What Makes Markets Predict Well? Evidence from the Iowa Electronic Markets*

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Abstract. We use the data from the Iowa Electronic Markets to study factors associated with the ability of markets to predict future events. These are large-scale, real-money experimental markets with contract payoffs determined by political election outcomes. They provide data about individual trader characteristics and market micro-behavior which is not available from larger exchanges. In this study we find that market characteristics motivated by financial theory and previous experimental research account for most of the variance in predictive accuracy across sixteen markets. Three variables are particularly important: 1) the number of contract types traded, 2) pre-election market volumes and 3) differences in election eve (weighted) market bid and ask queues.

1 Introduction

Do markets correctly impound information about future events? While a large body of evidence shows that financial markets respond in predictable ways to information releases,[1] whether this response is optimal is open to debate. In large part, this debate is difficult to resolve using data from naturally occurring markets because we can neither observe private information nor determine whether all information is completely impounded in prices. Further, the fundamental values of many assets are never revealed. These factors make it impossible to determine the informational efficiency of a market since we have no way of knowing whether prices truly reflect underlying fundamental values.

Controlled laboratory markets provide a complementary way to study information aggregation and efficiency in markets. In these markets, information and market

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* We thank Reinhard Selten for his continued support of the Iowa Electronic Markets and its predecessor, the Iowa Political Stock Market. With Professor Selten's help and encouragement, we were able to bring this technology to Germany so that we could conduct a Unified Germany Election Market on the outcome of the December 1990 German Federal election. We also wish to thank Daniel Friedman, Forrest Nelson and participants in the 1995 Economic Science Association meetings for many helpful comments and suggestion.

[1] For example, see Fama, 1991, for a review of the event study literature. As he puts it, "event studies can give a clear picture of the speed of adjustment of prices to information....The results indicate that on average stock prices adjust quickly..."

structure can be controlled and manipulated. Further, one can easily measure information aggregation and pricing efficiency.[2] However, laboratory market evidence is often criticized because the markets are very short-term, consists of a handful of traders[3] and, while cash incentives are used for motivation, traders do not self-select into these markets nor invest their own cash, as they would in most naturally occurring financial markets.

Here, we use data from the U.S. political markets conducted on the Iowa Electronic Markets (IEM) to identify factors which determine when markets accurately predict future events.[4] The IEM overcomes some criticisms of traditional laboratory research while retaining some of its advantages. In contrast typical laboratory markets, the IEM consists of longer term markets ranging from ten days to eleven months long. Large numbers of traders self-select into these markets and put their own money at risk in trading.[5] In contrast to typical futures markets, there are no simultaneous spot markets in the underlying fundamentals (vote shares). Thus, there are no arbitrage conditions that drive prices in the futures and spot markets together.[6] This results in a range of prediction errors (which we use as our dependent variable). In addition, the contract design insures risk neutral pricing with very few assumptions about traders or the outside hedging opportunities available to them. There are also no explicit transaction costs in this market, removing any resulting distortions. Finally, the IEM provides a great deal of detailed information on the markets and traders. This allows us to consider variables such as the number of active traders and their experience levels, all information about the queues (instead of simply considering bid/ask spreads), etc.

Because of these advantages, many studies, beginning with those of Forsythe, Nelson, Neumann and Wright, 1991a,b, 1992, use IEM technology to study market

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[2] Laboratory evidence shows that markets can be quite efficient in aggregating information. (Forsythe and Lundhom, 1990 and Plott and Sunder, 1982.) However, sometimes even very simple laboratory markets can exhibit anomalies such as price bubbles and information mirages. (Camerer and Weigelt, 1991; Rietz, 1995; Smith, Suchanek and Williams, 1988.) The evidence also suggests that the structure and distribution of information affect the ability of the markets to aggregate information. (Lundholm, 1991.)

[3] Most laboratory experiments consist of fewer than fifteen traders and are conducted over a period of three hours or less.

[4] In this paper, we have excluded all non-U.S. political markets. This allows us to disregard differences in cultures and political systems. These will be examined in a subsequent study.

[5] On the eve of the November 1992 U.S. election, 1102 traders were registered to trade with a total investment of approximately $83,000. On the eve of the November 1994 election, 3,150 individuals had trading rights in the political markets with a total investment of approximately $42,000.

[6] In this sense, our markets correspond more closely to markets such as corn yield futures or pari-mutual betting than traditional markets for futures on an underlying, market-traded asset.

and trading behavior.[7] Each of these studies has focused on describing and analyzing behavior in a single market. Ours is the first to use the data from a number of markets to study factors affecting predictive accuracy. To do this, we use the average absolute prediction error for each market and study differences in accuracies across markets. While the IEM predicts political outcomes well on average, some markets perform better than others.[8]

Here, we ask what election and market characteristics affect how well IEM prices predict actual U.S. election outcomes across sixteen markets and elections. Our goal is a descriptive one: to use existing data to develop a parsimonious model which explains variations in accuracies across markets. We find that characteristics motivated by financial theory and previous experimental research account for a great deal of the variance in predictive accuracy across these markets. In particular, three variables can explain most of the variation in predictive accuracy across markets (with an adjusted R^2 of 93%). These variables are: 1) the number of contract types traded in a market (corresponding roughly to the number of major candidates), 2) the pre-election market volumes, and 3) differences in election eve (weighted) market bid and ask queues. In addition, two more variables appear to have additional independent significance, but add little to our ability to explain the variance across markets (boosting the adjusted R^2 by 2%). These variables are: 4) pre-election (weighted) market spreads and 5) the average experience level of active traders in the market shortly before the election. We also observe that many other variables were highly correlated with predictive accuracy, but were also highly correlated with one or more of these five variables and do not have significant independent effects.

