Algorithmic Trading in the Iowa Electronic Markets

James Schmitz

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James Schmitz
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Abstract—We studied the market microstructure of the Iowa Electronic Markets and found that it was possible to develop profitable algorithmic trading strategies for their “Winner Takes All” market, an Arrow-Debreu economy composed of securities tracking the outcome of the U.S. 2008 Presidential Election. A trading system was built that profited from the market's inefficiencies, and using our own capital, traded 44% of the total market volume and achieved a Sharpe ratio of 9.9.

I. INTRODUCTION

IOWA Electronic Markets (IEM) are simple, transaction free futures markets run by the Henry B. Tippie College of Business at the University of Iowa. The purpose of these markets are to serve as an educational tool for students to learn about financial markets and how information is priced into security prices. Also, researchers can use the data to study price formation and theorize about how financial markets can predict future outcomes better than polls and if markets are better aggregators of information. This has been written about in many books\(^1\) and papers.\(^2\) One of the most popular markets the IEM offered was a “Winner Takes All” market based on the outcome of the 2008 U.S. Presidential election. Both in theory and in reality, the prices of the securities in this market rose and fell based on the aggregate opinion of the market participants. It is this futures market that is the focus of this paper.

Our interest in this futures market was very different from that of other researchers and market participants. We were interested in the market microstructure of this simple market, its short term price movements, arbitrage opportunities and potential profits from market making. We built a computer program to collect price data from the market, studied it, and then built an electronic market maker to trade the securities 24 hours a day. To the best of our knowledge, we were the only market participant to do something like this. If there were any other computer trading applications, they were only employing simple arbitrage strategies.

II. MECHANICS OF IOWA ELECTRONIC MARKET

A. Market Prices

This financial market was very simple: two securities, one representing the Democratic candidate (DEM), Barack Obama, and the other representing the Republican candidate (REP), John McCain. Technically, it is an Arrow-Debreu economy with two states of the world: one where the Democrats win, and the other where the Republicans win. For these securities, a win is when the candidate captures the majority of the votes and is not based on the electoral college. Each security pays $1 if that state of the world is realized and $0 if it is not. The two security prices must add up to $1 and they must be inversely correlated, because if the price of one goes up, the other must go down. Therefore, although there are two securities, there is only one risk factor and one real asset. Buying one security is the same as selling the other. In this paper, when the term “securities” is used it is referring to the two securities representing the two candidates, and when the term “asset” or “market asset” is used, it is referring to the one true asset that this market represents. A long position in the market asset is defined as a long position in the Democratic candidate and a short position in the Republican candidate, and a short position in the market asset is just the opposite. This could have just as easily been defined the opposite way.

The IEM provides three pieces of price information for each security: the bid price, the ask price, and the last trade price. Unlike many other financial markets, last trade size, bid size and ask size are not disclosed, nor is any information at all revealed about the depth of the order book. This poses unique challenges to an electronic market maker and to any researcher studying the microstructure of this market.

Since there are two securities that are by definition inversely correlated, it simplifies things to invert the price of one of them so it is comparable to the other. So, if these are the market prices:

\[
\begin{array}{lcc}
\text{Security} & \text{Bid} & \text{Ask} \\
\hline
\text{DEM} & 0.572 & 0.602 \\
\text{REP} & 0.424 & 0.450 \\
\end{array}
\]

Subtracting 1 from the REP bid-ask prices to get REP\(_{\text{INV}}\):

\[
\begin{array}{lcc}
\text{Security} & \text{Bid} & \text{Ask} \\
\hline
\text{DEM} & 0.572 & 0.602 \\
\text{REP\(_{\text{INV}}\)} & 0.550 & 0.576 \\
\end{array}
\]

REP\(_{\text{INV}}\) has the same market exposure as DEM. Notice that the REP bid price becomes the REP\(_{\text{INV}}\) ask price, and the REP ask price becomes the REP\(_{\text{INV}}\) bid price.

