TRADER SURVIVAL: EVIDENCE FROM THE ENERGY FUTURES MARKETS

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This study analyzes the adaptation of traders and the determinants of trader survival during a period of changing market structures. Our unique sample of transactions level data covers the introduction of electronic trading in the NYMEX energy futures market. The results show that most floor traders adapted to the side-by-side electronic and open outcry trading, although trader attrition increased and the profitability of surviving traders declined dramatically. It is also found that trading profits, trader experience and sophistication, and dual trading have a positive effect on the probability of trader survival. Scalpers are less likely to exit trading in pure open outcry trading, but are more likely to fail than traders who hold open positions longer in side-by-side trading. Finally, traders trading in multiple energy futures markets and those who use both the exchange floor and electronic trading appear to have a survival advantage in side-by-side trading. © 2011 Wiley Periodicals, Inc. Jrl Fut Mark 32:809–836, 2012

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1. INTRODUCTION

Financial markets are in a constant state of flux. The rate of change has been accelerated in recent years by the proliferation of new financial instruments and trading platforms. These rapid changes are exemplified by the recent move from physical trading floors to electronic trading platforms implemented by all of the major exchanges. This fundamental shift in the trading mechanism requires adaptation by market participants if they want to survive.

The influence of changing environments on biological processes has been extensively studied. For example, Darwin's theory of natural selection predicates that if a species does not adapt to changes in its environment it will disappear, and that only those who can adjust to the new conditions will survive. Two streams of financial economics literature are directly related to theories of evolution and natural selection. The first examines the evolutionary theory of games (Smith, 1982); the second focuses on the notion of market selection. Blume and Easley (1992, 2008) ask two questions: (1) Is it possible to characterize the rules of selection or who wins? and (2) If selection does take place, do traders who use rational decision rules survive, and do irrational traders vanish? Theoretical literature on market selection has focused on the question of survival of irrational traders and their impact on asset prices.[1]

Some research has examined how traders learn from their trading experience (Seru, Shumway, & Stoffman, 2010), but very little empirical work has been done on adaptation of traders to a change in market structure or on the determinants of trader survival. This study contributes to the existing literature in two ways: (1) by evaluating the adaptation of traders following a change in the trading mechanism, and (2) by examining individual trader characteristics that influence the probability of trader survival.

We evaluate local traders in four energy futures markets traded on the New York Mercantile Exchange (NYMEX): crude oil, natural gas, gasoline, and heating oil, over the period from January 2005 to February 2009. During this period, the energy markets experienced a large increase in trading activity and price volatility, attracting close attention from regulators and lawmakers (e.g., MacDonald, Chazan, & Cui, 2009). NYMEX floor traders resisted implementation of day-time electronic trading, even as most of the other large financial exchanges had already established electronic trading platforms. However, competition from the all-electronic Intercontinental Exchange (ICE) caused the management of NYMEX to quickly implement electronic trading after ICE began trading of crude oil futures contracts essentially identical to those traded on NYMEX. Trading of NYMEX's physically settled energy products on a

[1]For more theoretical work on market selection and investor survival, see Yan (2008) and Kogan, Ross, Wang and Westerfield (2006, 2009).

well-established electronic trading platform, Globex, began on September 5, 2006. Floor trading in the same contracts continued on regular schedule. Thus, similar to other US futures exchanges, NYMEX now uses a hybrid trading mechanism, with electronic and floor trading operating side by side.

Our unique data set allows for the tracking of positions and personal trading revenues of individual exchange locals. These professional traders have traditionally enjoyed exclusive access to open outcry trading that gave them an informational advantage over off-floor traders (e.g., Ferguson & Mann, 2001, Locke & Onayev, 2007). NYMEX's introduction of day-time electronic trading creates an opportunity to study the ability of local traders to adapt and survive when faced with drastic changes in their environment. These changes include a move of most of the customer order flow to Globex, anonymity of electronic trading, and increased competition for order flow from off-exchange Globex traders. As electronic trading is very different from floor trading, it may require different characteristics for a trader to survive and succeed.

We find that the introduction of daytime electronic trading on NYMEX was followed by a large drop in floor trading activity and by a large decline in trading revenues and profits of exchange locals. Despite the large drop in their income, most floor traders survived the transition to side-by-side trading and now use both trading platforms. Although side-by-side trading initially attracted new local traders, trader failures in side-by-side trading are much more frequent than during the pure open outcry period.

Profit is a key measure of trading success. As stated by Alchian (1950) ". . .those who realize positive profits are the survivors; those who suffer losses disappear." We identify several trader characteristics that are likely to influence trader profitability and, hence, the probability of survival. These characteristics include trader experience, sophistication, dual trading (i.e., the execution of trades for both personal and customer accounts), degree of concentration in a particular futures market, and trading style. The results of our hypotheses tests show a positive impact of trader experience, sophistication, and dual trading on profitability and survival in both pure open outcry trading and side-by-side trading. We also find that good open outcry traders continue earning above-average profits under the new trading mechanism.

Our survival analysis also shows that the effect of trader specialization in a particular market and trading style on trader survival depends on the trading mechanism. Traders using multiple energy futures markets appear to have a survival advantage in side-by-side trading but no significant advantage in floor trading. Scalpers, i.e., traders who quickly trade in and out of positions, are less likely to exit the market than traders who trade less frequently and hold open positions longer in pure open outcry trading; however, scalpers are more likely to fail in side-by-side trading. Finally, we find that traders who use both the

exchange floor and Globex during the side-by-side trading period are more likely to survive than those who trade exclusively on the floor or only on Globex.

2. DATA AND DESCRIPTIVE STATISTICS

2.1. Data

We use 50 months of transaction-level data from the crude oil, natural gas, heating oil, and gasoline futures markets traded on NYMEX, spanning January 2005 through February 2009.[2] The data set is obtained from the US Commodity Futures Trading Commission (CFTC) and contains the records of all open-outcry and electronic trades. The data include the price, number of contracts traded, trade date, trade time,[3] trade direction (buy or sell), delivery month and year of the contract, venue code (floor or electronic), trade type code, the executing broker identification, and customer type indicator (CTI). CTI range from 1 to 4 as follows: CTI 1 are trades executed by an individual exchange member for his own account; CTI 2 are trades executed for a proprietary account of an exchange member firm; CTI 3 are trades executed for a personal account of another individual exchange member; CTI 4 are trades executed for an account of any other trader. CTI 4 trades originate from off-exchange customers. Our primary interest is in local (CTI 1) trades because the executing broker identification allows tracking trading positions and revenues of individual exchange members.

Daily settlement prices used to mark to market are also obtained from the CFTC. Only futures trades executed during the regular floor trading hours (from 10:00 a.m. to 2:30 p.m. EST before February 1, 2007 and from 9:00 a.m. to 2:30 p.m. EST beginning February 1, 2007) are included in the sample.[4] We also remove trades identified as void, indicating that an error, for example an incorrect price or quantity, occurred in the execution of the trade. Trades where the difference between the trade price and settlement price exceeds 100%, indicating a likely data error, are also removed.

[2]The gasoline futures data includes two futures contracts: unleaded gasoline and RBOB gasoline. The RBOB gasoline futures started trading in March 2005 and gradually captured the bulk of trading volume from unleaded gasoline futures. The unleaded gasoline futures stopped trading in December 2006. For the period when both contracts traded simultaneously, we aggregate them into a single gasoline futures market.

[3]Trade execution times are reported to the nearest minute for open outcry trading and to the nearest second for electronic trading.

[4]We remove after-hours trades for several reasons. First, after-hours trading is relatively thin. Second, we are interested in examining the difference between pure electronic trading and side-by-side trading, but all after-hours trading is done electronically. Finally, settlement prices that we use to calculate trading revenues are determined based on the prices at the end of the regular trading day.

