecuniary involvement in election markets. 2) Vastly more American voters were aware of Silvers daily forecasts than IOWA prices. Our results leave open several important question of whether IOWA or SILVER was best election predictor. If SILVER was so widely regarded as a prognosticator, why was the SILVER-IOWA difference not exploited by investors? Alternatively, if prediction markets are acknowledged as optimal information aggregators, why did SILVER not update downward to close with IOWA? Was the IOWA prediction market a better estimator than SILVER? Or alternatively, for structural or non-pecuniary reasons, did IOWA not update sufficiently?

6. Conclusions

Predictions markets are increasingly seen as important vehicles for information aggregation (Bennouri et al. (2011); Plott (2000); Wolfers and Zitzewitz (2004); Wolfers and Zitzewitz (2009); Berg et al. (2009)). Prediction markets are used in a wide variety of areas including weather prediction and entertainment; as well as information gathering prior to initial public offerings and the market for treasury securities. The value of prediction markets to forecast future outcomes continues to be of great importance. And so research into the nature of how agents update their forecasts and behavior based on the information aggregation of prediction markets continues to be of considerable interest.

In this paper, we examine the potential cointegration and causal associations between IOWA and INTRADE, alongside the widely publicized election predictions of Nate Silver (SILVER) and the variety of election polls conducted over the same period. We do this in order to compare the relative efficiency of presidential futures markets and in order to investigate whether we could find evidence that during the 2012 US presidential election, the US presidential betting market hosted by INTRADE was price manipulated. As Granger (1988) posits, any cointegration necessarily implies some Granger causality. Therefore, we test for the cointegraton and Granger-causality amongst IOWA, INTRADE, SILVER and POLLS. We consider that if the other series Granger-cause INTRADE that this is consistent with INTRADE being manipulated for non-pecuniary reasons. This would especially be likely if INTRADE consistently reacts to predictions for an Obama victory with a lower Obama-victory prediction. This would be the result of investors bidding up the Romney ticket or shorting the Obama ticket.

We document strong evidence that IOWA, INTRADE and SILVER are highly cointegrated, but that POLLS is not related to the other three. We document strong evidence that IOWA Granger-caused INTRADE; and weaker evidence that SILVER also Granger-caused INTRADE. Overall, our findings, along with the consistently lower Obama victory predictions from INTRADE compared with IOWA, are consistent with the notion that INTRADE prices were manipulated during the 2012 US presidential election season for non-pecuniary reasons, providing tangential support for the findings of Rothstein and Sethi (2013). Furthermore, when we exclude the last two weeks of the campaign (i.e. the period studied by Rothstein and Sethi (2013)) from our analysis, our results show that INTRADE was consistently slow to update compared with IOWA and SILVER, which is what we would expect to see if there had been ongoing manipulation in the INTRADE market in the period prior to that studied by Rothstein and Sethi (2013). Indeed, this evidence of ongoing slow updating on INTRADE is consistent with what Berg and Reitz (2006) tell us about how past presidential campaign teams openly encouraged supporters to bet on their candidate in prediction markets during the campaign in order to manipulate public perception of that candidate's likelihood of winning.

Our results still leave open the question of why SILVER was so much bolder in his forecasts than prediction markets. To what degree did Silver himself have confidence in prediction markets? To what degree did prediction-market prices reflect the published predictions of Silver? We note that the SILVER forecasts, with respect to confidence in an Obama victory, strengthened and weakened over time in a similar manner to the prediction markets. Was IOWA or SILVER was the best election predictor? If SILVER was so widely regarded as a prognosticator, why was the SILVER-IOWA difference not exploited by investors such that the IOWA price increased? Alternatively, if prediction markets are acknowledged as optimal information aggregators, why did SILVER not update downward to close with IOWA? Was the IOWA prediction market a better estimator than SILVER? Or alternatively, for structural or non-pecuniary reasons, did IOWA not update sufficiently?

Our results should be of great interest to researchers interested in the efficacy of prediction markets as aggregators of information and the concomitant reactions of relevant agents. Additionally, our results will be of interest to researchers seeking to evaluate differing estimators of US election uncertainty, especially with regard to its accompanying consequences for financial markets.

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Table 1: Descriptive statistics.

Table reports mean, median, maximum, minimum, standard deviation, skewness, Kurtosis; as well as the Jarque-Bera test for the three data series SILVER, IOWA and INTRADE SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. POLLS is the average of election polls computed and published daily by Real Clear Politics on their website. Data ranges from May 31 2012 to November 5, 2012. JB is Jarque-Bera test for normalcy (significance indicating non-normality).