An important feature of this market is the exchange allows market participants to buy and sell “bundles” of securities with the exchange itself for $1. A bundle is a set of securities representing all of the possible outcomes; in this case, the DEM and REP securities. This is much like a creation or redemption of an ETF in the stock market, only there is no fee. This allows a trader two alternatives to trade into a position: they can either buy the one security they want or they can exchange their money for bundles and then sell the other undesired security. The end result will be the same.

\(^{1}\)"The Wisdom of Crowds,” by James Surowiecki

\(^{2}\)Citation [1] is one of many papers worth reading.

I wish to thank Jeff Miller, Lee Maclin, Petter Kolm and Ritesh Bansal for helpful comments and suggestions.

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Since there are two means for trading the same asset, the market asset’s true bid and ask prices must be identified. The asset’s bid price is simply the maximum of the DEM and REP, bid prices and the asset’s offer price is the minimum of the DEM and REP offer prices.

<table>
<thead>
<tr>
<th>Security</th>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>0.572</td>
<td>0.602</td>
</tr>
<tr>
<td>REP&lt;sub&gt;INV&lt;/sub&gt;</td>
<td>0.550</td>
<td>0.576</td>
</tr>
</tbody>
</table>

Obviously, if a trader wanted to trade in this market it would be efficient for them to only trade on the asset’s true bid and ask prices. Therefore, we call this spread the “good spread” and we call the other two prices the “bad spread.”

<table>
<thead>
<tr>
<th>Spreads</th>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good spread</td>
<td>0.572</td>
<td>0.576</td>
</tr>
<tr>
<td>Bad spread</td>
<td>0.550</td>
<td>0.602</td>
</tr>
</tbody>
</table>

It would be inefficient for a trader to use a market order to buy the market asset on the bad offer or sell the market asset at the bad bid. Nevertheless, this happened frequently. We cannot precisely determine how often this happened using our data but our educated guess is that market orders were filled at the bad bid or offer about 42% of the time.

For the market making efforts described in this paper we were valuing the market asset as the midquote of the good spread. This was considered to be the market asset’s efficient price. In the above example, this price is 0.574. This price can be used to value the DEM and REP securities. Therefore, we would price the DEM security as 0.574 and the REP security as 0.426. In both cases this happens to be closer to the bid side than the ask side of the displayed DEM and REP spreads. We consider this method to be more accurate than simply looking at the midquote of each individual security. Because there really is only one asset, the order books of both securities must always be considered together.

### B. Price Dynamics

Strictly speaking, the price of the market asset does not follow what a mathematician would call a random walk. In this market the price is constrained on the interval [0, 1], whereas a random price process is unbounded. Also, at maturity the securities will have a price that approaches either 0 or 1. This price process will reach one of those two points and not any other value, which is uncharacteristic of a random walk. However, for short term time horizons, the price process is essentially random. As time goes on there is an increasingly larger probability of the price going to 0 or 1.

Additionally, when we examined the data in small time scales we found that there was a short term alpha signal. This is also uncharacteristic of a random walk.

For our market making efforts we did consider the price to be a random walk, but we knew the assumption would no longer be true when the securities neared maturity. Making this assumption didn’t cause any noticeable problems, even when we allowed the system to continue running two days after the election was over. The market maker was profitable when the random walk assumption was clearly violated so it couldn’t have been important.

### C. Market Activity

Figure 1 shows plots of the market activity during the time of this research project. The upper subplot shows the price movements of the market asset, as defined in section II-A. The middle subplot shows the daily percent volatility of the market asset price, calculated with a 7 day rolling window. The lower subplot shows the 7 day moving average of market activity, measured in dollars. A few significant political events are annotated on the chart to show the effect they had on price, volatility and volume.