TABLE I
Summary Statistics

	Pure Open Outcry Trading 1/3/05–9/1/06	*Side-by-side Trading 9/5/06–2/27/09*		
		Floor	*Electronic*	*Overall*
Crude Oil				
Mean daily volume (contracts)	212,286	68,592	346,540	415,132
Mean number of trades per minute	37.2	5.6	467.6	473.2
Mean trade size (contracts)	21.10	37.17	2.26	2.67
Median trade size (contracts)	10	15	1	1
Mean all-trade effective spread (basis points)	3.16	1.31	0.07	0.11
Mean against-local effective spread (basis points)	4.26	2.09	0.12	0.32
Heating Oil				
Mean daily volume (contracts)	48,188	12,300	53,475	65,775
Mean number of trades per minute	15.4	2.4	90.3	92.7
Mean trade size (contracts)	11.62	15.51	1.81	2.16
Median trade size (contracts)	5	9	1	1
Mean all-trade effective spread (basis points)	5.28	2.19	0.26	0.39
Mean against-local effective spread (basis points)	7.37	10.11	1.36	1.87
Gasoline				
Mean daily volume (contracts)	48,719	11,901	55,700	67,601
Mean number of trades per minute	14.2	1.8	89.7	91.5
Mean trade size (contracts)	12.65	20.12	1.89	2.25
Median trade size (contracts)	7	10	1	1
Mean all-trade effective spread (basis points)	6.87	1.04	0.33	0.68
Mean against-local effective spread (basis points)	8.44	13.72	1.27	2.57
Natural Gas				
Mean daily volume (contracts)	75,716	21,125	95,212	116,337
Mean number of trades per minute	23.8	3.7	135.5	139.3
Mean trade size (contracts)	11.74	17.30	2.14	2.55
Median trade size (contracts)	5	5	1	1
Mean all-trade effective spread (basis points)	4.89	2.25	−0.04	0.004
Mean against-local effective spread (basis points)	5.80	6.25	0.17	0.28

Effective spread for off-exchange customers is computed as the average customer buy price minus the average customer sell price, divided by the average customer buy price, over a five-minute interval. Only the most actively traded contract for each market is used in calculation of effective spreads.

2.2. Summary Statistics

Table I provides summary statistics including the average daily volume, average trading frequency, average trade size, and customer execution costs across the crude oil, natural gas, heating oil, and gasoline futures markets. The overall trading activity measured by daily trading volumes increased in all four markets in the side-by-side period. This increase ranged from about 37% in the heating oil market to 96% in crude oil. The floor trading activity declined dramatically, with over 80% of the trading volume executed electronically in the side-by-side period. Trading frequency on Globex is extremely high, particularly in the

crude oil futures market. Most of the Globex trades are small, however, with a median trade size of only one contract. Floor trade sizes tend to be much larger, especially during the side-by-side period. This suggests that small traders have moved to electronic trading, whereas some larger traders continue using the exchange floor.

Following Kurov (2005), we calculate the effective spread as the average off-exchange customer buy price minus the average customer sell price, divided by the average customer buy price, over a five-minute interval. Before the introduction of daytime electronic trading, the average effective spread calculated across all customer orders ranged from about 3 basis points in the crude oil futures market to about 7 basis points in the gasoline futures market. The spreads collapsed when the energy futures were launched on Globex. For example, in the electronically traded natural gas futures market, the mean all-trade effective spread is negative, suggesting that off-exchange customers frequently supply liquidity to exchange members. In all four markets, effective spreads are much higher in floor trading than on Globex under side-by-side trading.

Many exchange locals trade in several markets of the energy complex rather than concentrating in just one market. Examining each market in isolation in our analysis of trader survival would lead to instances where, for example, a particular trader no longer trades natural gas futures but is still active in the crude oil market. To avoid classifying such instances as trader failures, we take a portfolio approach to studying trader's participation by consolidating all four markets of the energy complex into a single data set. This approach allows tracking the overall trading activity, profits and survival status of each local trader.

Figure 1 shows the time variation in the total number of local traders in the four energy futures markets that we consider. The average number of personal account traders in NYMEX's energy complex over the entire sample period is about 586. The number of personal account traders increased immediately after the introduction of daytime electronic trading, but then gradually declined. Figure 1 also shows the percentage of the total dollar trading volume and personal account (CTI1) volume executed on Globex. By the end of 2006, about 60% of the overall volume in these markets was executed electronically, and Globex's share continued to grow rapidly, exceeding 90% in 2008. In comparison, when MATIF introduced side-by-side floor and electronic trading in 1998, almost all of the trading volume quickly moved to the electronic platform and the floor was closed soon thereafter. The percentage of personal account trading executed electronically by exchange locals remained lower than the corresponding share of the overall trading activity. This indicates that exchange locals tend to execute a larger share of their trading volume on the exchange floor than do other traders.

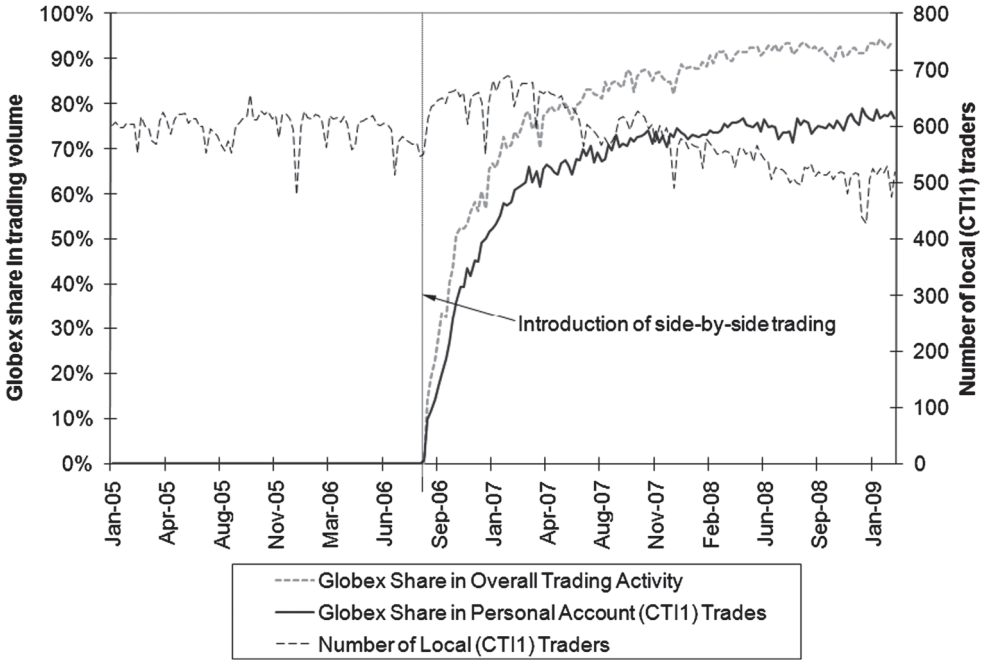

FIGURE 1
Number of local traders and Globex share in trading volume.

2.3. Trading Profits and Trader Exits

To estimate trading revenues, we follow Fishman and Longstaff (1992) by computing the difference between the settlement and trade prices, multiplying by the signed trade quantity (positive for buys and negative for sells) and cumulating over all trades for a given trader during a particular week. In order to find total portfolio revenues, personal account revenues are summed over all markets that a particular trader traded each week. To enjoy member trading privileges (and to have his trades classified as CTI1), a trader must own or lease an exchange seat. To estimate trader profits, we use the NYMEX lease renewal rate as a proxy for fixed costs.

Table II shows summary statistics for personal account trading revenues and profits before and after the move to side-by-side trading.[5] The profit is calculated as weekly revenue minus the average weekly lease renewal rate. The median

[5]To eliminate transient traders, this table and the rest of the study examines only local traders who executed personal account trades on at least ten days in the sample, which is similar to the culling process used by Locke and Mann (2005). The removal of transient traders from our sample eliminated 210 traders and left us with a sample of 1,065 traders. Although the percentage of transient traders comprised approximately 16% of the initial sample, these traders accounted for only 0.01% of the total trading volume.

TABLE II
Weekly Personal Account Trading Revenues and Profits

	Mean	*Median*	*St. Dev.*	*Observations*
Pure open outcry trading (1/3/05–9/1/06)				
Revenue	30.10	16.60	164.83	51,797
Profit	26.04	12.57	164.82	51,797
Side-by-side trading (9/5/06–2/27/09)				
Total Revenue	7.59	3.16	225.31	74,964
Total profit	6.49	2.21	225.30	74,964
Revenue from open outcry trading	5.68	2.59	226.35	48,186
Revenue from electronic trading	4.87	0.79	158.95	60,573

The table presents weekly trading revenues and profits (in thousands of dollars) for personal account trading. Revenues and profits are aggregated across all four futures markets of the NYMEX energy complex. When a particular trader did not trade on the floor or on Globex in a given week during the side-by-side period, the corresponding floor or Globex revenue observation is treated as missing.

weekly profit declined by more than 80%, from about $12,600 in pure open outcry trading to about $2,200 under side-by-side trading. In side-by-side trading, floor trading revenues are higher than revenues from electronic trading.[6] This is consistent with the higher effective spreads on the floor shown in Table I and with locals playing a market-making role on the floor.