2 Description of the IEM and Political Vote-Share Markets

The IEM is a real-money futures market operated over the Internet as a research and teaching tool by the University of Iowa College of Business Administration.[9] Participants invest their own funds, buy and sell listed contracts, and bear the risk of losing money as well as earning profits. The method of issuing contracts and making final payoffs on these contracts ensures that the IEM does not realize financial profits, nor suffer losses, and that all monies invested are redistributed to traders based on their holdings. No commissions or transaction fees are charged.

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[7] These include Bohm and Sonnegärd, 1995, Davis, Forsythe, and Holt, 1994, Forsythe, Frank, Krishnamurthy and Ross, 1995, Jacobsen, Potters, Schram, van Winden and Wit, 1995, Kuon, 1991, Lombardo, 1993, Ortner, Stepan and Zechner, 1994, Stepan and Ortner, 1995. The only political market study which does not use the IEM technology is reported by Beckman and Werding, 1994a,b who manually conducted a call market at Universität Passau.

[8] Average absolute prediction errors in the markets studied in this paper range from 0.06% (the 1992 Bush-Clinton market) to 8.59% (the 1992 Michigan Democratic Primary market).

[9] The interested reader can examine current markets by connecting to them over the World-Wide-Web. Our homepage address is: http://www.biz.uiowa.edu/iem.

The IEM operates under the regulatory purview of the Commodity Futures Trading Commission (CFTC). The CFTC has issued a "no-action" letter to the IEM, stating that as long as the IEM conforms to certain guidelines,[10] the CFTC will take no action against it. However, we do not file reports that would be required by regulation so, technically, the IEM is not regulated by, nor are its operators registered with, the CFTC.

Contracts in the IEM are based on the outcomes of political and economic events. In this study, we focus on the "vote-share" political markets because prices in these markets can be used to explicitly measure predictive accuracy. A vote-share market consists of two or more contracts each identified with a particular candidate or party.[11] The liquidating value of a contract in a vote-share market is determined by the percentage of the popular vote actually received by each candidate times $1. If, for example, a candidate receives 54 percent of the vote, the owners of contracts in that candidate receive a 54-cent liquidation payment for each contract held.[12]

The political markets are open to any individual worldwide. The total amount invested by an individual cannot exceed $500, although accumulated earnings can easily push a trader's balance beyond the $500 limit. To establish an account, the trader submits an application form and initial investment. The total amount invested by the trader is placed in his or her cash account with the IEM. Participants then use their funds to buy and sell contracts. Thus, traders have the opportunity to profit from their trades and bear the risk of losing money.

Contracts are placed into circulation when traders purchase bundles of contracts, termed "unit portfolios," for $1 each from the IEM.[13] Each unit portfolio consists of one contract of each candidate in the market. The contracts in a market are structured so that the total liquidation value for each unit portfolio is $1. Once purchasing a unit portfolio from the market, traders can unbundle the contracts immediately and trade them individually. The IEM also stands ready to repurchase unit portfolios for $1 each from any trader at any time.

Each contract is traded in a continuous electronic double auction with queues. Traders can issue bids to buy or asks to sell, or trade at the best outstanding bid or ask. Bids and asks are limit orders with defined prices, quantities and expiration

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[10] These are that 1) the IEM be conducted as a not-for-profit enterprise, 2) it engages in no paid advertising, 3) traders are limited to investing no more than $500 in their accounts, and 4) it does not charge transaction-based commissions.

[11] In some of these markets there is also a contract which is identified as Rest-of-Field. Its liquidation value is determined by the aggregate vote-share of all other candidates or parties not explicitly included in the market.

[12] There are two minor exceptions to this rule. First, in the markets run for the 1990 Iowa and Illinois senate races, the payoff was the fraction of the vote received times $2 for each candidate. Second, we are including the results from two markets conducted to predict the composition of the 1994 US Senate and House. These contracts paid off $1 times the fraction of the seats taken by each party.

[13] For the 1990 Iowa and Illinois Senate markets, unit portfolios cost $2 since such portfolios would ultimately return $2.

dates. Traders are not required to maintain an inventory to cover all of their outstanding asks, nor must they maintain cash to cover all their outstanding bids. However, if a bid or ask reaches the top of its queue, the trader must be able to trade at least one unit or the offer is ruled infeasible and canceled.

There can be many bid and ask prices in the system at any time. They are maintained in bid and ask queues ordered first by price and then by time entered (on a first-in-first-out basis). These queues function as continuous electronic limit order books. When an offer is entered, it remains in the queue until either (1) it is withdrawn by the trader, (2) it expires, (3) it reaches the top of the queue and is found to be infeasible, or (4) it reaches the top of the queue and is accepted by another trader. Purchases on margin and uncovered short sales are not permitted.[14]

In addition to these trading actions, this computerized market provides information about the trader's account and market activity. Trader-specific account information available to each trader includes the number of contracts held in each candidate, the cash account balance, a list of outstanding offers and a list of transactions. Market information available to all traders includes: the current high-bid, low-ask and last transaction price as well as a summary of all previous trading activity by day. Information about the depth of the bid and ask queues is not revealed. The market software records all market activity (logins, logouts, bids, asks, trades, withdrawals, expirations, etc.) in an audit trail.