It should be noted that the “Winner Takes All” market was not the only political financial market offered by the Iowa Electronic Markets. There were other political markets based on the Democratic and Republican nominations. The securities in those markets reached maturity when their respective party’s conventions ended, and at that time money flowed into the accounts of traders who held the securities representing Obama and McCain. Much of that capital was then reinvested in “Winner Takes All” securities, explaining the surge in market activity when the conventions ended. This also might partially explain the price fluctuations around the time of the conventions.

The stock market began a rapid decline at about the same time the market asset price started to approach $1. We measured the correlation between the daily S&P 500 returns with price movements of the market asset. The correlation was negative but not statistically significant.

We began collecting data in late February while researching strategies and developing the infrastructure to implement a market making system. The system was operating in a limited test mode by April and was fully operational by May. Until the conventions, the system was providing liquidity for the majority of the market’s trading. After the conventions the market and the system became much more active but our percent of market share declined. This happened because of our own capital limitations and position limitations built into the application. Because of the nature of this market it was important to have risk limits of some kind. Any computerized market maker has the risk of adverse selection because of the information asymmetry, but in this market the price is guaranteed to fall to either $1 or $0.

Volatility also increased noticeably around the time of the conventions. This makes sense as there was more information about the candidates being revealed every day as election time was getting closer.

An important question that we are unable to answer is what role our market maker played in reducing market volatility and helping price discovery. It makes sense that a liquidity provider that provided as much liquidity as we did would reduce price volatility. Also, we speculate that volatility after the convention might have been lower had we had more capital and less restrictive risk limits. Unfortunately it is not possible to quantitatively answer either of these questions.

### D. Arbitrage

In this market it is possible for an easy arbitrage opportunity to arise. The simplest would be if a trader adds a limit order
to one of the order books that causes the good spread to become crossed. For example, in this market:

<table>
<thead>
<tr>
<th>Security</th>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>0.572</td>
<td>0.602</td>
</tr>
<tr>
<td>REP</td>
<td>0.424</td>
<td>0.450</td>
</tr>
</tbody>
</table>

A bid of 0.580 on DEM would result in these spreads:

<table>
<thead>
<tr>
<th>Spreads</th>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good spread</td>
<td>0.580</td>
<td>0.576</td>
</tr>
<tr>
<td>Bad spread</td>
<td>0.550</td>
<td>0.602</td>
</tr>
</tbody>
</table>

Notice the good spread is now crossed.

The trader could have bought a bundle from the exchange and sold the REP security at the bid price of 0.424, which is a better price by 0.004, and gotten the trade filled immediately. But if they don’t realize that, the displayed market will become:

<table>
<thead>
<tr>
<th>Security</th>
<th>Bid</th>
<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
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<tr>
<td>REP</td>
<td>0.424</td>
<td>0.450</td>
</tr>
</tbody>
</table>

The arbitrage opportunity is to sell both the DEM and REP securities at their respective bid prices and then buy back bundles by trading with the exchange. This is profitable because the pair of securities can be sold at a price of 1.004 and bought back from the exchange for 1. The exchange has a special market order for buying and selling bundles using the sum of the displayed bid or ask prices that ensures equal numbers of each security are traded. After using one of these bundle market sell orders, the new displayed market could become:

<table>
<thead>
<tr>
<th>Security</th>
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<th>Ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>0.580</td>
<td>0.602</td>
</tr>
<tr>
<td>REP</td>
<td>0.416</td>
<td>0.450</td>
</tr>
</tbody>
</table>

In this example, the size of the REP 0.424 bid order was smaller than the DEM 0.580 bid order. When both bids were hit by the bundle market order the REP bid was eliminated but the DEM bid remained. Since the previous REP bid is now gone, the new REP bid is next order in its order book.