The dispersion of trader profits increased significantly in side-by-side trading. This increase in volatility of profits is due to a large increase in the incidence of extreme observations. For example, in pure open outcry trading, weekly revenues exceeding $1 million in absolute value were observed in only 0.25% of trader weeks. This percentage increased to 0.63% of trader weeks in side-by-side trading. Similarly, the maximum and minimum revenue observations are larger in absolute value during the side-by-side trading period. A possible reason behind the increase in the incidence of extreme revenue observations is that, despite our attempt to aggregate all of the major NYMEX's energy futures markets into a single data set, this data set leaves out several parts of the energy derivatives market, such as the options on futures, as well as the energy futures and options traded on the ICE. A trader may, for example, arbitrage between futures contracts on NYMEX and ICE by executing offsetting trades. Our data set includes only NYMEX futures trades, leading to profits from such arbitrage trades being measured with a potentially large error. Similarly, traders can use options to hedge their futures trades, and vice versa. After the introduction of side-by-side trading, it became easier for local traders to trade in different energy derivatives markets simultaneously, possibly making

[6]When a particular trader did not trade on the floor or on Globex in a given week, the corresponding floor or Globex revenue is treated as missing. Using revenue of zero for such observations would impart a downward bias to the mean and median revenues by trading platform.

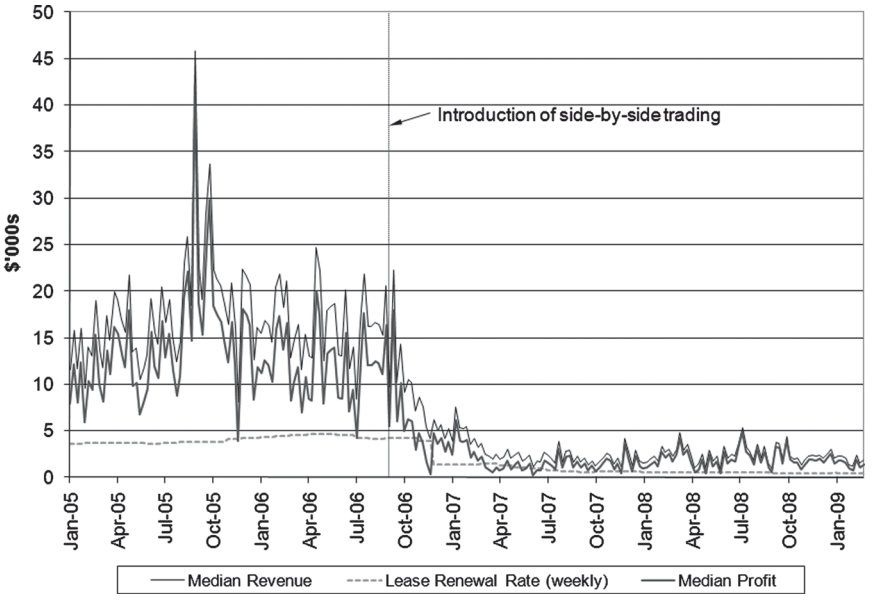

FIGURE 2
Median weekly revenues and profits for CTI1 personal account trading.

our revenue and profit measures noisier. In Section 5 of the study, we winsorize weekly profits at the 0.1 and 99.9 percentile to reduce influence of extreme values.

Figure 2 shows median weekly personal account trading revenues and profits for our sample period, as well as the average weekly lease renewal rates. The figure confirms a dramatic decline in local trader profitability immediately after the introduction of daytime electronic trading. The average weekly lease renewal rates also declined from about $4,200 immediately before the introduction of side-by-side trading to about $440 by the end of our sample period.

Panel A in Figure 3 shows the weekly number of local trader exits. A trader-week when a particular local trader appears in the data for the last time is classified as trader exit. In the pure open outcry period, floor trader exits are relatively rare, with less than one exit per week on average. The average number of failures per week increases to about 3.3 in the side-by-side trading period, suggesting a more difficult trading environment for local traders. Our sample during the side-by-side trading period includes 311 new traders and 690 incumbent traders, or those who were in the market before and after the introduction of side-by-side trading. The numbers of exits for these two groups of traders were 140 and 290, respectively. This implies a slightly higher attrition rate for new traders (about 45% vs. about 42% for incumbent traders). The

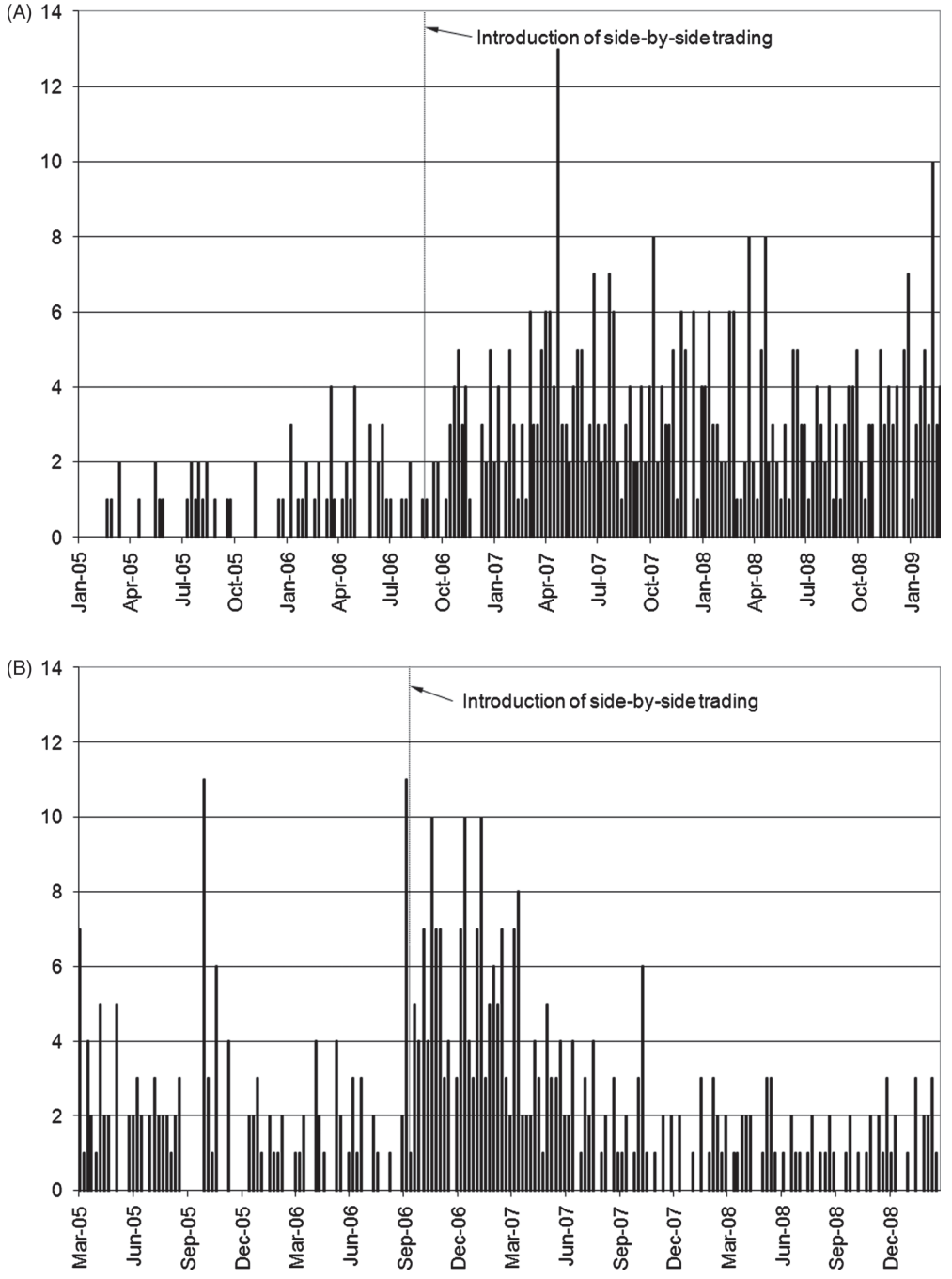

FIGURE 3
Weekly number of local trader exits and entrances. Panel A. Trader exits. Panel B. New trader entrances.

weekly number of new trader entrances (shown in Panel B of Figure 3) initially increases with the introduction of side-by-side trading, but then gradually declines.

It is also useful to examine how trading activity and profitability change before a trader's failure. Figure 4 presents this information for the period of 16 weeks immediately before a trader's exit. Following Coval and Shumway (2005), we standardize weekly profits and trading volumes by dividing them by trader-specific standard deviations. To remove patterns arising due to overall changes in the trading environment over the sample period, we demean standardized profits and trading activity variables used in Figure 4.

