Suckers are Born but Markets are Made:

Individual Rationality, Arbitrage and Market Efficiency on an Electronic Futures Market[*]

by

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Abstract

In theory, concepts of market efficiency are conveniently ordered: "Strong form" efficiency implies prices reflect all public and private information, "semi-strong form" implies they reflect only public information and "weak form" implies they reflect only past prices. Assumptions about individual trader rationality, no arbitrage and the law of one price underlie each. Here, we study this ordering in practice. Can a market be strong form efficient, yet violate weaker forms of efficiency? Do weakly rational strategies drive prices to efficient levels? Or, can markets display efficiency despite some sub-optimal trading behavior? We study these questions using a market that displays strong form efficiency. Finding violations of the most basic assumptions, we ask what distinguishes "rational" traders and what creates market efficiency in practice. We conclude that large, well informed, educated and experienced marginal traders drive the efficiency of market prices in spite of less rational traders who produce repeated efficiency and rationality violations.

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I. Introduction

The efficient market hypothesis (EMH) serves as a cornerstone for modern finance and the foundation for all rational asset pricing models. Simple as it sounds, the EMH is actually a hierarchical set of propositions about individual trader behavior and price movements in markets. "Strong form" efficiency implies that prices nearly instantaneously reflect all of the public and private information that traders have. The next weaker, "semi-strong form" implies that prices reflect all available public information. Finally, "weak form" efficiency implies that prices reflect all information contained in past price movements. The propositions are nested because all weaker forms are assumed necessary for stronger forms to hold. Behind all concepts of efficiency is the assumption of the law of one price and the assumption of rational optimizing traders driving "the" price to efficient levels.

Empirical research on the EMH shows that markets often violate no-arbitrage restrictions and weak form market efficiency (e.g., Galai, 1978; Bhattacharya, 1983; Evnine and Rudd, 1985; Halpern and Turnbull, 1985; Whaley, 1986; Figlewski, 1989; Followill and Helms, 1990; Chan and Chung, 1993; and Sternberg, 1994; among others). While noteworthy, this research is limited in several ways. It cannot test efficiency of prices relative to the (unknown) intrinsic values of the underlying assets. It cannot test price efficiency relative to non-public information since the econometric data set does not include such information. Finally, it is difficult to identify or analyze the sources of inefficiencies, because the data is not trade-by-trade, nor are trades generally attributable to specific traders.

In this paper we analyze a market with properties that make it ideally suited for studying individual rationality and the efficient market hypothesis. First, the true values of the traded contracts are revealed at a single point in time. Second, public information about contract values exists and is readily identified. Third, arbitrage constraints are easily identified and individual traders can exploit them with no explicit costs. Fourth, individual trades are stamped with trader identifications. Finally, since the market studied runs continuously, there should be no irregularities associated with openings, closings, weekends, etc. These properties allow an in-depth analysis of the full range of ideas embodied in individual trading rationality, the law of one price, arbitrage restrictions and all three forms of the EMH.

Specifically, we analyze data from one of the highest volume markets and, arguably, the most efficient market conducted during the 1992 election campaign on the Iowa Political Stock Market. Markets on this exchange are hybrids of a traditional experimental asset market and naturally occurring financial futures markets. The experimental nature of the market resulted in much more control and information about the market than in naturally occurring markets. The votes received by each candidate in the presidential race determined the true values of the contracts traded. Thus, values were revealed immediately after the election and poll results gave periodic public information about values. The contract and trading mechanism designs made arbitrage relationships well defined, violations easily identified and exploitation possible with no explicit costs. In addition, every significant action of every market participant was recorded with both a trader identification number and a time stamp. While having these advantages in information and control, the market was also a fully functioning (cash covered) financial futures market. This made the incentives and market dynamics parallel those in other naturally occurring futures markets (which are assumed among the most efficient of asset markets). This mixture of properties allows detailed investigation of the hypotheses while maintaining parallelism with naturally occurring markets.

Our results mirror and integrate results from both traditional experimental and naturally occurring markets. First, mirroring empirical research on naturally occurring data (see the cites above), we find frequent violations of the law of one price and weak form market efficiency. Second, mirroring both this empirical research and experimental research (Smith, Suchanek and Williams, 1988 and Rietz, 1992 and 1993), we find frequent violations of extremely simple arbitrage restrictions. Finally, mirroring the experimental research (Smith, Williams, Bratton and Vannoni, 1982; Gode and Sunder, 1991 and 1992 and Rietz, 1992 and 1993), we find efficient final market prices in spite of sub-optimal trading behavior. Thus, both this market, and the results from it, fit nicely in the gap between traditional experimental and naturally occurring markets.

Given these violations, we investigate their sources in some detail. We ask whether we can identify sets of individuals who are likely to violate arbitrage restrictions or individual rationality as characterized by the law of one price. We ask whether we can detect factors that make these violations less likely and what characterizes "good" traders in the sense that they make these violations less often. Our results show a dramatic difference between market making behavior (setting bids and asks) and price taking behavior (accepting and trading at outstanding bids and asks). Market makers violate arbitrage and individual rationality restrictions dramatically less often. While price takers violate these restrictions 37.7% of the time on average, market makers violate them only 5.39% of the time. Forsythe, Nelson, Neumann and Wright (1992) discuss how "marginal" traders defined as those who regularly submit bids and asks near the market drive market prices. Here, we show why these traders drive prices to efficient levels and analyze efficiency in more detail. We also find that education level, specific market experience and level of financial knowledge all decrease the rate of violations. Higher reported family income classes increased the violation rate, possibly because of the lower relative marginal utility cost of such violations.

Given these results on individual behavior, we go on to ask what can make the market strong-form efficient in spite of the violations of weaker forms of efficiency. Our results indicate two factors. First, market makers (who set the available trading prices) are much less prone to violations as discussed above. Second, more liquid markets (as characterized by a lower relative bid/ask spread) are less likely to produce violations. Thus, while individual traders may often violate assumptions underlying market efficiency, liquid markets with experienced, active market makers can still display price efficiency, nonetheless.

II. The Market and Data

Robert Forsythe, Forrest Nelson and George Neumann created the Iowa Political Stock Market (or IPSM) in 1988 as an alternative means of predicting the fortunes of political candidates.[1] Contracts are designed so the prices should predict the vote totals candidates will receive in elections, the election winners, or publicly available information about some other future event.[2] The markets have regularly proven strong form efficient in the sense that election eve market prices greatly outperform the most recent polls in predicting election outcomes (see Forsythe, Nelson, Neumann and Wright, 1992 and 1993).