	Mean	**Median**	**Max**	**Min**	**St Dev**	**Skewness**	**Kurtosis**	**JB**	**Obs**
SILVER	70.7377	69.10	91.40	59.00	6.9213	0.6570	2.8265	11.6386***	159
INTRADE	59.6472	57.80	78.90	52.30	5.9284	1.2842	4.2647	54.2971***	159
IOWA	62.4434	60.00	81.70	53.00	7.0041	1.0227	3.3796	28.6692***	159
POLLS	50.9970	51.0870	52.59	49.1996	0.8210	-0.2765	2.1265	7.0812**	159

***, **, * indicate significance at 1%, 5% and 10%

Table 2: Correlation and Covariance statistics.

Table reports correlation coefficients and corresponding covariance for the three pairing of the data series SILVER, IOWA, INTRADE and POLL data. SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. POLLS is the average of election polls computed and published daily by Real Clear Politics on their website. Data ranges from May 31 2012 to November 5, 2012. ***, **, * indicate significance at 1%, 5% and 10% respectively.

	Correlation	**Covariance**
SILVER–INTRADE	0.7888***	32.1629***
SILVER–IOWA	0.8527***	41.0765***
INTRADE–IOWA	0.9158***	37.8203***
POLLS-SILVER	0.1484	0.8379
POLLS-IOWA	0.1200	0.6859
POLLS-INTRADE	0.1163	0.5622

Table 3: Unit root test results on the logs of each series.

ADF is Augmented Dickey-Fuller test (Dickey and Fuller (1979)); PP is Phillips-Perron test (Phillips and Perron (1988)); KPSS is Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al. (1992)). SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. POLLS is the average of election polls computed and published daily by Real Clear Politics on their website. Data ranges from May 31, 2012 to November 5, 2012.

	Level No Trend			**First Difference No Trend**		
	ADF Test	**PP Test**	**KPSS Test**	**ADF Test**	**PP Test**	**KPSS Test**
SILVER	-0.6967	-1.1939	1.0235***	13.5511***	-13.6664***	0.0875
INTRADE	-1.2694	-1.3890	1.04636***	-12.6525***	-12.6531***	0.0783
IOWA	-1.0811	-1.0811	1.0932***	-14.71***	-14.7615***	0.1232
POLLS	-1.8283	-2.3193	0.3324***	-11.3800***	-11.5453***	0.0453

***, **, * indicate significance at 1%, 5% and 10% respectively

Table 4: Unit root test results for the Engle-Granger cointegration test on the residuals of equation 3.

SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. POLLS is the average of election polls computed and published daily by Real Clear Politics on their website. Data ranges from May 31 2012 to November 5, 2012. Columns show the test statistic of the three unit root tests. ***, **, * indicate significance at 1%, 5% and 10% respectively.

	ADF	PP	KPSS
SILVER–IOWA	-3.6650***	-3.7883***	0.1281
SILVER–INTRADE	-2.9432**	-3.0165**	0.1672
IOWA–INTRADE	-3.7938***	-5.4671***	0.2753
SILVER–IOWA–INTRADE	-3.3711**	-3.4736***	0.2680
POLLS-IOWA	-1.7795	-2.2309	0.4400*
POLLS-INTRADE	-1.8210	-2.2466	0.4377*
POLLS-SILVER	-1.7394	-2.1119	0.4853*

***, **, * indicate significance at 1%, 5% and 10% respectively

Table 5: Granger causality test for the three prediction markets

This table reports results of Granger causality testing. SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. POLLS is the average of election polls computed and published daily by Real Clear Politics on their website. Data ranges from May 31 2012 to November 5, 2012.

NULL	F-statistic	Probability
SILVER does not cause IOWA	10.4457	0.00
IOWA does not cause SILVER	1.74158	0.19
SILVER does not cause INTRADE	6.74856	0.01
INTRADE does not cause SILVER	0.85619	0.36
IOWA does not cause INTRADE	43.9662	0.00
INTRADE does not cause IOWA	2.14245	0.14
POLLS does not cause INTRADE	0.32755	0.57
INTRADE does not cause POLLS	0.1777	0.67
POLLS does not cause SILVER	0.69694	0.41
SILVER does not cause POLLS	0.01229	0.91
POLLS does not cause IOWA	0.15943	0.69
IOWA does not cause POLLS	0.03139	0.86

Table 6: The Error Correction Mechanism (ECM) results. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Panel A: Bivariate ECM

SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. Data ranges from May 31 2012 to November 5, 2012.