Panel A of the figure shows a gradual decline in the average trading activity in the weeks before a trader disappears from the sample. Panel B shows a relatively flat trajectory in average standardized profits, followed by a pronounced drop in performance in the last three weeks of trading. The figure also shows that exiting traders are less active and less profitable than average well before they exit the market.

3. THE ADAPTATION OF INCUMBENT TRADERS TO SIDE-BY-SIDE TRADING

As Figure 1 shows, the transition to electronic trading was not immediate, but rather occurred gradually over an approximately eight-month period from September 2006 through April 2007. Here we wish to examine the process of adaptation that incumbent traders went through when Globex was introduced. As such, we define an incumbent trader as one who traded both before and after the introduction of side-by-side trading. We omit traders who either exit the sample before the introduction of Globex or begin trading after the introduction of Globex.

After the introduction of side-by-side trading, locals had the ability (1) to continue trading only in the open outcry trading pit or (2) to trade on both platforms. The first option requires no immediate adaptation to take place, but dooms the trader to failure if the floor market withers away. The second option requires significant learning for the trader to adapt to electronic trading, and also allows the trader to use information generated in the trading pit to his advantage in the electronic marketplace. We classify incumbent traders into these two categories and examine the two categories separately. Out of 687 incumbent traders in the markets of the energy complex, 153 chose not to participate in trading on Globex and remain solely in the open outcry trading pits, and 534 traded in both the open outcry trading pits and on Globex.

We examine the trading characteristics of incumbent traders during two eight-month time periods immediately before and after the introduction of

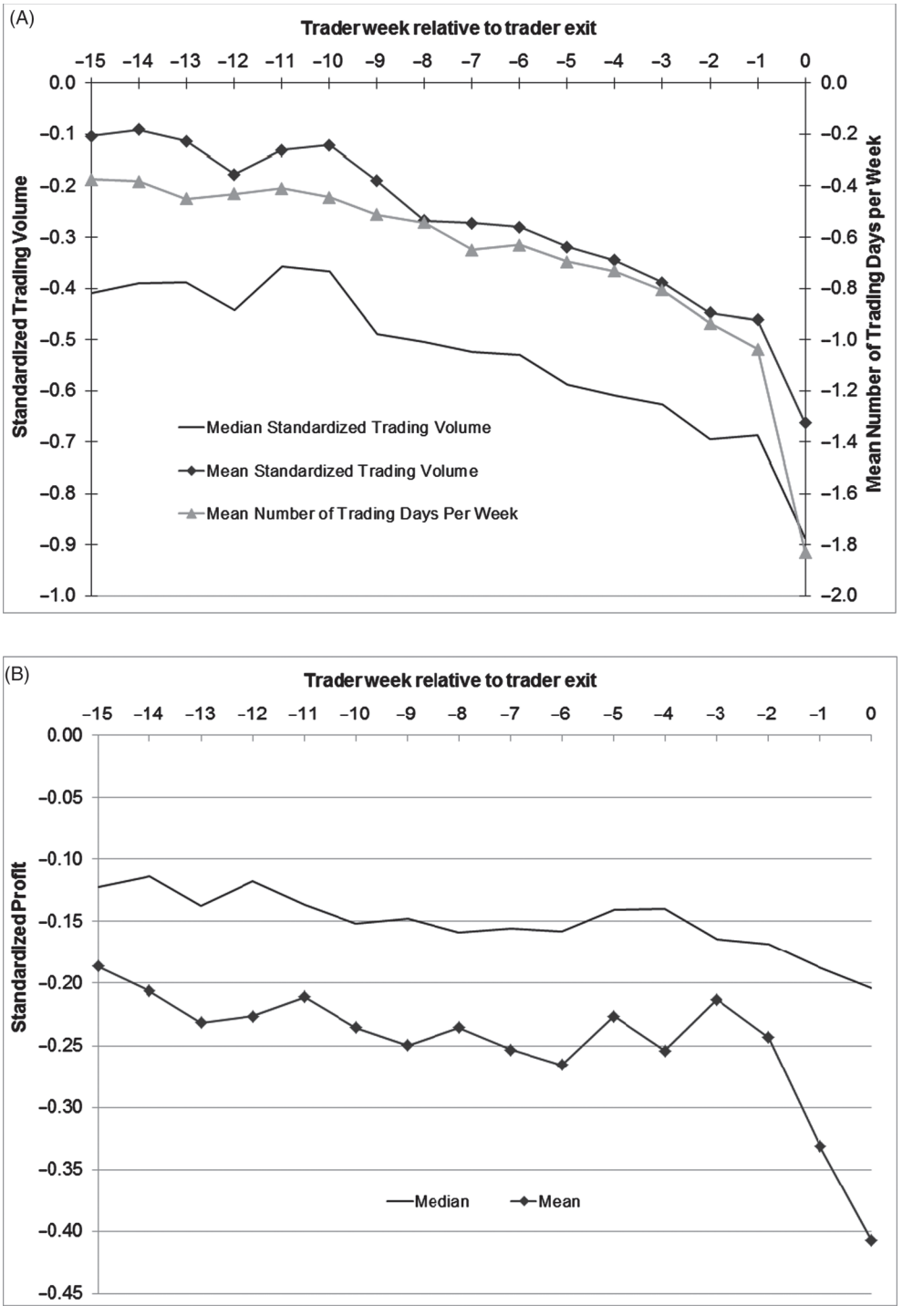

FIGURE 4

Personal account trading activity and profits before trader exits. Panel A. Demeaned personal account trading activity. Panel B. Demeaned standardized personal account profit. The sample includes 420 traders who appeared in the data for at least 16 weeks. Personal trading volume and profits are standardized by dividing them by trader-specific standard deviations and then demeaned by subtracting the mean for all traders for the corresponding week.

TABLE III
Incumbent Traders During the Transition Period

	Pure Open Outcry Trading 1/3/06–9/1/06		*Transition to Side-by-side Trading 9/5/06–4/30/07*	
	Category 1	*Category 2*	*Category 1*	*Category 2*
Number of incumbent traders	153	534	153	534
Mean daily volume per trader (contracts)	310.0	869.7	213.7	786.5
Mean daily total volume (contracts)	28,486	338,177	15,791	325,697
Mean daily number of trades per trader	26.5	64.1	16.3	136.5
Mean trade size (contracts)	11.70	13.57	13.08	5.76
Mean daily revenue	3.96	8.71	0.10	3.54
Median daily revenue	2.21	4.28	0.97	1.80
Number of trader days	15,437	65,327	11,968	67,503
Number of trader exits[a]	–	–	41	36
Exits as percentage of incumbent traders[a]	–	–	26.8%	6.7%

The table presents information on incumbent traders, i.e., those who traded both before and after the introduction of side-by-side trading, during the transition period (eight months before and eight months after the introduction of side-by-side trading). In both subperiods, traders are divided into two categories: (1) traders who traded only through open outcry during the transition to side-by-side trading, and (2) traders who traded on both platforms during the transition. The sample includes only incumbent traders who made personal account trades in at least two weeks during the eight-month period before the introduction of side-by-side trading. Both buy and sell trades are included in calculation of volume and number of trades. The mean daily total volume includes only trading volume for the given category of incumbent traders.

[a]These statistics are not reported for the pure open outcry trading time period because, by definition, an incumbent trader is one who was in the sample before and after the introduction of electronic trading, and, as such, could not have experienced failure during the pit only time period. Traders did experience failure during this time period, but those traders are excluded from the subsample used to study the transition period.

electronic trading and partition the sample based on the two trader categories identified above. The first period is evaluated to provide a baseline of trading activity and performance before the shift in market structure. The second period is studied to evaluate changes that followed the introduction of the new electronic trading platform. Table III provides statistics identified in the extant literature (i.e., Kuserk & Locke, 1993) to describe the trading characteristics of local traders in futures markets, which include the average daily volume per trader, average daily total volume for the particular trader category, average number of trades per trader, and average trade size per trader. We also document the average and median daily revenue, the number of trader days, and the number of trader exits.

Floor traders who chose not to participate in trading on Globex account for only a small portion of the local trading in the side-by-side period, indicating that these traders were relatively inactive. Traders who participated only on the floor struggled to stay profitable, with median daily revenues of approximately $970, which was less than half of their pre-period level of $2,210. For traders who remained in the open outcry trading pits throughout the sample period, their daily average volume and the number of trades decreased,

whereas their average daily trade size increased with the onset of electronic trading. Out of 153 traders in this category, 26.8% exited after the introduction of side-by-side trading as compared to 6.7% of traders who exited from the group of traders who utilized both trading platforms. This provides evidence that trading on the floor and electronically may result in a higher probability of survival due to higher overall profits.