For this paper, we analyze data from election vote-share markets run to predict outcomes in sixteen major US elections and primaries.[15] The particular markets and elections are detailed in Table 1. As discussed above, traded contracts correspond to candidates in these markets. When the election outcome is announced, the payoff for a candidate's contract equals the fraction of the vote received by that candidate times the price of a unit portfolio. The nature of the market results in no aggregate risk and insures that prices should reflect expected values regardless of risk preferences. Intuitively, this results because all agents can hold the well diversified, risk-free "market" portfolio consisting purely of unit portfolios. All other contracts can be priced from this portfolio and the risk/return tradeoff inherent in it. The return to holding unit portfolios is the same as the risk free rate which is zero in these markets. Thus, the reward for taking on risk is zero and the expected return for each risky asset must also be zero. This can only be true if all contracts are priced at their expected values.[16] In these markets, expected value pricing means prices should equal anticipated vote shares for each candidate in the ensuing election.

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[14] Traders can synthetically construct the payoffs to a fully covered short position.

[15] This includes all vote-share markets run on US elections to date except for the 1988 presidential election. The original market data necessary to generate the variables of interest here is currently unavailable because of changes in the computer systems used at the University of Iowa.

[16] See Rietz, 1995, for a detailed discussion of this point. The result can be derived from general equilibrium theory, the capital asset pricing model or arbitrage pricing theory.

Table 1. Election and Market Descriptions

Market No.	Election	Contracts	Candidates	Opening Date	Election Date	Predicted Share	Actual Share	Error	Average Absolute Error
1	92 Illinois Primary	I.TS	Tsongas	3/1/92	3/10/92	42.1%	26.2%	15.9%	5.3%
		I.HA	Harkin			0.2%	1.7%	-1.5%	
		I.CL	Clinton			43.0%	51.4%	-8.4%	
		I.KE	Kerry			0.2%	0.6%	-0.4%	
		I.BR	Brown			10.3%	15.3%	-5.0%	
		I.RF	Rest of Field			4.1%	4.8%	-0.7%	
2	92 Michigan Primary	M.TS	Tsongas	3/1/92	3/10/92	40.1%	17.0%	23.1%	8.6%
		M.HA	Harkin			1.0%	0.8%	0.2%	
		M.CL	Clinton			44.3%	51.8%	-7.5%	
		M.KE	Kerry			0.1%	0.2%	-0.1%	
		M.BR	Brown			8.2%	26.4%	-18.2%	
		M.RF	Rest of Field			6.2%	3.8%	2.4%	
3	92 Presidential (Perot vs Democrat and Republican)	D&R	Democrat and Republican Vote Share	5/19/92	11/3/92	80.7%	81.0%	-0.3%	0.3%
		PERO	Perot Vote Share			19.3%	19.0%	0.3%	
4	92 Presidential (Bush vs Clinton)	D.CL	Clinton Vote Share	1/10/92	11/3/92	53.5%	53.5%	0.1%	0.1%
		R.BU	Bush Vote Share			46.5%	46.5%	-0.1%	
5	94 AZ Senate	KYL	Kyl	9/29/94	11/8/94	54.1%	53.7%	0.4%	1.6%
		COP	Coppersmith			41.5%	39.5%	2.0%	
		AZROF	Rest of Field			4.4%	6.8%	-2.4%	
6	94 NJ Senate	HAY	Haytaian	8/29/94	11/8/94	45.9%	47.0%	-1.1%	2.3%
		LAU	Lautenberg			53.7%	50.3%	3.4%	
		NJROF	Rest of Field			0.4%	2.7%	-2.3%	

Table 1. Election and Market Descriptions (Continued)

Market No.	Election	Contracts	Candidates	Opening Date	Election Date	Predicted Share	Actual Share	Error	Average Absolute Error
7	94 NY governor	CUO	Cuomo	8/29/94	11/8/94	47.4%	45.1%	2.3%	4.1%
		PAT	Pakaki			40.8%	49.0%	-8.2%	
		ROS	Rosenbaum			2.5%	0.0%	2.5%	
		NYROF	Rest of Field			9.3%	5.9%	3.4%	
8	94 PA senate	WOFF	Wofford	9/15/94*	11/8/94	46.9%	46.9%	0.0%	1.1%
		SANT	Santorum			51.0%	49.4%	1.6%	
		PAROF	Rest of Field			2.0%	3.7%	-1.7%	
9	94 TX Governor	G.BUSH	Bush	4/13/94	11/8/94	55.1%	53.5%	1.6%	1.1%
		G.RICH	Richards			44.4%	45.9%	-1.5%	
		G.ROF	Rest of Field			0.5%	0.6%	-0.1%	
10	94 TX Senate	S.FISH	Fisher	4/13/94	11/8/94	36.8%	38.3%	-1.5%	3.3%
		S.HUTCH	Hutchinson			57.4%	60.8%	-3.4%	
		S. ROF	Rest of Field			5.8%	0.9%	4.9%	
11	94 US House Seats	HS.DEM	Democratic Fraction of House Seats	6/10/94	11/8/94	51.3%	46.7%	4.6%	3.1%
		HS.REP	Republican Fraction of House Seats			48.5%	53.1%	-4.6%	
		HS.OTH	Other Fraction of House Seats			0.2%	0.2%	0.0%	

Table 1. Election and Market Descriptions (Continued)