It may seem trivial but it is actually essential for the market to have at least one market participant who monitors the prices for this situation and acts accordingly. If this didn’t happen the market wouldn’t function correctly and the two security prices would not be properly inversely correlated. Researchers would not be able to use the price data for anything because, for example, a DEM price of 0.611 is meaningless when the REP price is 0.450. It is unlikely that the prices would fall that out of line but even small aberrations do result in a less meaningful situation.³

A second arbitrage opportunity involves providing liquidity to the bad spread and taking liquidity from the good spread. For example, in the current state of our example market:

³The method of determining the market asset’s price discussed here is undefined when the good spread is crossed. The arbitrage opportunity would have to be eliminated to determine the market asset’s value.
The good and bad spreads are:

<table>
<thead>
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<td>0.416</td>
<td>0.450</td>
</tr>
</tbody>
</table>

A trader could place a buy order for the market asset for a price of anything less than 0.580 and a sell order for the market asset for any price more than 0.584. This would correspond to a sell order for the REP security at a price above 0.420 and a sell order for the DEM security at a price above 0.584. If either of the trader’s sell orders are lifted, they can immediately sell the other security at its bid price. One flaw with this strategy is that since the order sizes are not visible in this market, the trader wouldn’t know how many shares they can sell by hitting the bids. This would force the trader to estimate and would occasionally result in a position in the market asset. Because of that, this strategy doesn’t work as well as it would in another market with visible order sizes. A better algorithm would be one that can properly manage risk, like a market making algorithm.

E. Market Gaming

Because of the absence of displayed order sizes there is the potential for traders to game this market or behave in a way that frustrates our attempts to determine the correct value for the market asset. The problem is a limit order for one share looks the same as a limit order for a larger size. All market participants know this and will often place one share orders to alter the appearance of the security prices. We cannot know what traders’ motivations are for doing this. One possible explanation is that it is an attempt to draw more favorably priced orders to the opposite side of the order book they intend to trade. For example, if a trader wanted to sell the DEM security but thought the spread was too large they could narrow the spread with a one share buy order and hope that someone else joins them on the bid or steps in front of their small order. Once that happens the trader could sell the DEM shares at the improved price and remove their one share order.

We know this kind of market manipulation happened a lot because often traders employing this technique would inadvertently place a limit order for one share that created an arbitrage opportunity by causing the good spread to become crossed, as described in II-D. When we would try to take advantage of the arbitrage opportunity, we would only trade one bundle. About 10% of our program’s arbitrage attempts only traded one bundle, indicating that the smaller order for the two securities was for one share.

Our trading program could have also manipulated the market using single share orders but we chose not to. We thought it would be unethical for us to attempt to manipulate the market in any way. There are other researchers using this data for their own studies and it might affect their research if a computer program was skewing the market to one side or the other. Additionally, since we could only see the top of the order book, we wouldn’t know what orders were below our fake order. Our method of determining the efficient price is based on the prices at the top of the order book for each security. Manipulating the market would take away our ability to determine what the real market asset price is. Finally, it would be almost impossible to analyze the market data in a meaningful way if we had been manipulating the quotes. As the most active participant in this market, our behavior had a huge effect on the short term microstructure. It would be even harder to work with this data if we were introducing effects that would be impossible to remove later. To as large of an extent as possible, we wanted the prices to be the result of human activity.

III. Software Design

The most important design feature of the market making application described in this paper was high availability. It was absolutely essential that the market maker be able to continuously stay logged in to the exchange, monitor prices, make markets and manage risk at all times.

The application was implemented in Java and was run on a Linux machine with a battery backup 24 hours a day. Data, including price data, order activity and portfolio data, was saved to a MySQL database and to flat files as a backup. All files were backed up to an external drive regularly.

This paper is not a software design document so we won’t go into full detail of all aspects of the system but we will outline what the key design features are. First, the Iowa Exchange offers a simple web interface for trading in the market. There are HTML forms for submitting orders which we could interface with using Apache Commons HttpClient. The website continuously informs traders what their cash and security positions are, in addition to the price information. Since there is no FIX protocol for communicating with the exchange, our only means of knowing if a limit order had been filled is by checking to see if our security positions changed since the previous data observation.