For traders who participated in both markets, the level of activity was significantly higher than those who remained in the open outcry trading pits. The average total personal account trading volume declined somewhat with the onset of side-by-side trading, whereas the daily number of trades more than doubled. The median daily revenues of this set of traders fell by more than 50%. The large increase in the number of trades per trader, along with the reduction in the trade size, indicates that this set of incumbent traders had to drastically change the way in which they traded with the onset of electronic trading. With increased competition, traders had to adapt to the new trading environment by processing more trades.

In the eight months preceding the introduction of side-by-side trading, 36 traders who started trading before January 2006 exited the market. This compares to 77 incumbent trader failures in the eight months following the introduction of Globex. Given the increased attrition rate under side-by-side trading, we now turn to an evaluation of the determinants of trader survival to study whether certain trader characteristics increase the chance of survival after the shift in market structure.

4. KEY VARIABLES AND HYPOTHESES

Multiple factors may affect the overall success and survival of traders in futures markets. We consider the following trader characteristics that are likely to influence trader profitability and the probability of survival:

(1) *Experience*: Trading in the NYMEX energy complex involves a high degree of knowledge about and specialization in energy markets, as well as the ability to react quickly to changes in these volatile markets. Such abilities are acquired through experience. Traders also tend to become better at trading with experience (e.g., Seru et al., 2010). Thus, experience is likely to increase trader performance and probability of survival through increased trading skill and ability to adapt to changing market conditions. We measure trader experience at week t as the number of days on which a trader has placed a trade up to and including week t. At the beginning of our sample period, this variable is equal to zero for all traders in the sample.

(2) *Trader sophistication*: Liu, Wang, and Zhao (2010) use combination orders, i.e., orders that combine put and call options, as a proxy for sophistication

for options traders. Non-regular trades in futures markets, such as calendar and intercommodity spread trades, also involve the trading of several futures contracts and account for about half of the personal trading volume in our sample.[7] To use spreads a trader must follow several contract maturities or several markets simultaneously and understand the fundamental factors driving their relative prices. Therefore, traders using spreads and other non-regular type trades are likely to be more sophisticated than traders using primarily regular trades.[8] We use the percentage of personal trading volume (with the volume expressed in dollars of notional contract value) in non-regular type trades as a proxy for trader sophistication. Similar to experience, trader sophistication should positively influence trader performance and adaptability.[9]

(3) *Dual trading status*: Dual trading has been shown to benefit futures traders in two ways: first, dual traders may glean useful information from customer order flow (e.g., Menkveld, Sarkar, & van der Wel, 2011); and second, brokerage commissions charged on customer trades provide an additional source of income that may be especially helpful in periods with low personal account trading income. Following Chakravarty and Li (2003) and Menkveld et al. (2011), we classify a trader as a dual trader in weeks when his trading volume for customer accounts is between 2 and 98% of his total trading volume, with the trading volume expressed in dollars of notional contract value. Based on this criterion, approximately one-third of the total number of trader weeks in the sample fall in the dual trading category.

(4) *The degree of specialization in a particular market of the NYMEX's energy complex*. Kuserk and Locke (1993) show that floor traders tend to specialize in a particular commodity rather than a portfolio of commodities. Some of this specialization is undoubtedly due to physical constraints of pit trading. A trader's exclusive focus on a single trading pit also helps him establish a reputation as a reliable counterparty and build trading relationships with other traders in the same pit. Therefore, the degree of specialization may have a positive effect on trader survival in floor markets. In electronic trading, however, the above considerations no longer apply, potentially making trading in multiple markets more attractive.

To measure the degree of market concentration in personal account trading, we compute a Herfindahl-like index for trader i in week t as $FOCUS_{it} = \sum_{j=1}^{4} s_{ijt}^2$, where s_{ijt} is the percentage of personal trading volume for

[7]Spread trades account for about 90% of the volume of non-regular type trades.

[8]The notion that trading spreads requires a certain degree of sophistication is a commonly held view in practice and is frequently noted in articles on the basics of trading in futures markets. Here, we attempt to formalize this notion to capture the degree of sophistication of a trader by analyzing the percentage of their volume traded in non-regular trades such as spreads.

[9]Feng and Seasholes (2005) show that experienced and sophisticated investors are less prone to behavioral biases.

that trader and week in market *j*. This variable can range from 1/4 if the trader splits his trading volume equally among the four markets to 1 if the trader uses only one market in a given week. The average value of this index in the pure floor trading period is about 0.94, with about 22% of trader weeks containing trades in more than one market. In the side-by-side trading period, the average value of the concentration index is 0.87, with about 41% of trader weeks containing trades in several markets.

(5) *Trading style*: Speculators in futures markets are traditionally classified as scalpers, day traders, or position traders. Scalpers tend to behave as market makers, attempting to buy at the bid and sell at the offer. These traders trade frequently and quickly reduce their inventory. Day traders have a somewhat longer trading horizon and attempt to profit from price changes that take place over the course of one trading day. Most local traders (presumably scalpers and day traders) end the trading day with a zero inventory level (e.g., Manaster & Mann, 1996).

We use three variables to identify scalpers: trading frequency, median trade holding time, and average end-of-day inventory as a percentage of the trader's personal trading volume.[10] Trading frequency is computed as the average number of trades per day.[11] Trade holding times are measured using the methodology of Locke and Mann (2005). This approach involves tracking position changes for a given trader over a trading day and computing weighted average holding times for the open position after each trade. If a trader increases his position, the position holding time is reduced. If the position is reduced but not eliminated, the holding time of the remaining position increases. Following Locke and Mann (2005), we use holding times for completed trades, computed at the time when a position is reduced, eliminated, or reversed.[12] We classify scalpers as traders who are in the bottom half of the median trade holding time, top half of trading frequency, and the bottom half of average end-of-day inventory. The percentile rankings are performed separately for each week in the sample to account for changes in distributions over time. Based on our classification, scalpers account for about 25% of trader weeks in the sample.

Position traders trade relatively infrequently and often keep open positions overnight. As Manaster and Mann (1996, p 957) note, our data set is not well suited for tracking inventory changes over intervals longer than a day; therefore, to identify position traders we use end-of-day inventory and trading frequency. Traders in the bottom half of trading frequency and the top quartile of average

[10]Kuserk and Locke (1993) use a somewhat similar set of measures to select scalpers.

[11]A single trade is often split into several trade executions, especially in electronic trading, as a market order walks up or down the limit order book. To compute the number of trades, we aggregate multiple trade executions of the same type (buy or sell) with the same execution time into a single trade.

[12]In calculation of trade holding times, we assume that any positions remaining open at the close of the regular trading session are closed at that time.

end-of-day inventory are classified as position traders. Based on this classification, position traders account for about 21% of trader weeks in the sample.

The effect of trading style on profitability and probability of survival may depend on the trading mechanism. In particular, scalping is well suited to traditional open outcry trading, because scalpers take short-term positions using short-lived information generated in the trading pit. When much of the trading activity shifted to the electronic platform, the informational advantage enjoyed by locals over off-floor traders may have diminished, making scalping more difficult.

(6) *Specialization in open outcry or electronic trading during the side-by-side period*: Many traders successfully adapted to the side-by-side trading and use both the floor and Globex for their personal trading. Some floor traders, however, continued trading exclusively on the floor after introduction of daytime electronic trading on NYMEX. Kurov and Lasser (2004) provide evidence that floor traders may be able to extract information from the order flow in the open outcry trading pits to trade profitably on Globex. These traders are also uniquely positioned to arbitrage between open outcry and electronic execution platforms. Therefore, traders using both trading platforms may have a survival advantage over their counterparts who are using only one of the platforms.

The considerations above lead to the following hypotheses:

Hypothesis 1: Trading experience has a positive effect on trader profitability and probability of trader survival.

Hypothesis 2: Trader sophistication has a positive effect on trader profitability and probability of trader survival.

Hypothesis 3: Dual trading increases trading profits and probability of trader survival.

Hypothesis 4: Traders trading in multiple markets of the energy complex have a survival advantage, particularly in side-by-side trading.

Hypothesis 5: The effect of trading style on profitability and probability of trader survival depends on the trading mechanism.

Hypothesis 6: Traders using both trading platforms in side-by-side trading are more likely to survive than those who trade exclusively on the floor or only on Globex.