Market No.	Election	Contracts	Candidates	Opening Date	Election Date	Predicted Share	Actual Share	Error	Average Absolute Error
12	94 US Senate Seats	SS.DEM	Democratic Fraction of Senate Seats	6/10/94	11/8/94	45.5%	48.0%	-2.5%	3.3%
		SS.REP	Republican Fraction of Senate Seats			49.7%	52.0%	-2.3%	
		SS.OTH	Other Fraction of Senate Seats			4.9%	0.0%	4.9%	
13	94 UT House	V.CO	Cook	4/15/94	11/8/94	17.7%	18.3%	-0.6%	3.6%
		V.GW	Green-Waldholtz			39.3%	45.8%	-6.5%	
		V.SH	Shepard			41.2%	35.9%	5.3%	
		V. ROF	Rest of Field			1.9%	0.0%	1.9%	
14	94 VA Senate	NOR	North	1/31/94	11/8/94	41.0%	42.9%	-1.9%	2.0%
		ROB	Robb			42.5%	45.6%	-3.1%	
		ROF	Rest of Field			1.8%	0.1%	1.7%	
		COL	Coleman			13.4%	11.4%	2.0%	
		WIL	Wilder			1.3%	0.0%	1.3%	
15	90 IA Senate	Hark	Harkin	7/11/90	11/6/90	52.7%	53.9%	-1.2%	1.2%
		Tauk	Tauke			47.3%	46.1%	1.2%	
16	90 IL Senate	Mart	Martin	7/11/90	11/6/90	41.2%	36.0%	5.2%	5.2%
		Simn	Simon			58.8%	64.0%	-5.2%	

3 Model Development

Our goal is to find market characteristics associated with a market's performance in predicting election outcomes. Because of the small number of observations, we focus on a few variables we believe will prove important because of theory and existing experimental evidence. Here, we describe the model development and our reasons for examining particular independent variables. We group our variables according to two broad categories that we call "election properties" and "market properties." We also describe how these variables are related to predictive accuracy and to each other. These variables and their descriptions are listed in Table 2.

3.1 Measuring Predictive Accuracy

Predictive accuracies are easily defined and measured by comparing the price predictions to actual vote shares. Specifically, we compare actual election outcomes to election-eve, normalized closing prices from the IEM. We use the last traded price of each contract at midnight on election eve as the closing price. We normalize prices by dividing each of them by the sum of closing prices for all contracts in the market. This insures that the normalized closing prices sum to the value of a unit portfolio which corresponds to 100% of the relevant vote.[17] The difference between the normalized closing price of a contract and the actual vote share received by the corresponding candidate is that contract's prediction error. Our measure of predictive accuracy is the average absolute prediction error of all contracts in a market. The individual and average absolute errors are given in Table 1 and the average absolute errors are shown in Figure 1. Individual contract errors range from 0% to 23% in absolute value. Average absolute errors range from 0.06% to 8.6%.

3.2 Election Properties: Level of Election

For the market to predict election outcomes accurately, traders must have information about the election and the market must aggregate this information. For traders to have information, it must exist and traders must be sufficiently motivated to obtain it. Our data includes markets run for national, state and primary level elections. The nature and scope of information available to traders varies greatly with the level of the election.[18] Moreover, the fraction of our traders that would be eligible to participate in each election varies with the level.[19] Typically, voter

[17] Prices may not sum to one because of nonsynchronous trading, the bid-ask spread and possible arbitrage violations.

[18] National elections typically generate more widespread interest than statewide elections and, as a result, have more media coverage than local elections.

[19] All traders who can vote in a primary election can also vote in state elections; those who can vote in state elections can also vote in national elections. The reverse is not the case. Each trader in a market who can also participate in the corresponding election has at least one piece of private information: whether and how they will vote in the election.

Table 2. Analysis Variables

Variable	Class	Description
Level of Election	Election Property	Categorical Variable: 1=National, 2=State, 3=Primary
Number of Contract Types	Election Property	Number of contract types traded on the IEM. Corresponds to number of major candidates and (usually) one for rest of field.
Volume	Market Property Market Activity	Total Market Dollar Volume between date of measurement and election. Measured from 1 to 7 days before the election.
Number of Active Traders	Market Property Market Activity	Total Number of Traders submitting limit or market orders between date of measurement and election. Measured from 1 to 7 days before the election.
Average Trader Order Numbers	Market Property Trader Experience	Average Order Number for Traders submitting limit or market orders between date of measurement and election. Measured from 1 to 7 days before the election.
Weighted Ask Queues	Market Property Queue Information	Average (over days and contract types) weighted ask queues between date of measurement and election. Measured at midnight from 1 to 7 days before election.
Weighted Bid Queues	Market Property Queue Information	Average (over days and contract types) weighted bid queues between date of measurement and election. Measured at midnight from 1 to 7 days before election.
Total Weighted Queues	Market Property Queue Information	Total average (over days and contract types) weighted bid and ask queues between date of measurement and election. Measured at midnight from 1 to 7 days before election.