The exchange interface worked well for human traders but posed difficulties for a computer trader. First, the website would crash sporadically, which would cause early versions of our application to crash with it. The system had to handle any possible way the exchange could fail and continue running, patiently waiting for it to come back online. Another issue is that since there was no FIX protocol, we were dependent on the exchange for the accounting of cash and security positions. Unfortunately that accounting was not as accurate as it needed to be. While doing the data analysis for this report, anomalies in the data were found that can only be explained by a small gap between the time a change in security positions is reported in the account and the time the resulting change in cash is reported in the account. The out of synch position data was

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4However, it should be noted that most researchers would have access to the order book data and could see the order sizes. See [1] for a more complex method of determining the efficient price using information that was not available to market participants that would not be thrown by such behavior.

5The longest period of time the system ran without being restarted for a code release was 6 weeks, but we believe it could have run indefinitely.
recorded in the database, making some performance analysis very difficult.

IV. Market Making Models

In the book “Market Microstructure Theory”[2], O’Hara writes about market inventory models and discusses the work of Hans Stoll. She writes:

For Stoll, the market maker is simply a market participant, or trader, who is willing to alter his own portfolio away from desired holdings to accommodate the trading desires of other traders. As a market participant himself, the dealer is assumed to be risk averse and therefore must be compensated for bearing this risk. This compensation arises from the bid and ask prices, and so the market spread reflects the “costs” the dealer faces in bearing this risk.

The book doesn’t contain a practical equation that can be applied to this market but it does suggest comparing the utility of the dealer’s portfolio before and after a transaction. It says that a dealer would be willing to undertake any transaction that keeps his expected utility of wealth the same:

\[ E[U(W_0(1 + \tilde{R})^t)] = E[U(W)] \]

The dealer’s initial portfolio is \( W_0 \), \( \tilde{R} \) is the uncertain return on his portfolio, \( U(W) \) is his utility function and \( W \) is the altered portfolio. This looks promising but unlike Stoll’s benevolent dealer, we want to maximize the increase in utility of the altered portfolio. This looks promising but unlike Stoll’s.

One approach for an inventory market making model is to calculate the spread \( s \) necessary for us to be willing to buy and sell \( X \) number of shares. Such a model could use the midquote of the market asset’s good spread to determine the current price and make a market around that price. The market maker’s buy and sell orders would move up and down as the price moved or as the algorithm accumulated a position. That would work but it would not capture a large share of the market volume when the good and bad spreads were smaller than our spread, so it would not be as profitable. To maximize profits we would be forced to try to balance an increase in the size of the spread, needed to profit on a transaction, with a decrease in the size of the spread, needed to capture market flow. Additionally, this would occasionally require us to step in front of orders placed by human traders. We did not want the market making application to do this. As a rule, we wanted the displayed security quotes to always be prices selected by human traders. The program would only join orders on the bid or at the ask. Because of this, we can analyze the historical data and know that within some limitations, whenever the price moved, it was because of human activity and not our own.

An alternate approach is to instead look at the market spreads and ask if we were to join the displayed bid or ask orders and if a human trader were to sell or buy the market asset at any of those prices, how much would we want to participate in that trade. This is the approach we used in the market maker. Instead of trying to pick the value of \( s \) that maximizes profits, we observed the current \( s \) in the market and tried to pick the optimal number of shares \( X \) to trade under those conditions. We wanted to pick the \( X \) value that, if filled, would maximize the increase in utility of wealth.