For the 1992 presidential election the creators of the market were allowed to operate the market internationally for up to 1000 individuals with investments not exceeding $500 apiece.[3] They filled their allotment of traders, with traders investing more than $83,000 of their own funds. The market ran continuously from January 1992 through the election.[4] All bids, offers, trades, etc., were stored with time stamps (in one second increments) for later analysis.

Markets on the IPSM and IEM share many common characteristics. There are no explicit transaction costs. Each market contains a complete set, or "slate," of event specific contingent claims. Each slate is a risk free bundle of contracts

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[1]Details of the 1988 market can be found in Forsythe, Nelson, Neumann and Wright 1992. The markets have now evolved into the Iowa Electronic Markets (or IEM) in which traders participate in markets trading numerous types of futures contracts.

[2]See Rietz (1993) for a brief description on how prices in such markets should reflect expected values regardless of risk preferences. See Borch (1960), Caspi (1974) and Malinvaud (1974) for more detailed discussions.

[3]The market operated with a no-action letter from the staff of the Commodity Futures Trading Commission.

[4]Notwithstanding occasional short "down" periods, because of mechanical problems.

paying off exactly $1 (or, in some cases, another known, fixed amount). Slates consisting of one of each contract could be purchased from or sold to the exchange for $1 (or its certain value) at any time. This structure provides a means for traders to create and eliminate contracts. It also creates a risk free portfolio, from which all contracts can be priced according to arbitrage pricing theory. Finally, it creates complete contingent claims with fixed aggregate payoffs. As Rietz (1992) discusses, this implies that prices should equal expected values.

Besides buying and selling whole slates, traders could buy or sell individual contracts. The market for each individual contract ran as a continuous, electronic double auction with bid and ask queues in price increments of $0.001. Traders could act as market makers by submitting bids above the outstanding best bid or asks below the outstanding best ask. Traders could act as price takers by accepting an outstanding bid (making a sale) or accepting an outstanding ask (making a purchase). In addition, traders could place limit orders by submitting bids and asks outside the outstanding spread. We concern ourselves here with the first two cases for reasons discussed below

A. The Presidential Market

The specific market we choose to study is the 1992 "presidential vote share" market from July 17, 1992 through the election.[5] This was among the most active and liquid of the markets conducted.[6] It was also one of the most efficient ever conducted in terms of deviations of final (election-eve) prices from true values and in terms of prices being better predictors of true values than other publicly available information such as polls. Final major poll predictions of the vote fractions received by the three candidates differed from the actual fractions received by average absolute errors of 1.2% (Harris) to 3.8% (Gallup). In contrast, the election eve forecast generated by market prices differed from the actual fractions received by an average absolute error of 0.2%. (See Forsythe, Nelson, Neumann and Wright, 1993, for this information and a discussion of the general accuracy of the markets relative to polls.)

In the presidential market, four contracts traded in two sub-markets. One sub-market predicted the vote split between the major candidates. The contract "R.BU" paid its holder $1 times the fraction of the Democratic and Republican vote that George Bush received in the election. Similarly, the contract "D.CL" paid its holder $1 times the fraction of the

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[5] This was the first day in which two securities were traded in each sub-market as discussed below. Before this date, securities that had values based on other democratic candidates' vote shares were traded.

[6] The "presidential plurality" (winner take all) market was more active. However, the prices in that market reflected only who would win the election and not vote percentages. While this market made the correct prediction, it is difficult to evaluate efficiency. In the market we studied, efficiency is easily evaluated. It is simply the error in predicted vote percentages relative to the poll predictions and relative to the actual election outcome.

Democratic and Republican vote that Bill Clinton received in the election. The second sub-market predicted the vote split between the two major candidates and Ross Perot. Discounting the other minor parties, the contract "PERO" paid its holder $1 times Perot's fraction of the Perot and major party vote. The contract D&R paid its holder $1 minus this amount (i.e., the Democratic and Republican fraction of this vote).

Given the market structure, there are two immediate ways a price-taking trader could take any position: directly by trading a single contract, or indirectly by combining a slate transaction with a simple transaction in the complimentary contract. Since there were no trading costs, these were equivalent. To see how this works, suppose that a price-taking trader wanted to take a position with one fewer of a particular contract. That trader could sell the contract immediately at the high outstanding bid. For example, a share of R.BU could be sold at the R.BU bid. Alternatively, that trader could purchase the complimentary share(s) at the market ask(s) and sell the slate to the exchange for $1. The alternative way to "sell" an R.BU was to purchase a D.CL at the market ask and then sell a slate to the exchange for $1. The net trade is identical: one less R.BU. Similarly, a price-taking trader could acquire a contract by either purchasing it directly at the ask or by purchasing a slate and selling the complimentary contract(s).

The market structure also led to two ways for a market-making trader to set a price for a position. Again, the trader could have made it directly by submitting an order for a single contract. Alternatively, the trader could have made it indirectly by submitting an order for the complimentary contract and making a slate transaction. To see how this works, suppose that a market maker wanted to quote a price for a position with one fewer of a particular contract. That trader could submit an ask for that contract. For example, a trader could offer to sell a share of R.BU by submitting an ask for R.BU. Alternatively, that trader could bid to purchase the complimentary share(s) and, if there was a purchase, sell a slate to the exchange for $1. Thus, the alternative way to offer to "sell" an R.BU was to bid to purchase a D.CL. If that bid was accepted, the trader would sell a slate to the exchange for $1. Conditional on the order being accepted, the net trade was identical: one less R.BU. Thus, both were means of offering the same position. Similarly, a market-making trader could offer to buy a contract either by submitting a bid for it or by purchasing a slate and submitting an ask (or asks) for the complimentary contract(s).

B. Arbitrage Restrictions and Pricing Relationships in the Presidential Market

Because of the market properties, tests of arbitrage relationships and the law of one price are immediately apparent for the presidential market (or any other markets on the IPSM or IEM). For each desired price taking transaction, there are two immediate methods to execute the transaction. There are also two analogous methods for market makers to set the price offered for the transaction. These methods should be priced the same according to the law of one price. There are also two different ways to purchase a slate: by purchasing a set of contracts individually at the market asks or by purchasing the slate from the exchange itself for $1. Similarly, there are two different ways to sell a slate: by selling a set of individual contracts at the market bids or selling the slate to the exchange itself for $1. No-arbitrage implies that a trader should not be able to profit by simultaneously buying a slate by one means and selling it by another. Because of the particular payoff structure used, when market makers violate of the law of one price, they also produce a no-arbitrage violation.