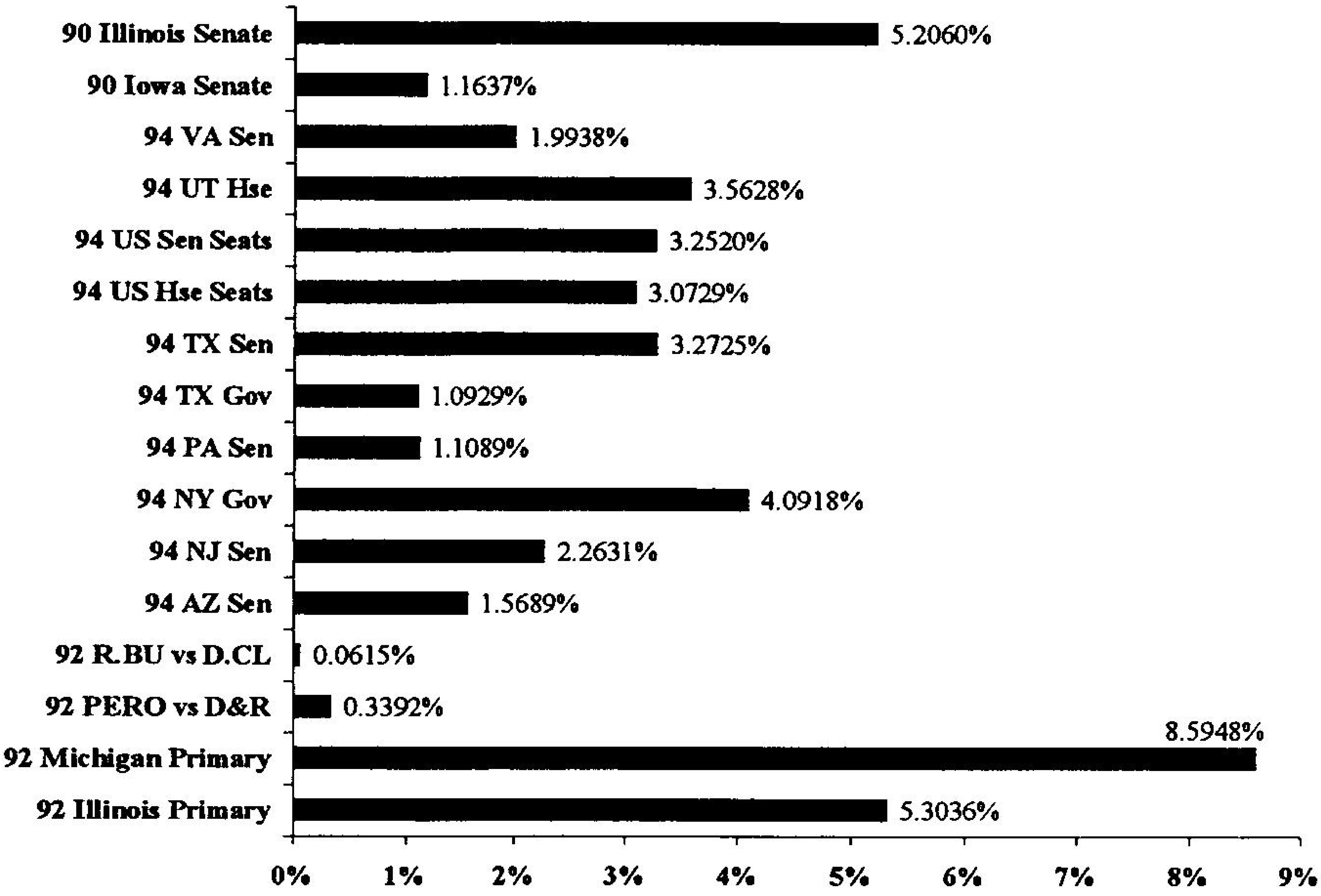

Figure 1: Average Absolute Prediction Errors

turnout also varies with the election level, reflecting the level of interest in the election to some degree.

We create a variable to provide a rough approximation of this by assigning a level of 1 to national (presidential) elections, 2 to state (governor, senate and house) elections and 3 to state primaries. Alone, this variable is significant with national elections resulting in higher predictive accuracy and state primaries in lower. The correlation between this variable and predictive accuracy is 0.7912. However, in our data, this level-of-election variable is also very highly correlated with the number of contract types traded in the market (with a correlation of 0.7883) and volume (with a correlation of -0.4736 with seven-day volume). Including this level-of-election variable with these other variables in a regression would create co-linearity problems. To eliminate the effects of the co-linearity and determine which variables to use, we regressed number of contract types on the level-of-election variable and vice versa. Similarly, we regressed volume on level-of-election and vice versa. We analyzed the resulting residuals by including them in the regressions we ran to explain predictive accuracy. This analysis shows that the number of contract types has significant independent effects while level-of-election does not. Similarly, volume has significant independent effects while level-of-election does not. For this reason, we choose to focus on number of candidates and volume.

3.3 Election Properties: Number of Candidates (Contract Types)

For each election, the IEM allows trade in a separate contract for each candidate deemed "important" by the IEM governors and, often, an additional contract representing the rest of the field. We include the number of different contract types traded as a potential explanatory variable for two reasons. First, increasing the number of contract types increases the number of variables that the market must predict. In markets with two contract types, the market only predicts one (independent) variable. This variable is the vote share of one of the candidates (since the vote share of the other candidate is simply one minus this vote share). In markets with three contract types, the market must predict two variables: the vote shares for two of the three candidates, etc. Second, the political science literature (e.g., Riker, 1982) suggests that, under the US system of plurality voting, the possibilities for strategic voter behavior and the number of voting equilibria increase with the number of candidates This could make the election outcome more difficult to predict.

For this variable, we use the number of contract types traded, which corresponds roughly to the number of major candidates. This is a significant explanatory variable. More contract types generally decrease predictive accuracy. The correlation coefficient between number of contract types and predictive accuracy is 0.6777. As noted above, this variable is highly correlated with election level in our data. Thus, this may be capturing effects of election level as well as the number of contract types traded. However, as also discussed above, the number of contract types traded has significance above that associated purely with the level-of-election variable.