To calculate the \( X \) value that maximizes the potential utility of trading we can use equations 1 and 2 to solve for \( X \) in the equation \( \frac{dU}{dX} = 0 \) and check that \( \frac{d^2U}{dX^2} < 0 \). Solving this equation for the bid side yields:

\[ X_{bid} = \frac{s - 2\lambda \sigma^2 t P^2 A}{2\lambda \sigma^2 t P^2} \]

The value \( X_{bid} \) must be non-negative, so:

\[ X_{bid} = \max(0, \frac{s - 2\lambda \sigma^2 t P^2 A}{2\lambda \sigma^2 t P^2}) \]

The comparable equation for the optimal number of shares to sell at the ask is:

\[ X_{ask} = \max(0, \frac{s + 2\lambda \sigma^2 t P^2 A}{2\lambda \sigma^2 t P^2}) \]

Figure 2 shows a plot of equations 4 and 5 using reasonable values of \( \lambda \), \( t \) and \( \sigma \) when \( P = 0.5 \) and \( A = 0 \). The y axis is the number of shares the market maker would be willing trade, given the opportunity to buy or sell at the prices on the x axis. Figure 3 shows the number of shares the market maker is willing to trade when \( A = 20 \). The sizes are shifted because of the risk aversion of holding a long position in the market asset. The market maker would require additional compensation before buying more shares and would require less compensation before selling shares.

This was the first market making model. It didn’t work very well because it would offer to trade too many shares when...
the spreads were narrow. It would lose money if those orders traded. If we adjusted the parameters to alleviate the problem, it wouldn’t offer to trade enough shares when the spreads were wide, missing potential profit making opportunities.

The next idea was to modify the utility function to include the permanent impact or information content of the orders the market maker was providing liquidity for. In this model it is assumed the trader taking liquidity is an informed trader and therefore the asset price will always move against the market maker by a small amount. Then the utility function for buying the asset becomes:

\[ U(X) = (A + X)P - X(P - s) \]

\[ -\gamma X P(A + X) \]

\[ -\lambda(\sigma\sqrt{t}(P(A + X)))^2 \]

The new variable, \( \gamma \), is a parameter for a simple linear permanent impact model that is a function of price and trade size. The permanent impact affects the value of the shares traded plus the shares in the existing position. The value of \( \gamma \) was derived from a kernel impact model constructed from observed trading activity. The details of the kernel impact model are not in the scope of this paper.

Solving for the \( X \) that maximizes \( U(X) \) gives:

\[ X_{bid} = \text{Max} \left[ 0, s - \gamma PA - 2\lambda\sigma^2tP^2A \right] \]

\[ X_{ask} = \text{Max} \left[ 0, s + \gamma PA + 2\lambda\sigma^2tP^2A \right] \]

Figure 4 shows the revised plot of \( X_{bid} \) and \( X_{ask} \) using the same values of \( \lambda \), \( t \) and \( \sigma \), and a realistic value for \( \gamma \). The plot is similar to figure 2 except that the slope of the line is more shallow.

This model did perform better but it didn’t adequately address the main shortcoming of the previous model. By multiplying \( \gamma \) times \( X \), the information content of the incoming buy or sell orders become a function of \( X \), the number of shares we chose to trade at that price. This is flawed because the size and information content of the incoming order we are providing liquidity for cannot be altered by \( X \), the number of shares the market maker decides to trade. In addition, since we are always joining another order on the bid or the ask, and that other order would be executed before ours, the model needs to estimate the size of that order to properly estimate the permanent impact or information content of the trade. Therefore, another variable, \( Y \), was added to incorporate the estimated size of the other order into the model.

\[ U(X) = (A + X)P - X(P - s) \]

\[ -\gamma P(X + Y)(X + A) \]

\[ -\lambda(\sigma\sqrt{t}(P(A + X)))^2 \]

Solving this for the bid size \( X_{bid} \) and ask size \( X_{ask} \) gives:
Fig. 4. Plot of number of shares market making model would be willing to trade at different prices when the current position $A=0$. Below an asset price of 0.5 the chart shows the number of shares placed on the bid and above 0.5 the chart shows the number of shares placed at the offer.

$$X_{bid} = \text{Max} \left[ 0, \frac{s - \gamma P(Y + A) - 2\lambda \sigma^2 t P^2 A}{2\gamma P + 2\lambda \sigma^2 t P^2} \right]$$  \hspace{1cm} (10)

$$X_{ask} = \text{Max} \left[ 0, \frac{s - \gamma P(Y - A) + 2\lambda \sigma^2 t P^2 A}{2\gamma P + 2\lambda \sigma^2 t P^2} \right]$$  \hspace{1cm} (11)

This is the basic model we used for the majority of the time the market making program was in operation. We estimated the parameters from historical data statistics, similar to what is described in section II-C. We would also adjust the parameters using our intuition and judgement. For example, before the party conventions and the election, we increased the volatility parameter because we expected volatility to be higher than it had been in the past.