We will discuss both pricing relationships and arbitrage relationships in more detail in the next section. To facilitate this discussion, we must introduce some notation. Let n different contract types exist in a market.[7] Denote these contracts by i, for i=1 to n. The highest (or "best") bid price, at time t, associated with contract i is denoted as B_t^i. The lowest (or "best") ask price, at time t, of that contract is denoted as A_t^i. If contract i trades at time t, the price is denoted by P_t^i. Given this notation, it is simple to describe violations of arbitrage: $\Sigma_{i=1}^n B_t^i > \$1$ or $\Sigma_{i=1}^n A_t^i < \$1$. Similarly, it is simple to identify a trade that violates individual rationality as embodied in the law of one price: $P_t^i > \min[A_t^i, 1-\Sigma_{j\neq i} B_t^j]$ for a purchase violation and $P_t^i < \max[B_t^i, 1-\Sigma_{j\neq i} A_t^j]$ for a sale violation. Strictly speaking, both of these are violations of the efficient market hypothesis. Since the current bids and asks are in each trader's information set, they can profit immediately from violations of the no arbitrage condition. Similarly, traders could strategically place bids to profit on average to patterns of violations of individual rationality.

C. The Data

Our data set consists of actions we can unambiguously classify as price taking or market making behaviors in the presidential market from July 17, 1992 through the election. Price taking behaviors are immediate purchases or sales. Thus, we classify accepting an outstanding best bid or ask as price taking. We also classify making a bid that exceeds the outstanding ask as pricing taking behavior because it results in an immediate purchase at the ask. Similarly, we classify making an ask that falls below the current outstanding bid as price taking behavior because it results in an immediate sale at

[7]Here n refers to the number of different security types in a market, not the total outstanding shares in a market. In our case, n will equal 2 in each sub-market.

the bid.[8] Market making behaviors are bids to buy or asks to sell that set new, best limit prices. Thus, we classify a newly submitted bid that strictly exceeds the outstanding best bid as market making behavior. Similarly, we classify a new ask that is strictly less than the outstanding best ask as market making behavior. We do not evaluate off-market limit orders for two reasons. First, having this order rise to the top of the queue is not necessarily an active choice of the trader. Second, the only way such an order could become a violation of arbitrage conditions is if another trader submits a new best bid or ask order in the complimentary contract that also violates the restriction. Thus, we capture such violations as market making violations when this other trader submits his or her order. Selecting data using these criteria leaves us with a data set of 5,858 observations.

For each observation in the data set (from now on referred to as each "order"), we have the type or order (bid, ask, purchase or sale[9]), the date and time of the order, the trader's identification number, the trader specific order number (1 for the trader's first order submitted to the market, 2 for the second, etc.), the quantity ordered or actually traded, the price of the order, the total dollar size of the order (price times quantity), the total dollar volume on the day of the order, the relative spread in the ordered contract to the spread in the complimentary contract and the outstanding best bids and asks for all securities in the market at the time of the order. Using the trader identification number, we link each order to available demographic information about the trader provided by the trader in response to on-line polls conduced by the IPSM. Most traders provided information about their sex, race, religious affiliation, age, income class, education level, academic status, college major if appropriate and levels of other financial market experience, participation and knowledge. Table I gives brief descriptions of each of these variables and all transformed variables that we use in the later data analysis.

III. Results

We categorize our results into five areas. First, we document the existence of violations. Second, we show how violation frequencies vary across types of activities. We show that market makers are much less likely to produce violations than price takers. We also show traders on the buy side of the market are much less likely to produce violations than sell-side traders. Third, we investigate the effects of some self-reported trader demographics and market specific experience on

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[8] If the quantity demanded in such orders exceeds the quantity available at the outstanding bid or ask, the transaction runs through the opposing queue and we account for each transaction at its actual price. This minimizes any violations that occur. Thus, we classifying such events in as conservative a manner as possible.

[9] As mentioned above, bids that cross the ask queue are classified as purchases at the ask and actual traded quantity. Similarly, asks that cross the bid queue are classified as sales at the bid and actual traded quantity.

violation frequencies. We show that decreases in violation frequencies are associated with increases in measured market specific experience levels, self-reported education levels and self-reported financial market knowledge levels. In contrast, increases in self-reported family income class are associated with increased violation frequencies. We find that no other collected demographic information helps significantly in explaining violations. Fourth, we discuss the impact of market liquidity on violation frequencies. We find that more competitive markets (those with lower relative bid-ask spreads) produce fewer violations. We also find that more hectic markets (those with higher total daily dollar volumes) produce more violations. Finally, we look to the collected demographic information to help identify who chooses to be market makers verses those who choose to be price takers. While it remains largely unexplained, we find this choice significantly affected by market specific experience, education, income, sex and religious affiliation.

A. Violations of Individual Rationality and No-Arbitrage Restrictions

We classify actions as violations of individual rationality or the no-arbitrage restrictions according to two very conservative definitions that we will call "market making" violations and "price taking" violations. Strictly speaking, market making violations are actions that force violations of the no-arbitrage restriction. Price taking violations are violations of individual rationality as embodied in the law of one price. Both are violations of efficient markets. When no-arbitrage conditions are violated, traders can profit immediately knowing only current market information. When the individual rationality conditions are regularly violated, traders can profit on average by placing strategic bids and asks and, conditional on acceptance, combining them with slate transactions with the exchange. Violation frequencies are given in Table II. In the next two sections, we explain the violation types and why they create inefficiencies in more detail.

1. Market Making Violations

A market making violation occurs when a trader acts as a market maker (posting the best bid or ask) and this action forces a violation of the no-arbitrage restriction. If a market maker submits a new best bid, we classify it as a violation if the bid submitted forces $\Sigma_{i=1}^{n} B_t^i > \$1$. This bid creates a violation at the market level because it creates an arbitrage violation.[10] This bid is also a violation at the individual level. The trader could have effectively purchased the contract *immediately* at a

[10] Any trader noticing this situation could purchase a slate of contracts from the exchange for $1, sell each contract at its best bid and make an immediate risk free profit. Note that, by ignoring new, non-best bids, we are potentially understating the total number of arbitrage violations. However, these are not clear examples of market making and we have chosen to focus only on those who knowingly make the market by submitting the best bid.

lower price by purchasing a slate of contracts from the exchange for \$1 and selling the other contract at its best bid.[11] If a market maker submits a new best ask, we classify it as a violation if the ask submitted forces $\Sigma_{i=1}^{n} A_t^i < \$1$. This ask creates a violation at the market level because it creates an arbitrage violation.[12] This ask is also a violation at the individual level. The trader could have effectively sold the contract *immediately* at a *higher* price by purchasing the other contract at its best ask and selling a slate of contracts to the exchange for \$1.[13] These violations create inefficient markets in the sense that traders who submit these orders give up certain immediate profits. Traders who observe only current market information can make immediate profits.