Exchange locals are trading professionals with heterogeneous levels of trading skill (e.g., Manaster & Mann, 1996). Electronic trading requires different skills than does traditional pit trading. It is an empirical question as to whether

locals who exhibited superior performance in open outcry trading remain superior traders in side-by-side trading. We test the following hypothesis:

Hypothesis 7: Trading profits of incumbent traders in side-by-side trading are positively related to their average profits in pure open outcry trading.

According to Massimb and Phelps (1994), "compared with open outcry, an electronic matching system imposes additional costs and risks on the local." Chow, Lee, and Shyy (1996) note that, given a choice between open outcry and electronic trading, exchange locals prefer floor trading because it allows them to use their trading skills and provides them with access to valuable information, such as the ability to observe behavior of other traders, hear ambient noises on the floor, etc. Floor trading activity and, therefore, the amount of information aggregated and generated in the trading pits, declined significantly after the introduction of side-by-side trading. To test whether the increased attrition of locals in side-by-side trading apparent in Figure 3 can be fully explained by the large decline in trading profits, we propose the following hypothesis:

Hypothesis 8: Controlling for trading profits, the introduction of side-by-side trading increases trader attrition.

5. EMPIRICAL RESULTS

5.1 Analysis of Trader Profits

Few profitable traders quit trading. Therefore, before turning to the analysis of trader survival, we examine determinants of trading profits. In addition to setting the stage for the survival analysis, this subsection tests several of our hypotheses relating to trader profits. The baseline regression specification is as follows:

$$Profit_{it} = \alpha_i + \beta_1 EXPER_{it} + \beta_2 EXPER_{it}^2 + \beta_3 NRT_{it} + \beta_4 DUAL_{it} + \beta_5 FOCUS_{it} + \beta_6 SCALPER_{it} + \beta_7 PTR_{it} + \varepsilon_{it}, \quad (1)$$

where $Profit_{it}$ is the standardized profit, $EXPER_{it}$ is the number of days (divided by 100) up until the end of week t on which a particular trader has placed a personal account trade, NRT_{it} is the percentage of non-regular type trades in the personal trading volume, $DUAL_{it}$ is the dummy variable for dual traders, $FOCUS_{it}$ is the Herfindahl-type index representing concentration of personal trading volume in a particular energy futures market, $SCALPER_{it}$ is the dummy variable for scalpers, and PTR_{it} is the dummy variable for position traders. The

model for the side-by-side period also includes dummy variables for trader-weeks with exclusively floor or exclusively Globex personal trading. All variables are measured at weekly intervals. To account for time variation in average profits and for trader heterogeneity, the model is estimated with period and/or individual fixed-effects.[13]

We estimate the model separately for the pure open outcry period, for incumbent local traders during the transition period from September 5, 2006 to April 27, 2007, for all local traders in the entire side-by-side trading period, and finally for the full sample period. The estimation results for all of these sample partitions are shown in Table IV. Consistent with hypothesis 1, in both the pure outcry period and side-by-side period, there is a significant positive relation between standardized profits and trader experience. The proxy for sophistication (the percentage of non-regular type trades) also has a significant positive effect on trading profits, which provides some support to hypothesis 2. On the other hand, one could argue that using non-regular trades increases the profits of a trader because such trades are more difficult to execute and are, therefore, more profitable on average. If this is the case, the positive relationship between sophistication and trader profitability would be driven by the higher associated profits earned by traders who engage in non-regular trades.

We examined whether non-regular type trades are in fact more profitable on average than regular trades. We found the opposite: non-regular trades tend to be significantly less profitable on a per contract basis than regular trades. Non-regular type trades also tend to be much larger than regular trades. Spread trades have less volatility and require lower margin requirements than regular trades, and traders use them to control the overall portfolio risk. The finding of lower profitability of non-regular trades is in line with the traditional risk-return tradeoff. We conclude that our results relating to the effect of trader sophistication on profitability are not being driven by higher profits earned from more complex trades.

Dual trading status is also positively related to profitability. Traders who focus on a single market of the energy complex tend to perform significantly better than less focused traders in pure open outcry trading.

To test hypothesis 7, we estimate the model for the incumbent traders during the transition period with the average standardized profit for a given trader in the eight-month period before the introduction of side-by-side trading included as an additional regressor.[14] This variable, named *Profit Before*, serves as a proxy for trading skill in open outcry trading. Consistent with hypothesis 7,

[13]We use panel-corrected standard errors that adjust for contemporaneous correlation and heteroskedasticity across traders.

[14]Because the *Profit Before* variable is fixed for a given trader, we omit the individual fixed effects from this estimation to avoid perfect multicollinearity.

TABLE IV

Determinants of Personal Account Trading Profits

	Pure Open Outcry Trading	*Incumbent Traders During Transition Period*		*Side-by-side Trading*	*Full Sample Period*	
Fixed effects	Period and Indiv.	Period and Indiv.	Period	Period and Indiv.	Period and Indiv.	Individual
EXPER	0.468 (0.060)***	−0.008 (0.122)	0.028 (0.032)	0.064 (0.017)***	0.084 (0.014)***	0.047 (0.021)**
$EXPER^2$	−0.068 (0.011)***	−0.046 (0.010)***	−0.005 (0.005)	−0.008 (0.001)***	−0.010 (0.001)***	−0.007 (0.002)***
NRT	0.102 (0.041)**	0.122 (0.038)***	0.261 (0.025)***	0.056 (0.018)***	0.035 (0.016)**	0.045 (0.018)**
DUAL	0.077 (0.021)***	0.043 (0.025)*	0.060 (0.014)***	0.040 (0.012)***	0.089 (0.010)***	0.096 (0.010)***
FOCUS	0.139 (0.066)**	0.227 (0.069)***	0.142 (0.052)***	0.038 (0.028)	0.142 (0.027)***	0.177 (0.030)***
SCALPER	0.281 (0.018)***	0.087 (0.021)***	0.101 (0.017)***	0.059 (0.010)***	0.160 (0.009)***	0.157 (0.009)***
PTR	−0.345 (0.030)***	−0.166 (0.033)***	−0.138 (0.025)***	−0.116 (0.015)***	−0.252 (0.015)***	−0.260 (0.015)***
Profit Before	–	–	0.366 (0.030)***	–	–	–
SBS	–	–	–	–	–	−0.430 (0.045)***
Only Floor	–	−0.003 (0.024)	−0.077 (0.017)***	0.045 (0.017)***	–	–
Only Globex	–	−0.114 (0.030)***	−0.201 (0.026)***	−0.107 (0.014)***	–	–
Sample period	1/3/05–9/1/06	9/5/06–4/30/07	9/5/06–4/30/07	9/5/06–2/27/09	1/3/05–2/27/09	1/3/05–2/27/09
Number of traders	770	687	687	1,000	1,064	1,064
Observations	51,797	19,663	19,663	74,963	126,760	126,760
R^2	0.283	0.195	0.114	0.165	0.226	0.193

The table reports coefficients for the following panel regression (base specification):

$$Profit_{it} = \alpha_i + \beta_1 EXPER_{it} + \beta_2 EXPER_{it}^2 + \beta_3 NRT_{it} + \beta_4 DUAL_{it} + \beta_5 FOCUS_{it} + \beta_6 SCALPER_{it} + \beta_7 PTR_{it} + \varepsilon_{it},$$

where $Profit_{it}$ is the standardized profit, $EXPER_{it}$ is the number of days (divided by 100) up until the end of week t on which a particular trader has placed a personal account trade, NRT_{it} is the percentage of nonregular type trades in the personal trading volume, $DUAL_{it}$ is the dummy variable for dual traders, $FOCUS_{it}$ is the Herfindahl-type index representing concentration of personal trading volume in a particular energy futures market, $SCALPER_{it}$ is the dummy variable for scalpers, and PTR_{it} is the dummy variable for position traders. $Profit\ Before_i$ is the average standardized profit for incumbent trader i over the period from January 3, 2006 to September 1, 2006. SBS_t is a dummy variable that is equal to one after the introduction of side-by-side trading on September 5, 2006. *Only Floor* and *Only Globex* are dummy variables for trader weeks with exclusively floor or exclusively Globex personal trading, respectively. All variables are measured at weekly intervals. Panel-corrected standard errors that adjust for contemporaneous correlation and heteroskedasticity across traders are shown in parentheses. *, **, *** indicate that the coefficient is statistically significant at 10, 5, and 1% levels, respectively.

the coefficient estimate of this variable shown in Table IV is positive and strongly significant, indicating that good open outcry traders continue earning above-average profits in side-by-side trading. The results for the full sample period with a dummy variable for side-by-side trading are shown in the last column of Table IV. The coefficient estimate of this dummy confirms that the introduction of side-by-side trading was followed by a significant decline in average trading performance.