3.4 Market Properties: Market Activity

3.4.1 Trading Volume

Traditional rational expectations theory predicts no trade if there is asymmetric information (Milgrom and Stokey, 1982). So, volume in the market represents consensus expectations. Under market microstructure theory, more trade means that private information is revealed faster (see O'Hara, 1994). So more volume implies either greater consensus or more information revelation.

As a measure of trading volume, we look at total dollar volume in the market over the last one to seven days before the election. These volumes are highly correlated with each other and with predictive accuracy.[20] Any one of these volume measures would be significant. The total volume over the last five to seven days gives the most explanatory power. The seven-day time span includes the weekend before each election (during which candidates are likely making their last campaign swings). In addition, major polling organizations typically release their final poll results during this period. For these reasons, we use seven-day, total volumes in our regressions.

[20] The correlations of volume with predictive accuracy are -0.3692, -0.3781, -0.3744, -0.4482, -0.5025, -0.4965 and -0.4262 for one through seven-day volumes respectively.

3.4.2 Number of Active Traders

We include the number of active traders in our regressions for two reasons. First, if more traders have more information, then a simple aggregation argument implies that there will be more information reflected in the market price. Second, market micro-structure models show that increasing the number of informed traders increases competition between them and, thus, increases the speed with which this information is incorporated in the market.[21]

We use the total number of traders submitting bid, ask, purchase or sale orders to the market over the last one to seven days before the election. This variable is highly correlated with predictive accuracy, but is also highly correlated with volume. For example, the number of active traders over the last seven days has correlations of -0.2579 and 0.8621 with predictive efficiency and volume over the last seven days, respectively. Including both independent variables would create co-linearity problems. Again, regressing seven-day volume on the number of active traders over this period and using the residuals shows that the number of traders had no independent additional significance. Thus, we choose to use volume in the regressions.

3.5 Market Properties: Participant Experience Level

Evidence from experimental markets shows that the experience level of traders may affect the efficiency of the market. Smith, Suchanek and Williams, 1988, show that markets with more experienced subjects are less prone to obviously inefficient pricing "bubbles." Forsythe and Lundholm, 1990, show that markets with more experienced traders are more likely to aggregate information efficiently. Thus, more experienced traders may increase efficiency levels. Oliven and Rietz, 1995, find that traders in the 1992 market tend to make fewer mistakes as they gain experience. They also show that more experienced traders are more likely to send limit orders to the market and limit orders are less likely than market orders to obviously violate arbitrage and individual rationality constraint. Thus, in this sense, more experienced traders in the IEM are better. Finally, more experienced traders may be those who have been studying this election longer and, potentially, bringing more information to the market.

The IEM provides a proxy for IEM trading experience. It assigns a trader-specific, sequential order number to all orders submitted by each trader. Thus, the order number reflects the trader's previous experience in submitting orders to the market. As a measure of experience level, we use the average order number for all orders submitted to the market over the last one to seven days before the election. While these one to seven-day measures are highly correlated with each other, they do not appear highly correlated with predictive accuracy. (The largest correlation coefficient in absolute terms is -0.0166 for the four-day experience level.) Nevertheless, when included in a regression with volume, number of contract types traded and spread information, the experience level is marginally significant. We

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[21] See Foster and Viswanathan, 1994

include the seven-day experience level in one model and drop it in the other. We find that dropping this variable has little effect on overall explanatory power.

3.6 Market Properties: Queue Information

3.6.1 Weighted Spreads

We include information about spreads because of their importance in market microstructure theory. In market microstructure models, the market maker increases the quoted spread in response to higher level of private information since a higher level of private information results in a larger adverse selection problem. To the extent that a consensus exists and information has been aggregated, spreads will shrink. We weight the spreads by the dollars committed at the bid and ask because our markets differ from those discussed in theory. In theoretical models, dealers stand ready to fill the maximum possible order size at all times (see O'Hara, 1995). In our markets, this is not true since traders specify the quantity they are willing to transact at a given price. To measure the "effective" spread, we aggregate across our traders to form a surrogate for an "aggregate" market maker. In aggregating, we weight the spread by the dollar quantity traders have committed to trade at the best bid and ask.

We compute weighted spread measures for the last one to seven days before the election. For each day and contract type, we take the difference between the closing best ask and closing best bid divided by the total dollar quantity committed at this bid and ask. We then average over days and contract types. These (seven) variables are highly correlated with each other and also with one to seven-day volumes. All reflect the level of market activity to some degree. Spreads reflect market-making, limit-order activity while volumes reflect price-taking, market-order activity. To eliminate effects of co-linearity, we use the residuals from a regression of seven-day volume on the seven-day weighted spread. The residuals from this regression show there is a significant independent effect of the weighted spread. However, the results also show that adding this variable does little to increase the explanatory power of the model overall.

3.6.2 Weighted Queues

Market microstructure theory also leads us to include weighted queue information. In market microstructure models, the market makers adjust the bid and ask to reflect the information revealed by each trade. When there is a great deal of private information, spreads are wide and adjustments are large. As this information is revealed, spreads narrow and adjustments become smaller. In our markets, the sensitivity of the market in response to a trade can be measured by the weighted queue, where larger weighted queues mean less price sensitivity.

The weighted bid queue is given by the average (across both contract types and days) of the sum of all closing bids weighted in the following manner. First, we multiply the bid times the dollar quantity committed at that bid. Then we multiply by the bid over the best bid. Thus, the weighting ranges from 0 for a bid at a price of $0 to 1 times the dollar quantity committed for the best bid. This serves as a measure of demand or depth on the bid side.