Table II shows the frequency and size of market making violations. Out of 3674 new best bids or asks submitted to the market, 5.39% resulted in arbitrage violations. The average total size of the violation (dollar size of the violation times quantity available) was 7.1 cents. This is within the range of payoffs conventionally regarded as salient for inducing trade (see Smith, 1976). Since the average bid or ask was for a total value of \$8.82 and there were no transactions costs, this represented an average violation of 0.8% of the order's total value. While 7.1 cents does not seem large, if errors of the same order of magnitude occurred in the Treasury Bill or Eurodollar futures markets, they would result in arbitrage opportunities worth thousands of dollars each.

The frequency and size of market making violations surprised us given the size and duration of the market. However, they paled in comparison to price taking violations. We will turn to these violations now.

2. Price Taking Violations

A price taking violation occurs when a trader accepts a price for a trade that is not the best available price. This violates individual rationality assumptions underlying the law of one price. In this market, there are always two ways to make a trade. We classify a trade as a violation only if the other means of making the trade was both at a better price and immediately available.

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[11] To see this, consider the two contract case and identify the new bid to be in contract 1: $\Sigma_{i=1}^{n} B_t^i > \$1$ implies $B_t^1 > \$1 - B_t^2$. The latter equation says that the trader is offering to purchase a contract at a price higher than the price at which he or she could have attained the same position through a slate purchase and immediate sale of the other contract. The later transactions give a lower price *and* eliminate execution risk. Similar arguments hold for larger numbers of contracts.

[12] Any trader noticing this situation could purchase each contract in a slate at its best ask, sell the slate to the exchange for \$1 and make an immediate risk free profit. Note that, by ignoring new, non-best bids, we are potentially understating the total number of arbitrage violations. However, these are not clear examples of market making and we have chosen to focus only on those who knowingly make the market by submitting the best bid.

[13] To see this, consider the two contract case and identify the new ask to be in contract 1: $\Sigma_{i=1}^{n} A_t^i < \$1$ implies $A_t^1 < \$1 - A_t^2$. The latter equation says that the trader is offering to sell a contract at a price lower than the price at which he or she could have attained the same position through the purchase of the other contract and a slate sale. The later transactions give a higher price *and* eliminate execution risk. Again, similar arguments hold for larger numbers of contracts.

Assume that a trader has decided to buy contract *i*. The trader could purchase the share from the contract's ask queue (by accepting the best ask or crossing the queue with a bid higher than the best ask). The trader could also effectively purchase the contract by purchasing a whole slate and selling the complimentary contracts in the market at their respective bids. Since there are no transactions costs, a trader should buy contract *i* at A^i_t if $A^i_t < \$1-\Sigma_{j\neq i}B^j_t$. Similarly, a trader should buy a whole slate and sell the complimentary contracts at their bids if $A^i_t > \$1-\Sigma_{j\neq i}B^j_t$.[14] A similar argument holds for a trader who wants to sell contract *i* immediately. In this case the trader could either sell at the bid queue (by accepting the bid or crossing the queue with an ask lower than this bid) or purchase the complimentary contracts at $\Sigma_{j\neq i}A^j_t$ and sell a slate for $1. In all these cases, the trader is trading at preexisting bids and asks. Thus, the trader is a price taker.

We classify a trade as a price taking violation if the trader purchases a contract at the ask when this is not the lowest available price or the trader sells a contract at the bid when this is not the highest available price.[15] These violations create inefficient markets in the sense that traders who submit these orders give up certain immediate better prices. Traders who observe differences between the offer prices for securities via the two available means can offer to sell at relatively high prices and buy at relatively low prices. Should their offers be accepted, they could make immediate profits by trading in the complimentary contract(s) and executing a slate transaction. Thus, knowing current bids and asks and knowing that such violations occur, traders who strategically place bids and asks can profit on average.

Table II shows the frequency and size of price taking violations. Out of 2039 accepted bids and asks, 37.7% were not at the best price, violating of the law of one price. The average violation size (dollar size of the violation times the actual traded quantity) was 10.4 cents.[16] Since the average accepted bid or ask was for a total value of $8.03 and there were no transactions costs, this represented an average violation of 1.3% of a typical transactions value. Again, violations of the same relative size in naturally occurring futures markets would be immense.

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[14] Equality makes the trader indifferent in theory, though any value the trader places on his or her time favors the single transaction of purchasing at the ask.

[15] At first, it may appear that we are ignoring some violations: those that may occur when a trader combines a slate transaction with a single-contract market transaction. In reality, we <u>do</u> identify such violations when they occur by identifying them as violations in the single contract portions of the transactions. To see why this is the case, consider a trader who effectively buys contract 1 by buying a slate and selling contract 2 at the best bid. This is a violation if $A^1_t < \$1-B^2_t$. We do not consider the slate transactions directly. However, we will look at the second half of this transaction: the sale of contract 2 at the bid. When will we tag this as a violation? When the sale price is less than the price the trader could have received by buying contract 1 and selling the slate to the exchange. We will identify this as a violation if $B^2_t < 1-A^1_t$. Rearranging gives $A^1_t < \$1-B^2_t$. This is exactly the same condition and, therefore, we will indeed tag this transaction as a violation. Similar arguments hold for other combinations of transactions.

[16] Again, this may understate the true size of the violations. If the trader put in a quantity larger than the quantity available at the best bid or ask, he or she was willing to make a larger violation than the violation we account for here.

B. Trader Role and Violation Frequencies

The results in this section follow partially from the observations in the last section and partially from the nature of the market rules.

The observations above suggest a difference between market making behavior and price taking behavior. Traders in the role of market makers (setting the best outstanding bids and asks) are much less likely to produce violations than traders acting as price takers (accepting outstanding bids and asks as trading prices). Table III shows the significance of market making versus price taking in determining violation frequencies (χ^2=974 with 1 degree of freedom).

The market rules themselves suggest a possible difference between the frequency of violations on the buy side versus the sell side of the market. All transactions must be cash-covered in the IPSM. This means that a trader must have sufficient cash on hand to place a best bid for a contract or to purchase it at the ask. A trader must also have enough contracts on hand to in order to place a best ask for a contract or to sell it at the bid. Thus, to avoid violations as discussed above, a trader may need to have either $1 in cash or a unit portfolio of contracts. If either budget constraint binds more often, we may see violations on one side of the market or the other more often.[17] Table IV shows that this is indeed the case. It shows a significant relationship between violation frequencies and market side (χ^2=23.33 with 1 degree of freedom).