Figure 5 shows a plot of the final model. Notice the slope of the line is the same as figure 4 and that the model is unwilling to trade any shares at prices that are too close to the efficient price. Figure 6 shows how the share sizes change when $A=20$.

There is one flaw with the model that should be pointed out. First, in this market the price $P$ will go to $0$ or $1$ but this model will not behave properly when $P$ approaches $0$. It is designed for a price process that is a random walk, not something that is constrained on the interval $[0, 1]$. A more robust solution would be to use a value of $\text{max}(P, 1-P)$ for the price $P$.

Also, a feature we added to the application is the ability to allow the market maker to take a long or short position. If we were bullish or bearish on the market asset we could have it accumulate a position in addition to making markets. To do

Fig. 5. Plot of number of shares market making model would be willing to trade at different prices when the current position $A=0$. Below an asset price of 0.5 the chart shows the number of shares placed on the bid and above 0.5 the chart shows the number of shares placed at the offer.

Fig. 6. Plot of number of shares market making model would be willing to trade at different prices when the current position $A=20$. Below an asset price of 0.5 the chart shows the number of shares placed on the bid and above 0.5 the chart shows the number of shares placed at the offer.
TABLE I
VOLUME ($) STATISTICS

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Our Trading</th>
<th>Market</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Period (4/15-11/07)</td>
<td>$82,368.34</td>
<td>$187,721.49</td>
<td>44%</td>
</tr>
<tr>
<td>Pre-Convention (4/15-8/24)</td>
<td>$23,354.23</td>
<td>$43,692.85</td>
<td>53%</td>
</tr>
<tr>
<td>Post-Convention (8/25-10/20)</td>
<td>$44,600.24</td>
<td>$106,389.07</td>
<td>42%</td>
</tr>
<tr>
<td>Election Time (10/21-11/04)</td>
<td>$13,344.23</td>
<td>$33,137.59</td>
<td>41%</td>
</tr>
</tbody>
</table>

TABLE II
VOLUME (SHARES) STATISTICS

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Our Trading</th>
<th>Market</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Period (4/15-11/07)</td>
<td>164,953</td>
<td>418,088</td>
<td>39%</td>
</tr>
<tr>
<td>Pre-Convention (4/15-8/24)</td>
<td>46,319</td>
<td>88,220</td>
<td>53%</td>
</tr>
<tr>
<td>Post-Convention (8/25-10/20)</td>
<td>88,918</td>
<td>228,846</td>
<td>39%</td>
</tr>
<tr>
<td>Election Time (10/21-11/04)</td>
<td>28,519</td>
<td>94,386</td>
<td>30%</td>
</tr>
</tbody>
</table>

day had a loss of more than $0.50. The system traded 44% of the total market volume when measured in dollars and 39% when measured in shares. Tables I and II show our trading activity measured in dollars and shares. Our application traded a total of $82,368.34 worth of securities and 164,953 shares. Additionally, our application performed 58,913 bundle transactions, creating or redeeming DEM and REP securities. Each of those transactions cost $1, so our application did a total of $141,281.34 worth of financial transactions. Most likely we were the most active market participant during the duration of this research project.