Dependent variable	Independent variable	α	γ	ρ	β	R^2
SILVER	IOWA	0.002841	-0.033131	-0.027268	0.056812	0.022
		(1.44)	(-0.39)	(-0.39)	(1.62)	
IOWA	SILVER	0.002217	-0.139471*	-0.003462	-0.122980***	0.087
		(0.95)	(-1.71)	(-0.03)	(-2.97)	
SILVER	INTRADE	0.002802	-0.057645	0.050094	0.037626	0.016
		(1.42)	(-0.70)	(0.55)	(1.08)	
INTRADE	SILVER	0.000809	-0.006129	0.080223	-0.073896**	0.057
		(0.47)	(-0.08)	(1.11)	(-2.42)	
IOWA	INTRADE	0.002188	-0.146472	0.039151	0.043096	0.033
		(0.92)	(-1.56)	(0.36)	(0.58)	
INTRADE	IOWA	0.000636	-0.006254	0.207965***	-0.192047***	0.286
		(0.42)	(-0.09)	(3.52)	(-4.11)	

Panel B: Multivariate ECM

Dependent variable	Independent variables	α	γ	ρ	θ	β	R^2
SILVER	INTRADE IOWA	0.002873	-0.056977	0.066996	-0.054965	0.077997	0.019
		(1.45)	(-0.68)	(0.74)	(-0.70)	(1.24)	
INTRADE	SILVER IOWA	0.000469	-0.033129	0.088818	0.219770***	0.170267***	0.268
		(1.45)	(-0.47)	(1.37)	(3.62)	(3.51)	
IOWA	SILVER INTRADE	0.002038	-0.081347	0.029710	0.027311	-0.170911**	0.067
		(0.86)	(-0.87)	(0.30)	(0.25)	(-2.28)	

Table 7: Nonlinear Granger causality test for the three prediction markets

This table reports results of nonlinear Granger causality testing using Diks and Panchenko (2006) procedure. SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. Data ranges from May 31 2012 to November 5, 2012.

NULL	T-statistic	Probability
SILVER does not cause IOWA	-0.18	0.57
IOWA does not cause SILVER	0.05	0.48
SILVER does not cause INTRADE	-0.23	0.59
INTRADE does not cause SILVER	-1.08	0.86
IOWA does not cause INTRADE	1.53	0.06
INTRADE does not cause IOWA	0.82	0.21

Table 8: Robustness check on data excluding the last two weeks of data.

SILVER is the daily published (*New York Times*) probability of an Obama victory. IOWA and INTRADE are the daily closing price of an Obama ticket in these presidential election futures markets. Data ranges from May 31 2012 to October 22, 2012. ***, **, * indicate significance at 1%, 5% and 10% respectively.

Panel A: Engle-Granger Cointegration Test

	ADF	PP	KPSS
SILVER–IOWA	-3.834653***	-3.868890***	0.169254
SILVER–INTRADE	-3.018048**	-3.157882**	0.265723
IOWA–INTRADE	-3.767300***	-5.129371***	0.308276
SILVER–IOWA–INTRADE	-3.786255***	-3.826977***	0.171593

Panel B: Granger Causality Test

NULL	F-statistic	Probability
SILVER does not cause IOWA	5.25580	0.02
IOWA does not cause SILVER	3.57089	0.06
SILVER does not cause INTRADE	3.28192	0.07
INTRADE does not cause SILVER	1.77767	0.18
IOWA does not cause INTRADE	40.1014	0.00
INTRADE does not cause IOWA	1.44692	0.23

Panel C: Univariate ECM

Dependent variable	Independent variable	A	γ	ρ	β	R^2
SILVER	IOWA	0.001202	-0.018849	-0.098070	-0.118505***	0.07
		(0.61)	(-0.22)	(-1.34)	(-2.83)	
IOWA	SILVER	0.000650	-0.146340*	0.011565	0.099636**	0.061
		(0.28)	(-1.72)	(0.12)	(2.04)	
SILVER	INTRADE	0.001146	-0.062091	0.116054	-0.080192**	0.053
		(0.58)	(-0.74)	(1.08)	(-2.21)	
INTRADE	SILVER	0.000564	0.045063	-0.004283	0.049786*	0.024
		(0.36)	(0.53)	(-0.06)	(1.74)	
IOWA	INTRADE	0.000608	-0.150435	0.119860	-0.039833	0.04
		(0.26)	(-1.54)	(0.96)	(-0.60)	
INTRADE	IOWA	0.000538	0.004435	0.145001**	0.165890***	0.259
		(0.40)	(0.06)	(2.53)	(4.26)	

Panel D: Multivariate ECM

Dependent variable	Independent variables	A	γ	ρ	Θ	β	R^2
SILVER	INTRADE	0.0001185	-0.061419	0.127100	-0.157491	0.142529**	0.001
	IOWA	(0.60)	(-0.73)	(1.18)	(-1.86)	(2.14)	
INTRADE	SILVER	0.000532	-0.012077	0.025195	0.152140***	0.181914***	0.248
	IOWA	(0.39)	(-0.16)	(0.43)	(2.59)	(3.94)	
IOWA	SILVER	0.000584	-0.098457	0.018887	0.123639	-0.133015	0.058
	INTRADE	(0.25)	(-1.00)	(0.19)	(0.99)	(-1.72)	

***, **, * indicate significance at 1%, 5% and 10% respectively

Figure 1: Time-series plot of the SILVER, INTRADE, IOWA and election polls.