Table VIII gives the results of a logistic regression, with violations as the dependent variable. The independent variables "Bid Dummy," "Ask Dummy," "Purchase Dummy" and "Sale Dummy" are dummy variables taking on the values of 1 for new best bids, new best asks, purchases (ask acceptances or bids crossing the ask queue) and sales (bid acceptances or asks crossing the bid queue), respectively. Again, the results show that market makers are much less likely to produce violations than price takers and the purchase side of the market is much less likely to produce violations, than the sale side. (We will discuss the other independent variables in Table VIII below.)

Last, we ask whether the size of the commitment that the trader is making affects the probability of violations. Another independent variable in Table VIII is "ln(Order Size)," which gives the natural log of the total dollar size of a bid, ask or trade (dollar value times quantity ordered or traded). The results show that traders submitting or executing larger orders are much less likely to produce violations (z=-4.099).[18]

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[17]Note that $1 can be converted to and from a slate of contracts very easily. Thus, in reality, these are only truly independent constraints for traders who have very low cash and contract balances. However, traders may perceive them as independent in the same way as they apparently fail to perceive the sale of a single contract as equivalent to the sale of a slate and the purchase of the other contracts in the slate.

[18]Raw order size gives similar results. However using the log of order reduces the effects of a few outliers and may better reflect the decreasing marginal utility of increments to wealth.

In summary, larger, buying-side and market making traders are less likely to produce violations than smaller, selling-side and price taking traders.

C. Trader Demographics and Violation Frequencies

IPSM traders were asked to complete surveys periodically. An initial survey asked traders about demographic information including sex, race, religion, age, income, education level, academic affiliation and major. A later survey asked about financial market knowledge, prior financial market experience and current financial market participation levels. Table I describes these variables in more detail. We investigated each to detect whether it significantly affected violation frequencies. We found several of these (self reported) variables that did: Education Level, Family Income Class Level and Financial Market Knowledge.

Table V shows the significance of Education Level alone in determining violation frequencies (χ^2=55.079 with 3 degrees of freedom). Recall that Table VIII gives the results of a logistic regression with violation as the dependent variable. The independent variable "Education Level" represents the four levels of education described in Table I. Again, the results show that more education significantly reduces violations (z=-3.758).

Table VI shows the significance of Family Income Class alone in determining violation frequencies (χ^2=10.0054 with 2 degrees of freedom). Taken alone, the direction of the effect is ambiguous. However, regressions that consider the interactions of more demographic variables can help clarify this. The independent variable "Family Income Class" in Table VIII represents the three levels of family income as described in Table I. The results show that higher reported family income classes significantly increase violations (z=3.036). One interpretation is that, in terms of marginal utilities, the cost of making violations is lower for higher income individuals. We also wonder whether individuals, particularly students, all held the same definitions of "family" when estimating family income and/or were unable to assess accurately their family's income levels relative to national standards.

Table VII shows the significance of Financial Market Knowledge alone in determining violation frequencies (χ^2=42.2261 with 2 degrees of freedom). Higher levels of Financial Market Knowledge reduce violation frequencies. The independent variable "Financial Market Knowledge" in Table VIII represents the three levels of financial market knowledge as described above. The results show that more knowledge significantly reduces violations (z=-4.122).

We also asked whether market-specific experience would affect violation frequencies. The exchange identified each order by a trader specific order number. (A trader’s first order was numbered 1, the second order numbered 2, etc.) Orders could be any bid, ask, trade or slate transaction (with other traders or directly with the exchange). As a proxy for market-specific experience, we included the trader-specific order number in the logistic regression with violations as the dependent variable. Again, Table VIII gives the results with "Order Number" representing the trader-specific Order Number. The results show more experience with the market, as given by higher Order Number, significantly reduces the probability of a violation (z=-7.199).

In summary, more experienced, knowledgeable and educated traders produced fewer violations. In contrast, higher income classes increased violation rates. None of the other demographic variables from Table I had significant effects on violation rates.

D. Market Characteristics and Violation Frequencies

Next, we ask whether the state of the market itself affects the chances of observing violations. We find that market activity (as measured by total daily dollar volume in the market) and relative market liquidity (as measured by relative bid-ask spreads) both effect violation frequencies. The market-level results here reinforce the individual level results from above. Again, the logistic regression results are contained in Table VIII.

The variable "Daily Dollar Volume" gives the total dollar trading volume on the date in which each order was submitted. Higher volume implies that more traders are accepting the outstanding bids and asks. The results above suggest that more activity from price takers should increase violations. Indeed, the results here coincide with this. Greater dollar volume increases the violation rate (z=2.474).

The variable "Relative Spread" gives the spread for the ordered contract relative to the complimentary contract in the market. It is simply the bid-ask spread for the ordered contract divided by the bid-ask spread in the complimentary contract in the same market. More market making activity should reduce the spread. The results above suggest that market makers produce relatively few violations. The results in Table VIII coincide with this. They show that a higher relative spread (less market maker competition) increases the frequency of violations (z=6.652).[19]

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[19] Absolute spreads give similar results. Note, however, that the two transactions being compared here are an acceptance in the market for one contract versus an acceptance in the complimentary contract's market combined with a slate transaction with the exchange. If a trader randomly chose between these two transactions, an acceptance in the market with the higher relative spread is more likely to produce a violation. On the other hand, rational traders will try to avoid the higher level of transactions costs by trading in the side of the market with the lower relative spread. Thus, since the probability of a violation resulting from an irrational trader and the side of the market chosen by a rational trader both depend on the relative spread, the relative spread is the appropriate variable to focus on here.

In summary, markets with more competitive market making (given by a lower relative bid-ask spread) and markets with less relative price taking behavior (as given by lower total dollar trading volumes) produce fewer violations.

E. Characteristics of Market Makers and Price Takers

Knowing that market makers produce fewer violations, we ask who chooses to become (or remain) a market maker. Can we characterize market makers versus price takers? In this section, we analyze the choice between market making and price taking behaviors--independent of violations.

Table IX gives the results of a logistic regression with the dependent variable taking on the value of 1 if the act represented market making behavior and 0 if the act represented price taking behavior.[20] The demographic information that proved important in the regression include "Education Level," "Family Income Class," "Sex," and "Religious Affiliation Dummy" as described in Table I. The demographic variable "Race" was not included due to insufficient representation in several categories. "College Major" was not included due to low response rates, collinearity with other variables (most notably age, income and education) and biases it may introduce by eliminating a large, non-representative portion of the sample. Finally, we include "Order Number" as a proxy for the trader's market specific experience level. Other variables discussed above were not significant in explaining the choice between market making and price taking. As Table IX shows, those who chose to make markets tended to be more experienced, more educated, lower income, male traders who were less likely to report a religious affiliation. However, while these variables are significant, the choice of role remains largely unexplained.