The weighted ask queue is given by the average (across both contract types and days) of the sum of all closing asks weighted in the following manner. First, we multiply the ask times the dollar quantity committed at that ask. Then we multiply by one minus the ask over the one minus the best ask. Thus, the weighting ranges from 0 for an ask at a price of $1 to 1 times the dollar quantity committed for the best ask.[22] This serves as a measure of supply or depth on the ask side.

The total weighted queue is the sum of the average (across both contract types and days) of the weighed bid and ask queues. These weighted queue variables are all highly correlated with each other and with volumes, each reflecting the general level of market activity. Alone, each is significantly correlated with predictive efficiency. However, there is no significant independent effect after the effects of volume are removed. Thus, we choose to focus on volumes instead of these weighted queue variables.

3.6.3 Differences in Weighted Queues

We include differences in weighted queues for two reasons. First, in the markets reported in Smith, Suchanek and Williams, 1988, imbalances between bids and asks affect subsequent price movements. Second, technical traders often try to determine "support" and "resistance" levels in stock prices and the strength of these levels. Hardy, 1978 (p. 73), defines "support" as "the price level where a declining security may be expected to be supported by buyers." He defines "resistance" as "the price level where an advancing security may be expected to be dumped by sellers." Technical traders cannot determine *actual* support and resistance levels nor their relative strengths. Instead, they estimate these levels and their relative strengths by charting past price movements. At any point in time on the IEM, the bid queue represents the current *actual* support level for the market *directly*. It shows exactly the prices at which buyers are willing to purchase any given quantity at that point in time. Similarly, the ask queue represents the current *actual* resistance level for the market. Their difference is a measure of relative strength. If the weighted bid queue is much smaller than the ask, then there is low support and much resistance and vice versa. Thus, large difference in weighted queues may imply that prices are moving and the market has not yet reached an equilibrium.

The difference in weighted queues is the absolute difference in the average (across both contract types and days) of the weighted bid queues and the average of the weighted ask queues. Measured in this way, the difference in weighted queues does not measure imbalances between buyers and sellers for individual contracts. Instead, it measures the imbalance overall in the market. Again, these measures are highly correlated with each other. We choose to use the election eve difference because this

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[22] Adjustments were made for the $2 maximum price in the 1990 Senate markets by using two minus the ask over two minus the best ask to weight the ask queues.

should reflect whether the market contains an imbalance between buyers and sellers at the time we measure predictive accuracy (with election eve prices). The election eve difference is very significant and, surprisingly, not particularly highly correlated with volume. (The correlation between this and the one day volume is only 0.0499.)

4 Regression Results

Analyzing the correlation structure indicates a strong relationship between many of our potential independent variables. To a large degree, they all represent the same things: interest in and information about the election, market activity and the level of "balance" from the bid and ask sides of the market. To construct a parsimonious model, we have systematically selected variables that reflect this information, have the most explanatory power and are not highly correlated with the other independent variables in the regression. To choose which of two correlated variables to place in the regression, we analyzed the errors from regressions of these two variables against each other. This showed whether the orthogonal components of the variables had independent significance. In only one case did they both have independent significance. The orthogonal components of both volume and average weighted spreads were significant. Therefore, we use volume and the component of spreads that was orthogonal to volume (i.e., the residuals from the regression of volume on spreads) as explanatory variables.

The final regression results are given in Table 3. Recognizing that there may be election specific effects, we report both OLS standard errors and standard errors corrected by Huber's, 1967, method for analyzing clustered data.[23] The regressions show that the number of contract types, seven-day dollar volumes and average election-eve differences in weighted queues were all significant in explaining variances in predictive accuracy across markets. Further, these three variables provided a great deal of explanatory power with an adjusted R^2 of 93%. Model II in Table III adds average trader order number (as a measure of experience) and the residuals from a regression of volume on average weighted spreads to the regression. While both variables were significant, they did little to increase explanatory power, increasing the adjusted R^2 only 2%. Figure 2 shows the actual predictive accuracy of each market and the accuracies predicted by Models I and II. Predictions correspond very closely to the actual data.

Given the correlation structure of the independent variables, we interpret the results to mean that there are several broad factors determining market efficiency: complexity, level of interest and market convergence. The Model I regression

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[23] Election specific effects may be present since some election outcomes were collected on the same election day. For example, the 1992 Illinois and Michigan primaries were on the same day and in both, Tsongas received unexpectedly low vote totals. This could have been due to a common factor such as speculation regarding the recurrence of his cancer. Similarly, unexpectedly low Democratic support during the 1994 election, possibly effecting errors in each 1994 election market we conducted. In adjusting the standard errors, we assumed each election date constituted a cluster of data. We thank Dan Friedman for pointing out how this may effect our results.

Table 3. OLS Models of Average Absolute Prediction Errors

Variable	Model I Coefficients (OLS Std. Err.) [Huber Std. Err.]*	Model II Coefficients (OLS Std. Err.) [Huber Std. Err.]*
Number of Contract Types	0.693734 (0.0928902†) [0.0894716†]	0.8412334 (0.1455499†) [0.1047139†]
Total Dollar Volume During Seven Days Before Election	-0.009712 (0.0025225†) [0.0017686†]	-0.0117971 (0.0021884†) [0.0017826†]
Average Difference in Weighted Bid/Ask Queues at Midnight Before Election	0.0515215 (0.0096603†) [0.0076805†]	0.0600437 (0.0091836†) [0.0086082†]
Average Submitted Order Number Over Seven Days Before Election	--	-0.0002093 (0.0001291‡) [0.0000649†]
Average Residual Weighted Spread Over Seven Days Before Election	--	16.66211 (5.582632†) [2.741727†]
F:	75.48†	71.14†
Adjusted R^2:	0.9332	0.9564
N:	16	16
Root MSE:	0.92465	0.74718