5.2 Analysis of Trader Survival

Survival analysis is used for studying the occurrence and timing of certain events, where an event is defined as a qualitative change that can be situated in time (e.g., Allison, 1995). A survival model describes the probability distribution of event times. Survival models are widely used in the biological and medical sciences. Such models have also been used in financial research. For example, Lo, MacKinlay and Zhang (2002) use survival modeling to examine the determinants of limit order executions. We apply a survival model to study the probability that a trader will exit the sample, i.e., will fail to survive.

A trader begins trading at $t = 0$, which is either the first week of the sample estimation period or the first week that the trader appears in our sample, whichever is later. We are interested in determining the factors affecting the likelihood that the trader will quit trading at time t. We model this likelihood using the Cox hazard regression. This model has two attractive features. First, as opposed to the accelerated failure model that is also used in survival analysis, the Cox regression does not require assumption of a probability distribution for survival times. Secondl the Cox hazard model accommodates time-varying covariates. This feature of the Cox model is useful because the trader characteristics that we examine change over time, and such changes may affect the probability of trader failure. The model represents the hazard of individual i at time t as a function of k time-varying covariates as follows:

$$h_{it} = h_{0t}\exp(\beta_1 x_{i1t} + \cdots + \beta_k x_{ikt}),$$

where h_{0t} is an unspecified non-negative baseline hazard function. In a log-linear form, the model becomes:

$$\log h_{it} = \alpha_t + \beta_1 x_{i1t} + \cdots + \beta_k x_{ikt},$$

where $\alpha_t = \log h_{0t}$.

A juxtaposition of median trading profits shown in Figure 2 with the number of trader exits in Figure 3 suggests a strong relation between profits and trader survival. Figure 4 shows a large decline in average standardized trading

profits in the weeks before a trader exits. Trader characteristics discussed in Section 4 may affect trader survival either directly or through their effect on trading profits or, more likely, both. In other words, the effect of trader characteristics on survival may not be fully captured by profits. To examine the effect of profits on trader survival, as well as the effect of our other explanatory variables, controlling for profits, we include the standardized personal account trading profit in the survival model. To test whether traders are more likely to exit trading after a streak of losses, we include the number of losing weeks for trader i in the last five trading weeks as another covariate. We test our hypotheses relating to survival of local traders using the following Cox regression:

$$\log h_{it} = \alpha_t + \beta_1 Profit_{it} + \beta_2 LW_{it} + \beta_3 EXPER_{it} + \beta_4 NRT_{it} + \beta_5 DUAL_{it} + \beta_6 FOCUS_{it} + \beta_7 SCALPER_{it} + \beta_8 PTR_{it}, \quad (2)$$

where h_{it} is the hazard of trader failure, LW_{it} is the number of losing weeks for trader i in the last five weeks of trading. The remaining variables are defined in the previous subsection.[15] The model for the side-by-side period also includes a dummy variable for traders who started trading during the open outcry period. The model is estimated for the same four sample partitions as the profits regression in the previous subsection. The survival time for a particular trader is divided into a series of intervals, where the length of each interval represents the number of calendar weeks between the end of week t and the end of the previous week when the trader appeared in the sample. The trader survival status is represented by an indicator variable that, for example, takes the value of 1 if an event (trader failure) occurred in that interval and 0 if the event has not occurred (signifying a censored observation). As trader failures are only present in a small proportion of trader weeks, the percentage of censored observations exceeds 99% in all cases.

The survival model estimation results are shown in Table V. As expected, higher profits reduce the trader failure hazard. Controlling for current profits, the number of recent losing weeks is strongly positively related to failure hazard across the four sample partitions. In the full sample, one additional loosing week in the last five weeks of trading increases failure hazard by about 40%.

Supporting hypothesis 1, the proxy for trader experience is negatively related to the hazard of trader failure. The hazard ratio of this coefficient during the pure open outcry period is about 0.41.[16] This means that for a 100-day

[15]If the square of the experience variable is included in the model, the coefficient estimates of *EXPER* and $EXPER^2$ become insignificant. Adding the squared experience term in the survival model reduces the model fit adjusted for the number of parameters, as measured by the Schwarz criterion (SBC). We also performed a robustness check that showed that the effect of experience on failure hazard is approximately linear.

[16]The hazard ratio for coefficient β_k is simply e^{β_k}.

TABLE V

Survival Model Estimates

	Pure Open Outcry Trading		*Incumbent Traders During Transition Period*		*Side-by-side Trading*		*Full Sample Period*	
	Coefficient	*Hazard Ratio*	*Coefficient*	*Hazard Ratio*	*Coefficient*	*Hazard Ratio*	*Coefficient*	*Hazard Ratio*
Profit	−0.30 (0.09)***	0.74	−0.27 (0.12)***	0.76	−0.18 (0.05)**	0.84	−0.21 (0.04)***	0.81
LW	0.39 (0.10)***	1.48	0.33 (0.09)***	1.40	0.27 (0.04)***	1.32	0.34 (0.04)***	1.40
EXPER	−0.89 (0.21)***	0.41	−0.22 (0.09)**	0.81	−0.05 (0.04)	0.95	−0.13 (0.03)***	0.88
NRT	−1.76 (0.38)***	0.17	−0.29 (0.35)	0.75	−0.52 (0.16)***	0.59	−0.61 (0.14)***	0.54
DUAL	−1.34 (0.35)***	0.26	−0.48 (0.28)*	0.62	−0.17 (0.13)	0.84	−0.41 (0.12)***	0.66
FOCUS	0.16 (0.87)	1.17	1.08 (0.80)	2.95	0.97 (0.31)***	2.65	0.85 (0.28)***	2.35
SCALPER	−1.26 (0.54)**	0.28	0.13 (0.33)	1.13	0.33 (0.13)***	1.39	0.18 (0.13)	1.19
PTR	0.19 (0.34)	1.20	−0.73 (0.33)**	0.48	0.04 (0.14)	1.04	0.24 (0.12)**	1.27
Only Floor	–	–	1.52 (0.35)***	4.55	1.15 (0.19)***	3.15	–	–
Only Globex	–	–	0.99 (0.37)***	2.71	0.98 (0.16)***	2.67	–	–
SBS	–	–	–	–	–	–	0.85 (0.17)***	2.33
Incumbent Trader	–	–	–	–	0.23 (0.16)	1.26	–	–
Sample period	1/3/05–9/1/06		9/5/06–4/30/07		9/5/06–2/27/09		1/3/05–2/27/09	
Observations	48,763		19,637		73,746		122,509	
Number of Failures	60		77		430		490	

The table reports coefficients for the following Cox survival regression (base specification):

$$\log h_{it} = \alpha_t + \beta_1 Profit_{it} + \beta_2 LW_{it} + \beta_3 EXPER_{it} + \beta_4 NRT_{it} + \beta_5 DUAL_{it} + \beta_6 FOCUS_{it} + \beta_7 SCALPER_{it} + \beta_8 PTR_{it},$$

where h_{it} is the hazard of trader failure, $\alpha_t = \log h_{0t}$ is a baseline hazard rate, $Profit_{it}$ is the standardized profit, LW_{it} is the number of losing weeks for trader i in the last five weeks of trading, $EXPER_{it}$ is the number of days (divided by 100) up until the end of week t on which a particular trader has placed a personal account trade, NRT_{it} is the percentage of nonregular type trades in the personal trading volume, $DUAL_{it}$ is the dummy variable for dual traders, $FOCUS_{it}$ is the Herfindahl-type index representing concentration of personal trading volume in a particular energy futures market, $SCALPER_{it}$ is the dummy variable for scalpers, and PTR_{it} is the dummy variable for position traders. *Only Floor* and *Only Globex* are dummy variables for trader weeks with exclusively floor or exclusively Globex personal trading, respectively. SBS_t is a dummy variable that is equal to one after the introduction of side-by-side trading on September 5, 2006. *Incumbent Trader*$_i$ is a dummy variable for traders who started trading before introduction of side-by-side trading. All variables are measured at weekly intervals. Standard errors are shown in parentheses. *, **, *** indicate that the coefficient is statistically significant at 10, 5, and 1% levels, respectively.

increase in trading experience the hazard of failure declines by about 59% ($0.41 - 1 = -0.59$). The coefficient estimate of the experience variable for the side-by-side trading period is also negative, although it is not statistically significant. A possible explanation for the relatively weak effect of experience on survival in side-by-side trading is that traders with the most experience were incumbent traders who primarily had experience of open outcry trading. To test this conjecture, we re-estimate the survival model after decomposing the experience variable into open outcry experience and experience in side-by-side trading. The results reported in Table VI show that the experience of side-by-side trading has a strong negative effect on failure hazard.