IV. Summary and Conclusions

We have shown that traders in the presidential market of the IPSM during the 1992 presidential race regularly violated assumptions underlying the efficient markets hypothesis. Both of the violations we study imply that the markets are not weak-form efficient in the traditional sense. Traders could have made money by exploiting arbitrage opportunities or setting bids and asks to exploit violations of the law of one price. However, the final prices in the market proved to be very efficient. Indeed, most markets run on the IPSM have proven to be very efficient. (See Forsythe, Nelson, Neumann and

[20] Again, market making is defined as submitting the best bid or ask. Price taking is defined as accepting an outstanding bid or ask or submitting a bid or ask that crosses the opposite queue. We do not analyze bids and asks that are off the market.

Wright, 1993.)

At first brush, this leaves us with a quandary: How can market traders repeatedly violate concepts assumed necessary for any kind of market efficiency and simultaneously drive final market prices to efficient levels? More in-depth analysis shows that active, knowledgeable, experienced and educated market makers with larger orders can drive prices to efficient levels while profiting from other (pricing-taking) traders' mistakes. This accords well with Kyle's (1985) interpretation of market dynamics. In Kyle-type models, "informed" traders drive prices to efficient levels in the presence of uninformed "noise" or "liquidity" traders and optimizing market makers. Similar dynamics appear to hold here, though the clear distinctions between trader types do not hold.

In many ways, this study falls in the gaps between existing work. We analyze a market that falls between traditional experimental asset markets and naturally occurring financial markets. The results show market dynamics that fall between traditional "identical rational agent" financial models and "Kyle-type" models with strictly classified trader types. The conclusions drawn lie between the assumptions of academics that all traders are rational and the conventional wisdom of the "real world" that there is a sucker born every minute. In short, we do find "suckers" in the market who appear to violate the most basic of academic assumptions. Yet we also find rational, market making traders who, at least at the margin and at least in this market, make markets efficient in the strongest sense predicted.

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Table I: Variables in the Data Set

Order Specific Variables

Variable Name	Description	Obs.	Mean	Std. Dev.
ID	Trader's ID #	5713	598.73	309.14
Order Number	Trader's order #	5713	950.07	1839.18
Bid Dummy	1 if order is Bid	5713	0.33	0.47
Ask Dummy	1 if order is Ask	5713	0.31	0.46
Sale Dummy	1 if order is Purchase	5713	0.17	0.37
Purchase Dummy	1 if order is Sale	5713	0.19	0.39
Quantity	Ordered or traded quantity	5713	19.53	53.14
Price	Order bid, ask or trade price	5713	0.47	0.25
Order Size	Price times quantity	5713	8.54	22.96
ln(Order Size)	Natural log of Order Size	5713	0.93	1.54
Daily Dollar Volume	Daily Total $ Volume	5713	142.08	115.02
Bid	Outstanding best bid at order	5713	0.46	0.25
Ask	Outstanding best ask at order	5713	0.49	0.25
Cross Bid	Cross Market Bids	5713	0.51	0.25
Cross Asks	Cross Market Asks	5713	0.53	0.26
Relative Spread	Spread in ordered market over spread in complimentary market	5713	1.56	2.84

Trader Demographic Variables

Variable Name	Description	Obs.	Mean	Std. Dev.
Sex	Sex 1=F, 0=M	5711	0.20	0.30
Race	Race[I]	5439	1.54	1.38
Religion	Religion[II]	5353	2.84	1.62
Religious Affiliation Dummy	1 if any religious affiliation reported	5713	0.68	0.47
Age	Age	5061	30.09	9.54
Family Income Class	Family Income Class[III]	5139	2.46	0.70
Education Level	Highest Degree Attained[IV]	4817	2.50	1.02
Academic Status	Academic Status (College)[V]	5264	6.48	2.43
College Major	Major (if Student)[VI]	4680	4.75	2.56
Financial Market Knowledge	Knowledge of Financial Markets[VII]	5021	2.13	0.79
Financial Market Experience	Financial Market Experience[VIII]	5039	2.00	1.02
Financial Market Participation	Other Financial Market Participation Level (Hours per Week)	5048	6.98	14.86

[I] 1=White, non-Hispanic origin, 2=Black, non-Hispanic origin, 3=Hispanic, 4=Asian or Pacific Islander, 5=American Indian or Alaskan native, 6=other
[II] 1=Protestant, 2=Catholic, 3=Jewish, 4=Other, 5 No religious affiliation
[III] Best estimate of family's income class: 1=lowest 1/3 of US families, 2=middle 1/3, 3=top 1/3
[IV] 1=High school, 2=Bachelor's, 3=Master's, 4=Doctorate
[V] 1=Freshman, 2=Sophomore, 3=Junior, 4=Senior, 5=MA/MBA candidate, 6=Law or Medical student, 7=Ph.D. candidate, 8=Faculty, 9=Other
[VI] 1=Business, 2=Social Science, 3=Humanities, 4=Natural Science, 5=Mathematics or Engineering, 6=Other, 7=Not a student
[VII] 1=Beginner level, 2=Intermediate level, 3=Advanced level
[VIII] 1=Novice, 2=Limited, 3=Experienced Amateur, 4=Professional

Table II: Violations of No-Arbitrage Restrictions and Individual Trader Rationality						
Action Type	Data	Obs.	Violation Frequency	Average Size	Max	Total
All	All Bids,[I] Asks[I] & Trades[II]	5713	16.93%	$0.97	$4.26	$89.24
Market Making	All Bids and Asks[I]	3674	5.39%	$0.071	$1.345	$14.06
	Bids[I]	1900	3.26%	$0.061	$0.720	$3.77
	Asks[I]	1774	7.67%	$0.076	$1.345	$10.29
Price Taking	All Trades[II]	2039	37.7%	$0.104	$4.260	$75.18
	Purchases[II]	1074	34.7%	$0.115	$4.260	$40.21
	Sales[II]	965	41.0%	$0.095	$1.580	$34.97

[I]Excluding bids and asks that crossed the opposite queue and traded immediately.
[II]Including bids and asks that crossed the opposite queue and traded immediately.