*Corrected using Huber's, 1967, method clustering on election date.
†Significant at the 99% level of confidence
‡Significant at the 85% level of confidence

coefficients indicate adding one contract increases the prediction error by about 0.7%. Since the number of contract types is correlated highly with election level, this likely shows the differences between, and differences in complexity between, state primaries, state elections, and national elections. Similarly, increasing volume by an average of $10 a day over the last week decreases prediction error by about 0.7%. Volumes are highly correlated with election levels, numbers of active traders, average weighted queues and average weighted spreads. Thus, the volume results also likely indicate a higher general level of interest in the election, which increases accuracy. Finally, the results indicate increasing the election eve difference in weighted queues by $10 increases the prediction error by about 0.5%.

5 Conclusion

Prices from the Iowa Electronic Market can be used to predict election outcomes. Just as pollsters are concerned with the margin of error in their polls, we are

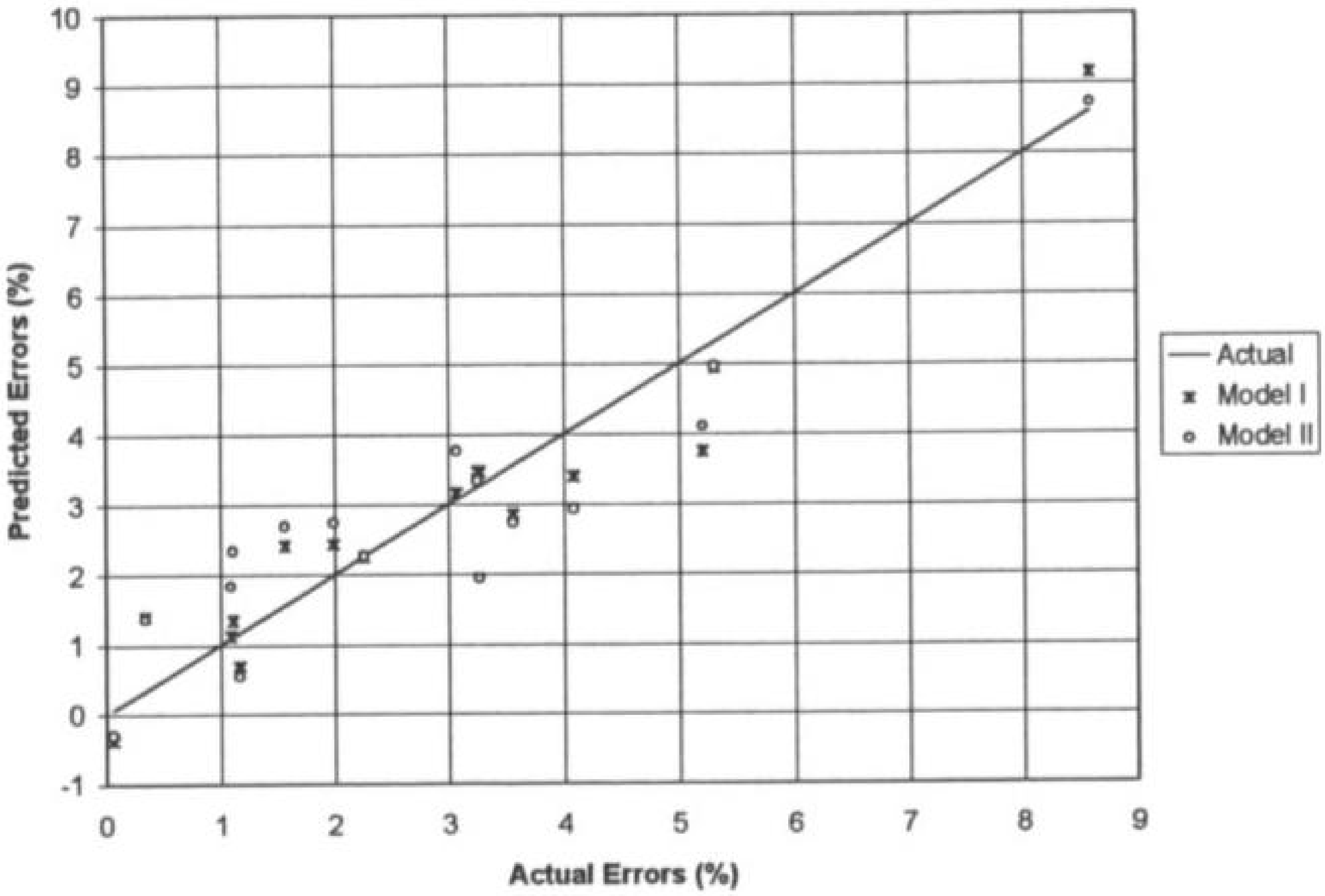

Figure 2: Actual versus Predicted Levels of Average Absolute Market Prediction Errors

concerned with the predictive accuracy of our markets. Here, we relate the accuracy of the markets in predicting election outcomes to various observable election and market specific factors.

In explaining market accuracy, we find many significant factors motivated by financial theory and previous experimental research. In particular, across the markets we examine, variations in accuracy are largely explained by: 1) the number of contract types traded in a market (corresponding roughly to the number of major candidates), 2) the dollar volume of trade over the week before the election and 3) differences in election eve (weighted) market bid and ask queues.

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