Figure 7 shows plots of the cumulative results. The profits from the arbitrage strategy and market making strategies are comparable to each other except for the period right before the election. However, that is partly because the market maker was making markets while also maintaining a long position

V. RESULTS

The system started with capital of $150 and earned a profit of almost $550. Almost every week (and day) was profitable, with an average daily return of 0.756%. There was one serious drawdown on the day before the election, 11/3, where the market maker lost $44.84 due to a technical problem. No other day had a loss of more than $0.50. The system traded 44% of the total market volume when measured in dollars and 39% when measured in shares.

Tables I and II show our trading activity measured in dollars and shares. Our application traded a total of $82,368.34 worth of securities and 164,953 shares. Additionally, our application performed 58,913 bundle transactions, creating or redeeming DEM and REP securities. Each of those transactions cost $1, so our application did a total of $141,281.34 worth of financial transactions. Most likely we were the most active market participant during the duration of this research project.

Figure 7 shows plots of the cumulative results. The profits from the arbitrage strategy and market making strategies are comparable to each other except for the period right before the election. However, that is partly because the market maker was making markets while also maintaining a long position in the market asset using the model described in equations 12 and 13.

It is clear from the upper chart there was a profit surge around the time of the party conventions. Much of this was from the arbitrage strategy, most likely because traders that were unaware that buying one security is the same as selling the other were creating arbitrage opportunities for us. On the last day of the Democratic convention we earned over $25 from arbitrage alone.

The lower chart in figure 7 shows the cumulative activity of the two strategies. The system made a total of 1205 arbitrage attempts, 1202 of which were profitable. Three attempts resulted in a small loss because one leg of the arbitrage disappeared before our market order was executed. Most likely this was from random market activity and not an electronic competitor for arbitrage opportunities. The market making strategy made a total of 2282 trades, more than half of which were after the conventions.

Table III shows the annualized performance statistics of our application. The Sharpe ratio for the entire trading period is 9.9. The Sharpe ratios for the different periods are also calculated to show how the system performed during the different periods of market activity. For some of the pre-convention period we were still in test mode and figuring out
the best market making model to use. Not all of the models worked well and some of them hurt performance. During the post-convention period no changes were made to the system and the risk aversion and risk limit parameters were set to make the system reasonably aggressive, and system performed very well. During the election time period the Sharpe ratio was only 2.5, mostly because of the drawdown caused by the technical error. If that day is excluded the Sharpe ratio becomes 20.2. However, it should be repeated that before the election the system was making markets while maintaining a long position in the market asset, and the high Sharpe ratio partially reflects that.

It is useful to compare our trading system to the performance of the traditional buy and hold trader. Table IV shows the same performance statistics for a trader who bought the DEM security and held it to maturity. Returns and standard deviation are calculated using the returns of the market asset and any initial market impact costs are ignored. These performance statistics understate the risk because a trader couldn’t have known for certain that the DEM security would reach $1 at maturity. It wouldn’t be informative to show statistics for the REP security however. The returns for the DEM security seemed like a reasonable choice for a benchmark because it is the best result a trader could achieve when using a buy and hold strategy.

The Sharpe ratio for a buy and hold strategy is lower than our system’s performance for each period except for the period right before the election.

Finally, we calculated the residual returns and risk for our trading system using the buy and hold strategy’s returns as a benchmark. This is similar to an asset manager’s performance evaluation to determine if they are adding value compared to a passive benchmark. Table V shows the results. The information ratio is positive for every period except for the period right before the election. Surprisingly, removing the one day with the drawdown only increases the information ratio to -1.56. Also note that if we hadn’t instructed our market making system to accumulate a long position in the market asset, the information ratio would be even lower. Therefore, our trading system underperformed right before the election and it would have been more profitable to shut the system off and invest all of our capital in a buy and hold strategy.

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6This was perplexing but is correct. When the day with the drawdown is excluded from the election time period the annualized return is 263% but the annualized standard deviation is only 13%, resulting in a Sharpe ratio of 20.2. But, the return is still less than the return for the buy and hold strategy for the same period, so the residual return and the information ratio are both negative.

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REFERENCES