Table III: The Effects Of Activity Type On Violation Frequency				
	Frequency			
Activity Type	No Violation	Violation	Total	Pearson $\chi 2(1)$
Market Making	1270 62.29%	769 37.71%	2039 100%	974.4346 Pr = 0.000
Price Taking	3476 94.61%	198 5.39%	3674 100%	
Total	4746 83.07%	967 16.93%	5713 100%	

Table IV: The Market Side Effects on Violation Frequency

Market Side	Frequency: No Violation	Frequency: Violation	Frequency: Total	Pearson χ2(1)
Bid or Purchase	2539 85.37%	435 14.63%	2974 100%	23.3276 Pr = 0.000
Ask or Sale	2207 80.58%	532 19.42%	2739 100%	
Total	4746 83.07%	967 16.93%	5713 100%	

Table V: Education Level Effects On Violation Frequency

Reported Education Level (Highest Degree Attained)[I]	Violation Frequency: No Violation	Violation Frequency: Violation	Violation Frequency: Total	Pearson χ2(3)
High School	702 78.26%	195 21.74%	897 100%	55.079 Pr = 0.000
Bachelor's	1218 77.19%	360 22.81%	1578 100%	
Master's	1174 86.5%	183 13.49%	1357 100%	
Doctorate	834 84.67%	151 15.33%	985 100%	
Total	3928 81.54%	889 18.46%	4817 100%	

[I]A category for "other" was dropped due to unclear interpretation.

Table VI: Family Income Level Effects On Violation Frequency

Self Reported Family Income Level	Violation Frequency			Pearson $\chi 2(2)$
	No Violation	Violation	Total	
Lowest 1/3 of US Families	527 85.97%	86 14.03%	613 100%	10.0054 (0.007)
Middle 1/3 of US Families	1260 80.35%	308 19.65%	1568 100%	
Highest 1/3 of US Families	2445 82.66%	513 17.34%	2958 100%	
Total	4232 82.35%	907 17.65%	5139 100%	

Table VII: Financial Knowledge Effects On Violation Frequency

Self Reported Level of Financial Market Knowledge	Violation Frequency			Pearson $\chi 2(2)$
	No Violation	Violation	Total	
Beginner	1022 81.30%	235 18.70%	1257 100%	42.2261 (0.000)
Intermediate	1508 82.27%	325 17.73%	1833 100%	
Advanced	1712 88.66%	219 11.34%	1931 100%	
Total	4242 84.49%	779 15.51%	5021 100%	

Table VIII: Logistic Regression on Violations
(Dependent Variable = 1 If Violation Occurs)

Log Likelihood = -1463.887	chi2(10) = 858.82
Number of obs = 4103	Prob > chi2 = 0.0000
Model Sensitivity: 23.31%	Pseudo R2 = 0.2268
Model Specificity: 96.64%	Area under ROC curve = 0.8238

Independent Variable[I]	Estimated Coefficient	Std. Err.	z-Stat
Bid Dummy	-2.957983	0.265039	-11.161[I]
Ask Dummy	-2.052586	0.237622	-8.638[I]
Purchase Dummy	-0.389000	0.224144	-1.735[II]
Sale Dummy	0.035214	0.230169	0.153
ln(Order Size)	-0.128440	0.031337	-4.099[I]
Education Level	-0.147395	0.050012	-2.947[I]
Family Income Class	0.244737	0.080625	3.036[I]
Financial Market Knowledge	-0.281601	0.068320	-4.122[I]
Order Number	-0.000467	0.000065	-7.199[I]
Daily Dollar Volume	0.001033	0.000417	2.474[I]
Relative Spread	0.121237	0.018226	6.652[I]

Model Classification Table

Predicted	Observed Negative (Non-Violation)	Observed Positive (Violation)	Total
Negative	3277 (85.72%)	546 (14.28%)	3823 (100%)
Positive	114 (40.71%)	166 (59.29%)	280 (100%)
Total	3391 (82.65%)	712 (17.35%)	4103 (100%)

[I]See Table I for descriptions of variables.
[I]Significant at the 95% level in two sided tests.
[II]Significant at the 90% level in two sided tests.