As shown in Table V and consistent with our second hypothesis, trader sophistication, proxied by the percentage of non-regular type trades, also reduces failure hazard in both sub-sample periods. The negative coefficient estimate of the dual trading dummy indicates that dual traders are less likely to fail. The effect of dual trading on survival is especially strong in the pure floor trading period, implying a decline of the probability of failure for dual traders of about 74%. This finding supports hypothesis 3. The relatively weak effect of dual trading on survival in side-by-side trading is consistent with lower demand for floor broker intermediation under this trading mechanism. The degree of concentration of personal trading in a particular energy market has no significant effect on trader failure hazard during the pure open outcry period. In contrast, traders who trade in multiple energy markets seem to have a significant survival advantage in side-by-side trading. This result lends some support to hypothesis 4.

Consistent with hypothesis 5, the survival model estimates in Table V show that the effect of trading style on the probability of trader survival depends on the trading mechanism. In pure floor trading, scalpers appear to have a significant survival advantage. In the side-by-side trading period, however, scalping seems to increase failure hazard. Scalpers tend to act as market makers in open outcry futures markets, maintaining bid-ask spreads to compensate them for providing liquidity. Their ability to trade profitably depends on short-lived information signals generated in open outcry trading pits. The bid-ask spreads collapsed with the introduction of electronic trading. The floor trading activity declined, possibly eroding the informational advantage enjoyed by locals over off-floor traders. These changes are likely to contribute to the high failure rate of scalpers in side-by-side trading.

Further, traders who trade exclusively on the floor or only on Globex have much higher failure hazard than traders who use both trading platforms in side-by-side trading. For example, based on the estimated hazard ratio, for traders who trade only on the exchange floor, the failure hazard is more than three times as high as for traders who utilize both trading platforms. These

TABLE VI
Survival Model Estimates with Open Outcry and Side-by-side Experience

	Incumbent Traders During Transition Period		*Side-by-side Trading*	
	Coefficient	*Hazard Ratio*	*Coefficient*	*Hazard Ratio*
Profit	−0.28 (0.12)***	0.75	−0.18 (0.05)**	0.83
LW	0.31 (0.09)***	1.37	0.26 (0.04)***	1.30
OOEXPER	**−0.11 (0.12)**	**0.90**	**0.10 (0.06)***	**1.10**
SBSEXPER	**−1.13 (0.52)****	**0.32**	**−0.24 (0.06)*****	**0.78**
NRT	−0.24 (0.35)	0.79	−0.45 (0.16)***	0.64
DUAL	−0.43 (0.28)	0.65	−0.13 (0.13)	0.87
FOCUS	0.96 (0.79)	2.62	0.83 (0.31)***	2.30
SCALPER	0.12 (0.33)	1.13	0.33 (0.13)***	1.39
PTR	−0.73 (0.33)**	0.48	0.08 (0.14)	1.09
Only Floor	1.36 (0.36)***	3.89	1.07 (0.19)***	2.93
Only Globex	0.98 (0.37)**	2.67	1.00 (0.17)***	2.71
Incumbent Trader	–	–	−0.06 (0.18)	0.94
Sample period	9/5/06–4/30/07		9/5/06–2/27/09	
Observations	19,637		73,746	
Number of Failures	77		430	

The table reports coefficients for the following Cox survival regression:

$$\log h_{it} = \alpha_t + \beta_1 Profit_{it} + \beta_2 LW_{it} + \beta_3 OOEXPER_{it} + \beta_4 SBSEXPER_{it} + \beta_5 NRT_{it} + \beta_6 DUAL_{it}$$
$$+ \beta_7 FOCUS_{it} + \beta_8 SCALPER_{it} + \beta_9 PTR_{it} + \beta_{10} OnlyFloor_{it} + \beta_{11} OnlyGlobex_{it},$$

where h_{it} is the hazard of trader failure, $\alpha_t = \log h_{0t}$ is a baseline hazard rate, $Profit_{it}$ is the standardized profit, LW_{it} is the number of losing weeks for trader i in the last five weeks of trading, $OOEXPER_{it}$ is the number of days during the pure open outcry period (divided by 100) on which a particular trader placed a personal account trade, $SBSEXPER_{it}$ is the number of days during the side-by-side trading period (divided by 100) up until the end of week t on which a particular trader has placed a personal account trade, NRT_{it} is the percentage of nonregular type trades in the personal trading volume, $DUAL_{it}$ is the dummy variable for dual traders, $FOCUS_{it}$ is the Herfindahl-type index representing concentration of personal trading volume in a particular energy futures market, $SCALPER_{it}$ is the dummy variable for scalpers, and PTR_{it} is the dummy variable for position traders. *Only Floor* and *Only Globex* are dummy variables for trader weeks with exclusively floor or exclusively Globex personal trading, respectively. *Incumbent Trader*$_i$ is a dummy variable for traders who started trading before introduction of side-by-side trading. All variables are measured at weekly intervals. Standard errors are shown in parentheses. *, **, *** indicate that the coefficient is statistically significant at 10, 5, and 1% levels, respectively. The coefficients of primary interest are shown in bold.

results provide strong support to hypothesis 6. The coefficient estimate of the incumbent trader dummy is not statistically significant, indicating that, controlling for trader characteristics and performance, traders who started trading during the open outcry period are about as likely to exit the market as newer traders.

The estimates for incumbent traders during the initial transition to side-by-side trading presented in Table V show a large detrimental effect of trading only on the exchange floor on trader survival.[17] This finding is consistent with the counts of trader exits in Table III showing that traders who failed to adapt

[17]A large majority of incumbent traders trading only on the floor in week t have never traded on Globex up to the end of week t. Therefore, the *Only Floor* dummy can be viewed as a variable that identifies floor traders who failed to adapt to the new trading mechanism.

to the new hybrid trading mechanism accounted for a disproportionate share of trader failures after the introduction of side-by-side trading.

To test hypothesis 8 that the introduction of side-by-side trading increases trader attrition even after controlling for trading profits, we use the full sample period to estimate the survival model that includes a dummy variable for the side-by-side period. The results are shown in the last column of Table V. The coefficient estimate of the side-by-side dummy is positive and strongly significant. The corresponding hazard ratio indicates that, controlling for profits and trader characteristics, the probability of trader failure more than doubled in side-by-side trading. This finding lends evidence supporting hypothesis 8.

Overall, we find that trading profits, trader experience and sophistication, dual trading status, market specialization and trading style have strong effects on survival of futures traders. Most of these characteristics, with the exception of market specialization and trading style, have qualitatively similar effects on survival in pure floor trading and in side-by-side trading.

6. CONCLUSION

This research serves to evaluate the impact of an exogenous change in market structure on the behavior and survival of traders. Our data covers NYMEX's introduction of electronic trading on Globex and allows for the tracking of individual trading activity for exchange local traders. We study the shift of local traders from open-outcry to side-by-side trading. This shift creates a natural experiment to examine trader adaptation, profitability and survival under two different trading mechanisms: pure floor trading and side-by-side floor and electronic trading.

We find that most incumbent floor traders made a transition to the new market structure, although the rate at which they exit the market increased significantly. Most of these incumbent individual exchange locals also chose to utilize both trading platforms, which facilitated the use of information gleaned from order flow in the open outcry trading pits for transactions on Globex. Further, these traders had to adapt to the new, more competitive, trading environment, which eroded profits and required them to transact more frequently using smaller trades in order to survive. We find that skillful traders who showed superior profitability in pure open outcry trading continue to earn above-average profits in side-by-side trading.

Estimates of our survival model show that the survival of local traders is positively influenced by trader profitability, experience, sophistication, and dual trading under both trading mechanisms. In side-by-side trading, traders using several energy futures markets tend to survive longer. Furthermore, we show that locals who use both trading platforms have a survival advantage under side-by-side

trading compared to those who trade only on the floor or exclusively in the electronic market. We also find that scalpers have a survival advantage in pure open outcry trading, but are more likely than other traders to exit the market in side-by-side trading. This result is consistent with the notion that increased competition from off-floor limit order traders, sharply lower bid-ask spreads and declining floor trading activity have made scalping more difficult in side-by-side trading. Overall, we find that most local traders have been able to adapt to a dramatic change in the trading mechanism, although the surviving traders are not nearly as profitable as they were under pure open outcry trading.

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