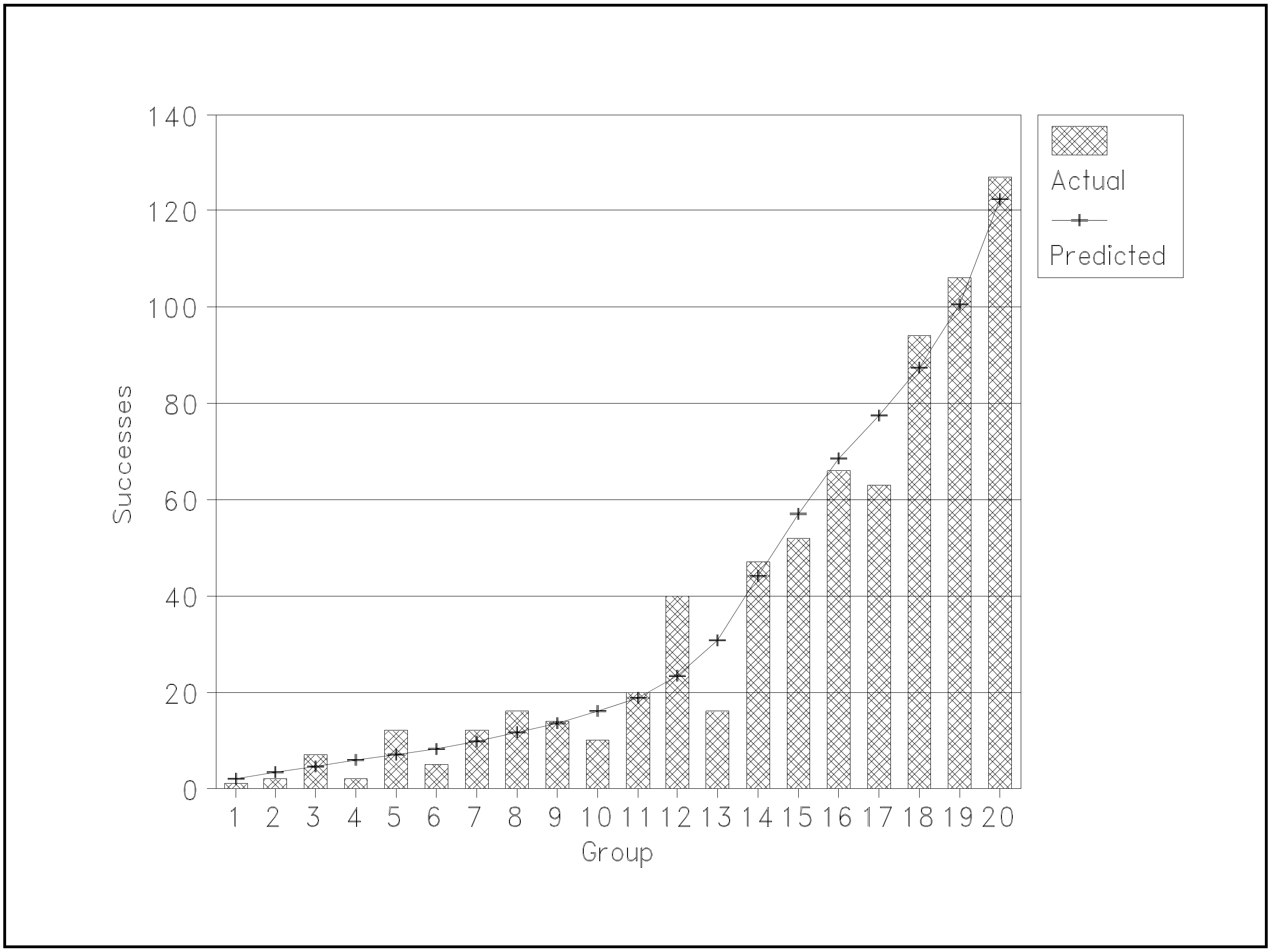

Figure 1: Predicted versus Actual Violations (Classified as "Successes")
Collapsed on 20 Groups Of Predicted Probabilities

Table IX: Logistic Regression on Trader Role
(Dependent Variable = 1 If Market Making)

Log Likelihood = -2923.6898	chi2(5) = 230.09
Number of obs = 4558	Prob > chi2 = 0.0000
Model Sensitivity: 95.39%	Pseudo R2 = 0.0379
Model Specificity: 11.95%	Area under ROC curve = 0.6209

Independent Variable[I]	Estimated Coefficient	Std. Err.	z
Education Level	0.144885	0.031590	4.586[II]
Family Income Class	-0.119580	0.052793	-2.265[II]
Sex	-0.882008	0.106592	-8.275[II]
Religious Affiliation Dummy	-0.292303	0.074502	-3.923[II]
Order Number	0.000273	0.000034	8.075[II]
Constant	0.531107	0.143864	3.692[II]

Model Classification Table

Classified	Observed Negative (Price Taking)	Observed Positive (Market Making)	Total
Negative	210 (61.95%)	129 (38.05%)	339 (100%)
Positive	1547 (36.67)	2672 (63.33%)	4219 (100%)
Total	1757 (38.55%)	2801 (61.45%)	4558 (100%)

[I]See Table I for descriptions of variables.
[II]Significant at the 95% level in two sided tests.

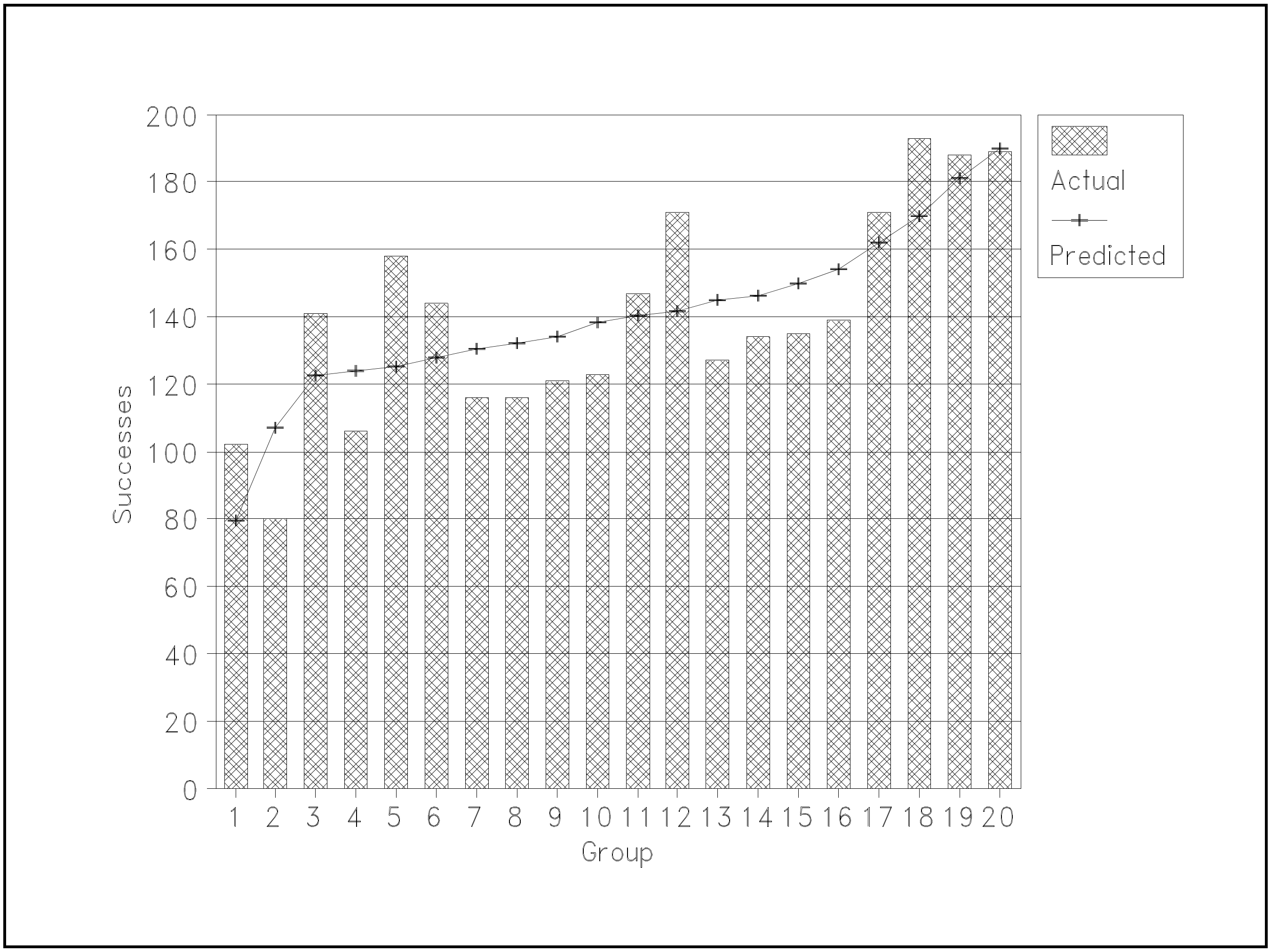

Figure 2: Predicted versus Actual Market Making Behavior (Classified as "Successes")
Collapsed on 20 Groups Of Predicted Probabilities